

Information Asymmetries, Volatility, Liquidity, and the Tobin Tax

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Outline

- 1 The Bigger Picture
 - Introduction
 - (Other) Related Literature
- 2 An Equilibrium Theory of Volatility and Liquidity
 - The Set Up
 - Equilibrium
 - Time Change(s) and Lower Frequencies
- 3 Conclusion


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In market data:

- Volatility is time varying and clusters at high/medium frequency \Rightarrow ARCH/GARCH/SV models
 - Highest degree of clustering at high frequency.
 - Market vol \neq fundamental vol (e.g. Campbell-Kyle (1993)).
 - A relation between volatility and number/volume of trade (e.g. Gallant-Rossi-Tauchen (1992), Jones-Kaul-Lipson (1994)) & frequency (e.g. Engle-Sun (2007))
- \Rightarrow Gaussian log returns under a number of trades (stochastic) time change (Ané-Geman (2000)) 
- Links between information asymmetries, volatility and liquidity and return dynamics (e.g. Kelly-Ljungqvist (2013), Easley-Hvidkjaer-O'Hara (2002)).
 - Transaction taxes (seem to) \uparrow volatility (e.g. Jones-Seguin (1997), Umlauf (1993))
 - Joint volatility spikes and liquidity dry-ups (e.g. recent crises)

Our paper: a (non trivial) theory that can explain all the above facts and, more broadly, the equilibrium determinants of volatility (at different frequencies), and liquidity (tightness, depth, resilience).

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(Other) Related Literature

- **Sequential trade models** e.g. Glosten-Milgrom (1985), Easley-O'Hara (1987), Glosten (1989), Brunnermeier-Pedersen (2009) etc.

But: a) complete order book; b) dynamic info; c) *weakly* exogenous arrivals; d) arrival intensity to infinity → approximate continuous market → make arrival process irrelevant;

- **Time Deformation and Volatility** e.g. Clark (1973), Ghysels-Gourieroux-Jasiak (1995), Yor-Madan-Geman (2002), Andersen-Bollerslev-Dobrev (2007), Kalogeropoulos-Roberts-Dellaportas (2007), etc.

⇒ a distributional characterisation (via stochastic time change) of equilibria on different time scales (trade, calendar, business).

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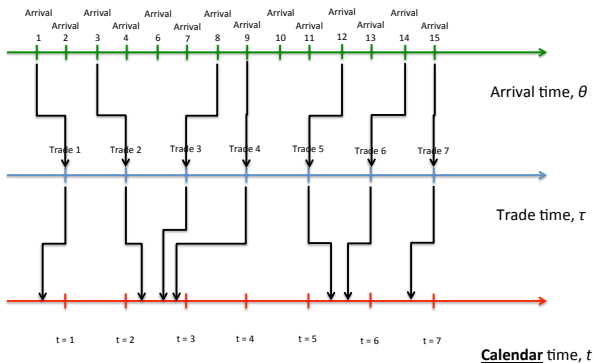
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- 3 time scales, hence needs to define variables accordingly



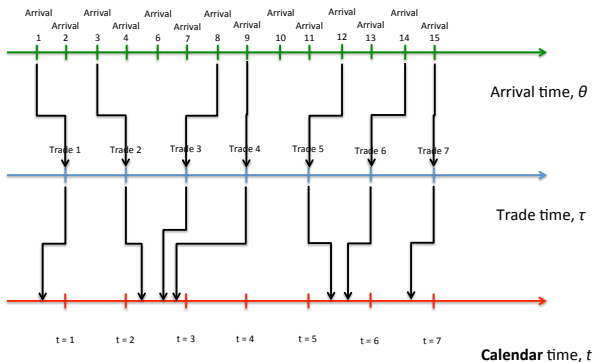
X_t : on calendar time scale

x_i : on arrival time scale i.e. $x_i = X_{\theta_i}$

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Market Structure

Assets: a riskless bond ($r = 0$) and a **stock with final value** e^{D_T}

$$dD_t = \mu dt + \sigma dW_t^d, \quad D_0 = \text{const}, \quad W_t^d \text{ is B.M. w.r.t. to } \mathcal{F}_t.$$

Utilities: risk neutral traders and (competitive) market maker (M).

A1: Traders arrive to the market and meet M according to a stochastic counting process, N_t , with stopping time θ_i

- When the trader arrives at time θ_i , she **observes bid**, $B_{\theta_i}(v^-)$, and **ask**, $A_{\theta_i}(v^+)$, prices per-share posted by M , and **decides if and how much to trade** ($v \in \mathbb{R}$).

Friction: **proportional transaction cost** δ (like Tobin tax), i.e. M receives $v^+ A_{\tau_i}(v^+) (1 - \delta)$ (spends $v^- B_{\tau_i}(v^-) (1 + \delta)$)

if $v = 0$ M does not observe the arrival.

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M: common knowledge: preferences, parameters, and the price and trade history ($\mathcal{G}_t^M := \mathcal{F}_t^P \vee \mathcal{F}_t^V$)

I type: i -th (more) informed trader, in share $1 - q$, observes D
 ($\mathcal{G}_t^{I,i} = \mathcal{G}_t^M \vee \mathcal{F}_t^D \vee \sigma \{ \theta_i^I \wedge s, s \leq t \}$)

U type: i -th uninformed/liquidity/noisy, in share q , with $\delta \in (0, q)$,
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A2: fundamental shocks, arrivals, and noise/liquidity-shocks are conditionally independent.

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Traders' optimisation problem

- The **expected utility** from holding v^+ shares until time T for an agent of type $k \in \{I, U\}$ that arrived at θ_i^k is

$$\mathbb{E} \left[v^+ e^{D_T} \mid \mathcal{H}_i^k \right] =: v^+ z_i^k.$$

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$$\max_{v^+, v^-} v^+ \left[z_i^k - A_{\theta_i^k}(v^+) \right] + v^- \left[B_{\theta_i^k}(v^-) - z_i^k \right]. \quad (1)$$

Notation: z_i (shadow price) is the **expected value** of holding one share of the asset for the agent that arrives at time θ_i

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Market Maker's optimisation problem

- M sets time t bid and ask prices as a functions of the order size v :

$$A_t(v^+) (1 - \delta) = \underbrace{\sum_{i=1}^{\infty} \mathbf{1}_{\{i=1+L_{t-}\}} \mathbb{E} \left[e^{D_T} | \tilde{\mathcal{H}}_i^M, N_{\tau_i} = L_{\tau_i} \right] \Big|_{\tilde{v}_i=v^+