

From Theoretical Results to Real-World Applications in Bonds, FX, Commodities and Cryptocurrencies: An Overview on Market Making

Olivier Guéant

FDD & FiME seminar – Sep. 2024

A personal note

Fond memories from 2009 or 2010.



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Remark: I mainly focused on market making in OTC markets. Not market making in limit order books (no tick size, no queue, no priority).

The early literature

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Models regarding inventory cost / management

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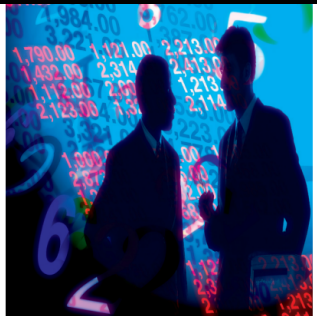
An economic literature about the determinants of bid-ask spreads in the 1980s and 1990s: Hasbrouck, Huang and Stoll, MRR, etc.

From economists to mathematicians

The financial mathematics community only got interested in market making from 2008 following the paper by Avellaneda and Stoikov.

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High-frequency trading in a limit order book

MARCO AVELLANEDA and SASHA STOIKOV*

Mathematics, New York University, 251 Mercer Street, New York, NY 10012, USA

Overview of my journey

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The roots

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- Post-PhD inspiration (2010): met C.-A. Lehalle (Crédit Agricole Cheuvreux) through J.-M. Lasry. Charles put in my hands Avellaneda-Stoikov's paper.

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- OTC trading (neglected area of academic research): Contacted by bond dealers and FX+commodity dealers in London and NYC, for adapting models to match real-world trading environments.

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Multiple interactions with the industry

- OTC trading (neglected area of academic research): Contacted by bond dealers and FX+commodity dealers in London and NYC, for adapting models to match real-world trading environments.
- DeFi: More recently contacted by decentralized finance players to build new Automated Market Makers.

Setup of the model (I)

One asset: reference price process ("mid"-price) $(S_t)_t$

Brownian dynamics

$$dS_t = \sigma dW_t.$$

→ Can be the CBBT / CP+ for corporate bonds or a homemade reference price.

→ Can be EBS / Refinitiv mid price or a homemade composite.

Setup of the model (II)

Bid and ask prices proposed by the MM

$$S_t^b = S_t - \delta_t^b \text{ and } S_t^a = S_t + \delta_t^a.$$

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for two point processes N^b and N^a .

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Competition and demand are modeled indirectly through the probability / intensity of jumps.

Setup of the model (III)

Intensities $(\lambda_t^b)_t$ and $(\lambda_t^a)_t$ of N^b and N^a

$$\lambda_t^b = \Lambda^b(\delta_t^b)1_{q_t < -Q} \text{ and } \lambda_t^a = \Lambda^a(\delta_t^a)1_{q_t > -Q}.$$

They depend on the distance to the reference price: Λ^b, Λ^a decreasing (of course!)

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Cash process $(X_t)_t$

$$dX_t = \Delta S_t^a dN_t^a - \Delta S_t^b dN_t^b = -S_t dq_t + \delta_t^a \Delta dN_t^a + \delta_t^b \Delta dN_t^b.$$

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Three state variables: X (cash), q (inventory), and S (price).

PnL and objective function

PnL at time T of a market maker

$$PnL_T = X_T + q_T S_T = X_0 + q_0 S_0 + \int_0^T \underbrace{\delta_t^a \Delta dN_t^a + \delta_t^b \Delta dN_t^b}_{\text{spread capture}} + \underbrace{\sigma q_t dW_t}_{\text{inventory+price risk}}$$

PnL and objective function

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The original Avellaneda-Stoikov's model considers a CARA utility (Model A):

CARA objective function

$$\sup_{(\delta_t^a)_t, (\delta_t^b)_t \in \mathcal{A}} \mathbb{E} [-\exp(-\gamma(X_T + q_T S_T))],$$

where γ is the absolute risk aversion parameter, and \mathcal{A} the set of predictable processes bounded from below.

HJB equation

HJB equation

In what follows, u is a candidate for the value function.

Hamilton-Jacobi-Bellman

$$\begin{aligned} \text{(HJB)} \quad 0 &= \partial_t u(t, x, q, S) + \frac{1}{2} \sigma^2 \partial_{SS}^2 u(t, x, q, S) \\ &+ 1_{q < Q} \sup_{\delta^b} \Lambda^b(\delta^b) [u(t, x - \Delta S + \Delta \delta^b, q + \Delta, S) - u(t, x, q, S)] \\ &+ 1_{q > -Q} \sup_{\delta^a} \Lambda^a(\delta^a) [u(t, x + \Delta S + \Delta \delta^a, q - \Delta, S) - u(t, x, q, S)] \end{aligned}$$

with final condition:

$$u(T, x, q, S) = -\exp(-\gamma(x + qS))$$

Change of variables

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Ansatz

$$u(t, x, q, S) = -\exp(-\gamma(x + qS + \theta(t, q)))$$

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New equation

$$0 = \partial_t \theta(t, q) - \frac{1}{2} \gamma \sigma^2 q^2$$

$$+ 1_{q < Q} \sup_{\delta^b} \frac{\Lambda^b(\delta^b)}{\gamma} (1 - \exp(-\gamma(\Delta \delta^b + \theta(t, q + \Delta) - \theta(t, q))))$$

$$+ 1_{q > -Q} \sup_{\delta^a} \frac{\Lambda^a(\delta^a)}{\gamma} (1 - \exp(-\gamma(\Delta \delta^a + \theta(t, q - \Delta) - \theta(t, q))))$$

with final condition $\theta(T, q) = 0$.

Equation for θ

A new transform

$$H_{\xi}^b(\rho) = \sup_{\delta} \frac{\Lambda^b(\delta)}{\xi \Delta} (1 - \exp(-\xi \Delta (\delta - \rho)))$$

$$H_{\xi}^a(\rho) = \sup_{\delta} \frac{\Lambda^a(\delta)}{\xi \Delta} (1 - \exp(-\xi \Delta (\delta - \rho)))$$

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New equation

$$0 = \partial_t \theta(t, q) - \frac{1}{2} \gamma \sigma^2 q^2 + 1_{q < Q} \Delta H_{\gamma}^b \left(\frac{\theta(t, q) - \theta(t, q + \Delta)}{\Delta} \right) \\ + 1_{q > -Q} \Delta H_{\gamma}^a \left(\frac{\theta(t, q) - \theta(t, q - \Delta)}{\Delta} \right)$$

with final condition $\theta(T, q) = 0$.

Another objective function

Variant (Cartea, Jaimungal *et al.*) with a running penalty:

Risk-neutral with running penalty (Model B)

$$\sup_{(\delta_t^a), (\delta_t^b) \in \mathcal{A}} \mathbb{E} \left[X_T + q_T S_T - \frac{\gamma}{2} \sigma^2 \int_0^T q_t^2 dt \right]$$

i.e.

$$\sup_{(\delta_t^a), (\delta_t^b) \in \mathcal{A}} \mathbb{E} \left[\int_0^T \left(\Delta \delta_t^a \wedge^a (\delta_t^a) \mathbf{1}_{q_{t-} > -Q} + \Delta \delta_t^b \wedge^b (\delta_t^b) \mathbf{1}_{q_{t-} < Q} - \frac{\gamma}{2} \sigma^2 q_t^2 \right) dt \right]$$

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→ Optimal control on a very simple finite graph (truncated $\Delta\mathbb{Z}$)

Value function θ (Model B)

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Hamilton-Jacobi equation (Model B)

$$0 = \partial_t \theta(t, q) - \frac{1}{2} \gamma \sigma^2 q^2 + 1_{q < Q} \Delta H_0^b \left(\frac{\theta(t, q) - \theta(t, q + \Delta)}{\Delta} \right) \\ + 1_{q > -Q} \Delta H_0^a \left(\frac{\theta(t, q) - \theta(t, q - \Delta)}{\Delta} \right)$$

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Same kind of transform

$$H_0^b(p) = \sup_{\delta} \Lambda^b(\delta)(\delta - p)$$

$$H_0^a(p) = \sup_{\delta} \Lambda^a(\delta)(\delta - p)$$

Analysis

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Light assumptions of the intensity functions

- 1 $\Lambda^{b/a}$ is C^2 .
- 2 $\Lambda^{b/a'} < 0$.
- 3 $\lim_{\delta \rightarrow +\infty} \Lambda^{b/a}(\delta) = 0$.
- 4 The intensity functions $\Lambda^{b/a}$ satisfy:

$$\sup_{\delta} \frac{\Lambda^{b/a}(\delta) \Lambda^{b/a''}(\delta)}{(\Lambda^{b/a'}(\delta))^2} < 2.$$

The functions H_ξ^b and H_ξ^a

The functions H_ξ^b and H_ξ^a

Proposition

- $\forall \xi \geq 0$, $H_\xi^{b/a}$ is a decreasing function of class C^2 .
- In the definition of $H_\xi^{b/a}(p)$, the supremum is attained at a unique $\tilde{\delta}_\xi^{b/a*}(p)$ characterized by

$$\tilde{\delta}_\xi^{b/a*}(p) = \Lambda^{b/a-1} \left(\xi \Delta H_\xi^{b/a}(p) - H_\xi^{b/a'}(p) \right).$$

- The function $p \mapsto \tilde{\delta}_\xi^{b/a*}(p)$ is increasing.

Existence and uniqueness

Results for θ

There exists a unique C^1 (in time) solution $t \mapsto (\theta(t, q))_{|q| \leq Q}$ to

$$0 = \partial_t \theta(t, q) - \frac{1}{2} \gamma \sigma^2 q^2 + 1_{q < Q} \Delta H_\xi^b \left(\frac{\theta(t, q) - \theta(t, q + \Delta)}{\Delta} \right) \\ + 1_{q > -Q} \Delta H_\xi^a \left(\frac{\theta(t, q) - \theta(t, q - \Delta)}{\Delta} \right)$$

with final condition $\theta(T, q) = 0$.

Solution of the initial problem (verification argument)

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By using a verification argument, the function u is the value function associated with the problem.

Optimal quotes

The optimal quotes in models A ($\xi = \gamma$) and B ($\xi = 0$) are:

$$\delta_t^{b*} = \tilde{\delta}_\xi^{b*} \left(\frac{\theta(t, q_{t-}) - \theta(t, q_{t-} + \Delta)}{\Delta} \right)$$

$$\delta_t^{a*} = \tilde{\delta}_\xi^{a*} \left(\frac{\theta(t, q_{t-}) - \theta(t, q_{t-} - \Delta)}{\Delta} \right)$$

where

$$\tilde{\delta}_\xi^{b/a*}(p) = \Lambda^{b/a-1} \left(\xi \Delta H_\xi^{b/a}(p) - H_\xi^{b/a'}(p) \right).$$

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (I)

The functions $H_\xi^{b/a}$ and $\tilde{\delta}_\xi^{b/a^*}$

If $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$, then $H_\xi^{b/a}(p) = \frac{A}{k} C_\xi \exp(-kp)$, with

$$C_\xi = \begin{cases} \left(1 + \frac{\xi\Delta}{k}\right)^{-\frac{k}{\xi\Delta}-1} & \text{if } \xi > 0 \\ e^{-1} & \text{if } \xi = 0. \end{cases}$$

and

$$\tilde{\delta}_\xi^{b/a^*}(p) = \begin{cases} p + \frac{1}{\xi\Delta} \log\left(1 + \frac{\xi\Delta}{k}\right) & \text{if } \xi > 0 \\ p + \frac{1}{k} & \text{if } \xi = 0, \end{cases}$$

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (II)

The system of ODEs

$$0 = \partial_t \theta(t, q) - \frac{1}{2} \gamma \sigma^2 q^2 + \\ + \frac{A\Delta}{k} C_\xi \left(\mathbf{1}_{q < Q} e^{k \frac{\theta(t, q+\Delta) - \theta(t, q)}{\Delta}} + \mathbf{1}_{q > -Q} e^{k \frac{\theta(t, q-\Delta) - \theta(t, q)}{\Delta}} \right),$$

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with final condition $\theta(T, q) = 0$.

Change of variables: $v_q(t) = \exp\left(\frac{k\theta(t, q)}{\Delta}\right)$

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (III)

A linear system of ODEs

$$v'_q(t) = \alpha q^2 v_q(t) - \eta_\xi (1_{q < Q} v_{q+\Delta}(t) + 1_{q > -Q} v_{q-\Delta}(t)),$$

with

$$\alpha = \frac{k}{2\Delta} \gamma \sigma^2, \quad \eta_\xi = AC_\xi$$

and the terminal condition $v(T, q) = 1$.

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and the terminal condition $v(T, q) = 1$.

This simplifies a lot the equations of Avellaneda and Stoikov. See the paper Guéant-Lehalle-Fernandez-Tapia (2013) (when $\Delta = 1$ and $\xi = \gamma$).

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (IV)

Optimal quotes

The optimal quotes in models A ($\xi = \gamma$) and B ($\xi = 0$) are:

$$\delta_t^{b*} = \delta^{b*}(t, q_{t-}) := D_\xi + \frac{1}{k} \ln \left(\frac{v_{q_{t-}}(t)}{v_{q_{t-} + \Delta}(t)} \right)$$

$$\delta_t^{a*} = \delta^{a*}(t, q_{t-}) := D_\xi + \frac{1}{k} \ln \left(\frac{v_{q_{t-}}(t)}{v_{q_{t-} - \Delta}(t)} \right)$$

$$D_\xi = \begin{cases} \frac{1}{\xi\Delta} \log \left(1 + \frac{\xi\Delta}{k} \right) & \text{if } \xi > 0 \\ \frac{1}{k} & \text{if } \xi = 0, \end{cases}$$

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The optimal quotes are made of two components:

- D_ξ corresponds to the static trade-off.
- $\frac{1}{k} \ln \left(\frac{v_q(t)}{v_{q+\Delta}(t)} \right)$ or $\frac{1}{k} \ln \left(\frac{v_q(t)}{v_{q-\Delta}(t)} \right)$: dynamic aspects.

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (V)

The optimal quote functions far from T only depend on q :

Asymptotics

$$\delta_{\infty}^{b*}(q) = \lim_{T \rightarrow \infty} \delta^{b*}(0, q) = D_{\xi} + \frac{1}{k} \ln \left(\frac{f_q^0}{f_{q+\Delta}^0} \right)$$

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$f^0 \in \mathbb{R}^{2Q+1}$ is characterized by:

$$\operatorname{argmin}_{\|f\|_2=1} \sum_{|q| \leq Q} \alpha q^2 f_q^2 + \eta_{\xi} \left(\sum_{q=-Q}^{Q-\Delta} (f_{q+\Delta} - f_q)^2 + (f_Q)^2 + (f_{-Q})^2 \right).$$

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (VI)

Continuous counterpart

$\tilde{f}^0 \in L^2(\mathbb{R})$ characterized by:

$$\operatorname{argmin}_{\|\tilde{f}\|_{L^2(\mathbb{R})}=1} \int_{-\infty}^{\infty} \left(\alpha x^2 \tilde{f}(x)^2 + \eta_{\xi} \Delta^2 \tilde{f}'(x)^2 \right) dx.$$

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$$\tilde{f}^0(x) \propto \exp\left(-\frac{1}{2\Delta} \sqrt{\frac{\alpha}{\eta_\xi}} x^2\right)$$

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$$\tilde{f}^0(x) \propto \exp\left(-\frac{1}{2\Delta} \sqrt{\frac{\alpha}{\eta_\xi}} x^2\right)$$

Hence, we get an approximation of the form:

$$f_q^0 \propto \exp\left(-\frac{1}{2\Delta} \sqrt{\frac{\alpha}{\eta_\xi}} q^2\right)$$

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (VII)

Using the continuous counterpart, we get:

Closed-form approximations: optimal quotes (Model A: $\xi = \gamma$)

$$\delta_{\infty}^{b*}(q) \simeq \frac{1}{\Delta\xi} \ln \left(1 + \frac{\Delta\xi}{k} \right) + \frac{2q + \Delta}{2} \sqrt{\frac{\gamma\sigma^2}{2kA\Delta} \left(1 + \frac{\Delta\xi}{k} \right)^{1 + \frac{k}{\Delta\xi}}}$$

$$\delta_{\infty}^{a*}(q) \simeq \frac{1}{\Delta\xi} \ln \left(1 + \frac{\Delta\xi}{k} \right) - \frac{2q - \Delta}{2} \sqrt{\frac{\gamma\sigma^2}{2kA\Delta} \left(1 + \frac{\Delta\xi}{k} \right)^{1 + \frac{k}{\Delta\xi}}}$$

Remark: these formulas are used by many practitioners in Europe and Asia on quote-driven markets.

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (VIII)

Using the continuous counterpart, we get:

Closed-form approximations: optimal quotes (Model B: $\xi = 0$)

$$\delta_{\infty}^{b*}(q) \simeq \frac{1}{k} + \frac{2q + \Delta}{2} \sqrt{\frac{\gamma\sigma^2 e}{2kA\Delta}}$$
$$\delta_{\infty}^{a*}(q) \simeq \frac{1}{k} - \frac{2q - \Delta}{2} \sqrt{\frac{\gamma\sigma^2 e}{2kA\Delta}}$$

The case $\Lambda^b(\delta) = \Lambda^a(\delta) = Ae^{-k\delta}$ (IX)

A good way to analyze the result is to consider the spread $\psi = \delta^b + \delta^a$ and the skew $\zeta = \delta^b - \delta^a$.

Closed-form approx.: spread and skew (Model A, $\xi = \gamma$)

$$\psi_{\infty}^*(q) \simeq \frac{2}{\Delta\xi} \ln \left(1 + \frac{\Delta\xi}{k} \right) + \Delta \sqrt{\frac{\gamma\sigma^2}{2kA\Delta} \left(1 + \frac{\Delta\xi}{k} \right)^{1 + \frac{k}{\Delta\xi}}}$$

$$\zeta_{\infty}^*(q) \simeq 2q \sqrt{\frac{\gamma\sigma^2}{2kA\Delta} \left(1 + \frac{\Delta\xi}{k} \right)^{1 + \frac{k}{\Delta\xi}}}$$

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Closed form approx.: spread and skew (Model B, $\xi = 0$)

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Extensions

Basic ideas

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- Other objective functions.

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- Including a drift and / or price jumps (easy).
- Including stoch. vol. models (easy but lead to a system of parabolic PDEs in dimension depending of the number of factors).
- Modeling price by microstructural models / point processes:
→ lead to a system of PDEs with nonlocal terms.

Extensions

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- D2C vs. D2D (internalization vs. externalization) + market impact on the D2D segment.

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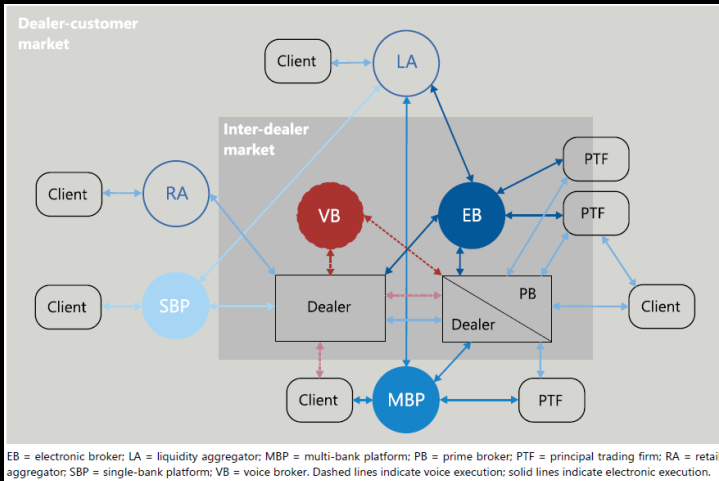
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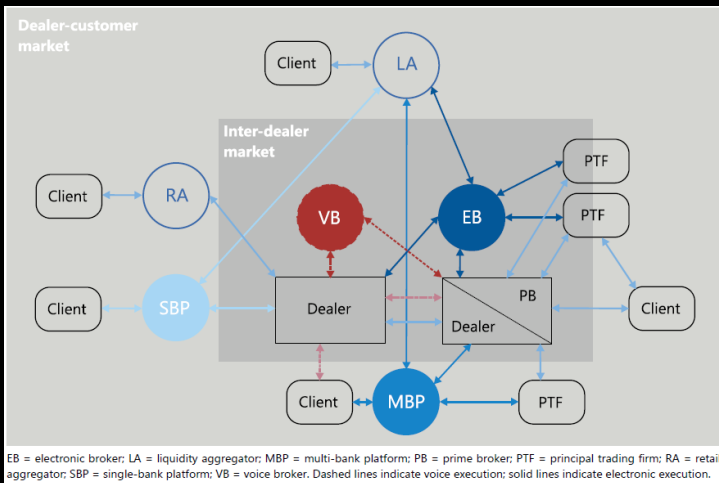
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 - Less than a year later, we released a paper to build AMM based on price oracles or offchain reference prices (Bergault, Bertucci, Bouba, Guéant).
- Not really satisfying for FX (correlations + triplets) or corporate bonds (many securities for one issuer).
 - diversification and liquidity differences must be taken into account.

Organization of the FX market (Schrimpf-Sushko)

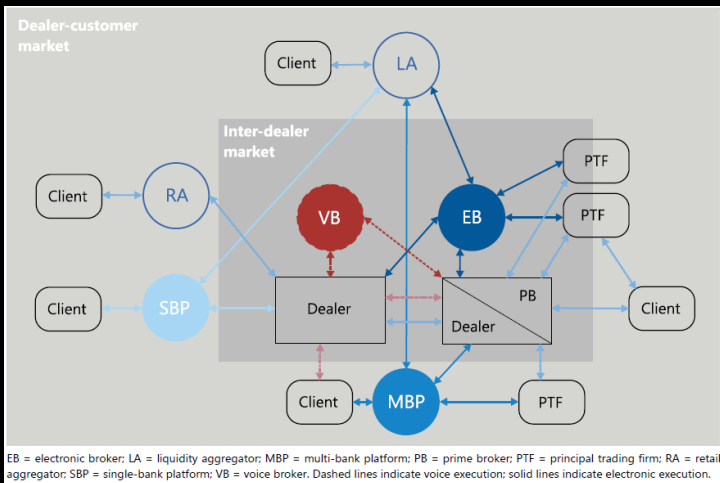


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RFs and RFQs (D2C) and access to multiple platforms (D2D and all-to-all) → dealers can internalize or externalize the flow

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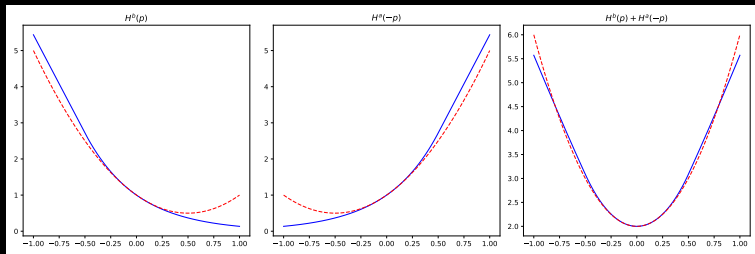
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 - $\tilde{\theta}$ is plugged in the above equations to get great pricing and hedging strategies.

Approximation of the Hamiltonians

$$H^b \left(\frac{\theta(t, q) - \theta(t, q + \Delta)}{\Delta} \right) + H^a \left(\frac{\theta(t, q) - \theta(t, q - \Delta)}{\Delta} \right) \\ \rightsquigarrow H^b(p) + H^a(-p)$$



Example (video)

Time for a short animation

The problem with precious metals

The problem with precious metals

- In many cases, market making on the spot market and hedging on both the (illiquid) spot market and the (liquid) futures market.
- Futures hedging is imperfect \rightarrow the remaining (basis) risk cannot be modelled with a Brownian motion: it is stationary.

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- Spot: $dS_t = \sigma_S dW_t^S$, $\sigma_S > 0$.

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- Spot: $dS_t = \sigma_S dW_t^S$, $\sigma_S > 0$.
- Futures: $F_t = S_t + E_t$.

We want prices with linear dynamics to stay in the quadratic value case:

$$\begin{aligned}dE_t &= -k_E (E_t - D_t) dt + \sigma_E dW_t^E, & k_E, \sigma_E > 0, \\dD_t &= -k_D (D_t - \bar{D}) dt + \sigma_D dW_t^D, & k_D, \sigma_D \geq 0, \quad \bar{D} \in \mathbb{R},\end{aligned}$$

where $(W_t^S, W_t^E, W_t^D)_t$ is a three-dimensional Brownian motion with correlation matrix R (covariance matrix: Σ).

Other state variables

Inventories

- Spot – jumps (trade with clients) and execution:

$$dq_t^S = \int_{z=0}^{\infty} zJ^b(dt, dz) - \int_{z=0}^{\infty} zJ^a(dt, dz) + v_t^S dt.$$

- Futures – execution: $dq_t^F = v_t^F dt.$

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where the intensities are

$$\Lambda^b(z, \delta) = \Lambda^a(z, \delta) = \Lambda(z, \delta) = \lambda(z)f(\delta) \quad \text{with} \quad f(\delta) = \frac{1}{1 + e^{\alpha + \beta\delta}}.$$

Other state variables

Cash

The resulting cash process $(X_t)_t$ follows:

$$\begin{aligned} dX_t = & \int_{z=0}^{\infty} S^a(t, z) z J^a(dt, dz) - \int_{z=0}^{\infty} S^b(t, z) z J^b(dt, dz) \\ & - v_t^S S_t dt - L^S(v_t^S) dt - v_t^F F_t dt - L^F(v_t^F) dt \end{aligned}$$

where $L^S(v_t^S)$ and $L^F(v_t^F)$ account for execution costs upon externalizing.

Stochastic optimal control

Objective function

The goal is now to maximize

$$\mathbb{E} \left[-\exp \left(-\gamma \left(X_T + q_T^S S_T + q_T^F F_T - K \left((q_T^S)^2 + (q_T^F)^2 \right) \right) \right) \right]$$

by selecting δ^b , δ^a , v^S and v^F optimally.

Hamilton-Jacobi-Bellman equation

$$\begin{aligned} 0 = & \partial_t u - k_E (E - D) \partial_E u - k_D (D - \bar{D}) \partial_D u \\ & + \frac{1}{2} \text{Tr}(\Sigma \nabla_{SED}^2 u) + \mathcal{L}^b u + \mathcal{L}^a u \\ & + \sup_{v^S} (v^S \partial_{q^S} u - (L^S(v^S) + v^S S) \partial_x u) \\ & + \sup_{v^F} (v^F \partial_{q^F} u - (L^F(v^F) + v^F (S + E)) \partial_x u), \end{aligned}$$

with terminal condition

$$\begin{aligned} & u(T, x, q^S, q^F, S, E, D) \\ = & -\exp(-\gamma(x + q^S S + q^F (S + E) - K((q^S)^2 + (q^F)^2))). \end{aligned}$$

Hamilton-Jacobi-Bellman equation

Nonlocal jump operators:

$$\begin{aligned} & \mathcal{L}^b u(t, x, q^S, q^F, S, E, D) \\ = & \int_0^\infty \sup_{\delta^b} f(\delta^b) (u(t, x - z(S - \delta^b), q^S + z, q^F, S, E, D) \\ & - u(t, x, q^S, q^F, S, E, D)) \lambda(z) dz \end{aligned}$$

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$$\begin{aligned} & \mathcal{L}^a u(t, x, q^S, q^F, S, E, D) \\ = & \int_0^\infty \sup_{\delta^a} f(\delta^a) (u(t, x + z(S + \delta^a), q^S - z, q^F, S, E, D) \\ & \quad - u(t, x, q^S, q^F, S, E, D)) \lambda(z) dz \end{aligned}$$

Change of variables

Ansatz

$$\begin{aligned} & u(t, x, q^S, q^F, S, E, D) \\ = & -\exp(-\gamma(x + q^S S + q^F(S + E) + \theta(t, q^S, q^F, E, D))) \end{aligned}$$

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New equation for θ

The equation for θ becomes:

$$\begin{aligned} 0 = & \partial_t \theta - k_E (E - D) (q^F + \partial_E \theta) - k_D (D - \bar{D}) \partial_D \theta + \frac{1}{2} \text{Tr}(\tilde{\Sigma} \nabla_{ED}^2 \theta) \\ & - \frac{\gamma}{2} \begin{pmatrix} q^S + q^F \\ q^F + \partial_E \theta \\ \partial_D \theta \end{pmatrix}^\top \Sigma \begin{pmatrix} q^S + q^F \\ q^F + \partial_E \theta \\ \partial_D \theta \end{pmatrix} + \mathcal{J}_H \theta + \mathcal{H}^S (\partial_{q^S} \theta) + \mathcal{H}^F (\partial_{q^F} \theta) \end{aligned}$$

Notations

- $\tilde{\Sigma}$ is the submatrix of Σ obtained by removing the first row and the first column
- \mathcal{H}^S and \mathcal{H}^F are the Hamiltonian functions defined by

$$\mathcal{H}^S : p \in \mathbb{R} \mapsto \sup_{v^S} (v^S p - L^S(v^S))$$

$$\mathcal{H}^F : p \in \mathbb{R} \mapsto \sup_{v^F} (v^F p - L^F(v^F))$$

- Nonlocal jump operators:

$$\begin{aligned} & \mathcal{J}_H \theta(t, q^S, q^F, E, D) \\ &= \int_0^\infty z H \left(z, \frac{\theta(t, q^S, q^F, E, D) - \theta(t, q^S + z, q^F, E, D)}{z} \right) \lambda(z) dz \\ & \quad + \int_0^\infty z H \left(z, \frac{\theta(t, q^S, q^F, E, D) - \theta(t, q^S - z, q^F, E, D)}{z} \right) \lambda(z) dz \end{aligned}$$

with $H : (z, p) \in (0, +\infty) \times \mathbb{R} \mapsto \sup_{\delta} \frac{f(\delta)}{\gamma z} (1 - e^{-\gamma z(\delta - p)})$.

Solution

If we approximate the Hamiltonian terms by polynomials of degree 2, the resulting approximation of θ will be a polynomial of degree 2, with coefficients solving simple ODEs (Riccati and linear).

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Optimal strategy

$$\left\{ \begin{array}{l} \delta^{b*}(t, z) = \bar{\delta} \left(z, \frac{\theta(t, q_{t-}^S, q_t^F, E_t, D_t) - \theta(t, q_{t-}^S + z, q_t^F, E_t, D_t)}{z} \right) \\ \delta^{a*}(t, z) = \bar{\delta} \left(z, \frac{\theta(t, q_{t-}^S, q_t^F, E_t, D_t) - \theta(t, q_{t-}^S - z, q_t^F, E_t, D_t)}{z} \right) \\ v_t^{S*} = \mathcal{H}^{S'}(\partial_{q^S} \theta(t, q_{t-}^S, q_t^F, E_t, D_t)) \\ v_t^{F*} = \mathcal{H}^{F'}(\partial_{q^F} \theta(t, q_{t-}^S, q_t^F, E_t, D_t)) \end{array} \right.$$

where $\bar{\delta}(z, p) = f^{-1}(\gamma z H(z, p) - \partial_p H(z, p))$.

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Assuming $d\langle W^S, W^E \rangle = \rho dt$ and $\langle W^S, W^D \rangle = \langle W^E, W^D \rangle = 0$, we get:

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$$\begin{aligned}dE_t &= -k_E (E_t - \widehat{D}_t) dt + \sigma_E d\widehat{W}_t^E \\d\widehat{D}_t &= -k_D (\widehat{D}_t - \bar{D}) dt + \frac{1}{\sqrt{1-\rho^2}} \frac{k_E}{\sigma_E} \nu_t^2 d\widehat{W}_t^D\end{aligned}$$

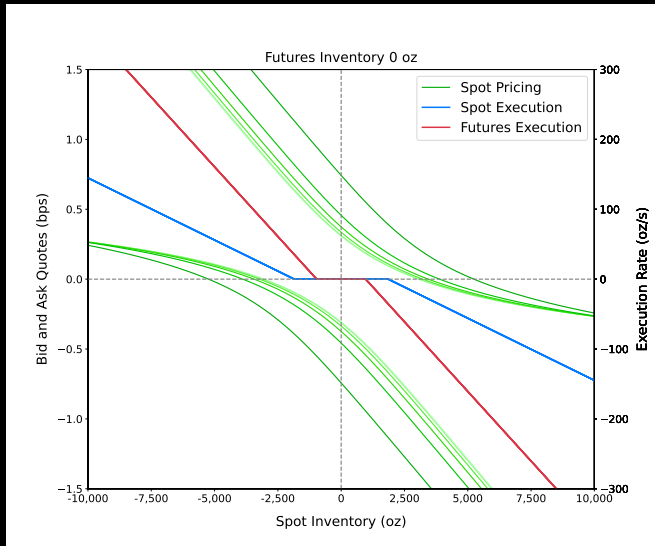
where

$$\widehat{D}_t = \mathbb{E}[D_t | (S_s)_{s \leq t}, (E_s)_{s \leq t}], \quad \nu_t^2 = \mathbb{V}(D_t | (S_s)_{s \leq t}, (E_s)_{s \leq t}),$$

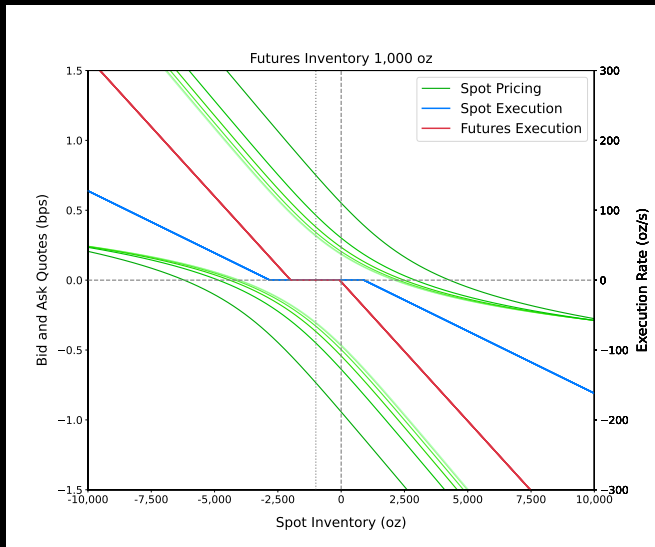
and

$$\widehat{W}_t^E = W_t^E + \frac{k_E}{\sigma_E} \int_0^t (D_s - \widehat{D}_s) ds \quad \text{and} \quad \widehat{W}_t^D = \frac{\widehat{W}_t^E - \rho W_t^S}{\sqrt{1-\rho^2}}$$

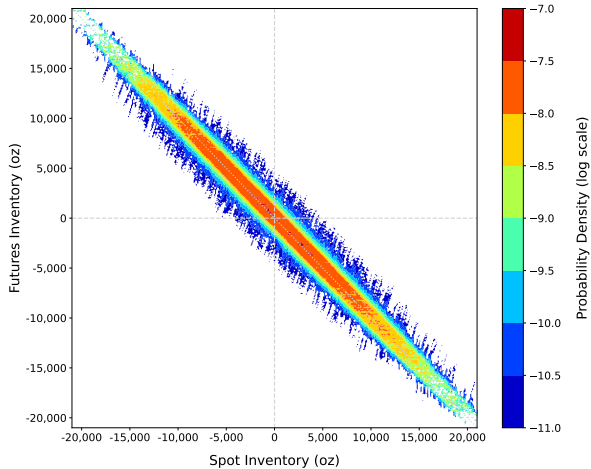
Optimal strategies



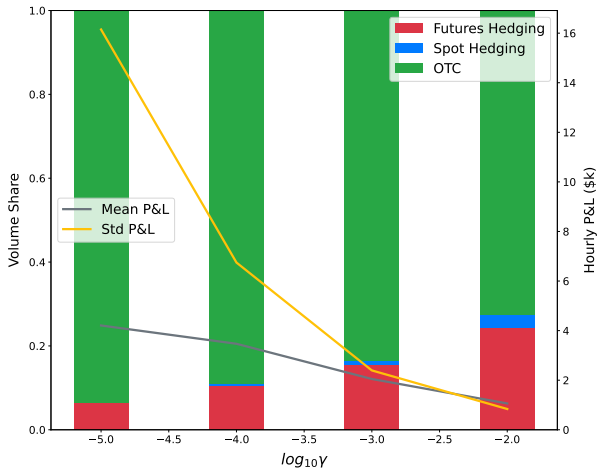
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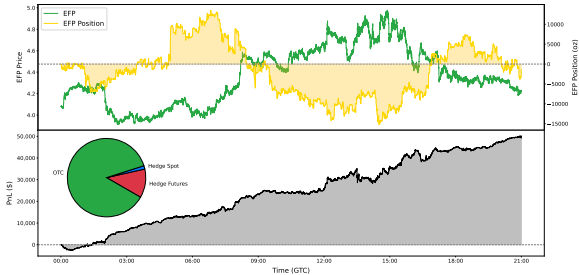
Inventory probability distribution



Volume shares



Performance



Questions



Thanks for your attention.
Questions?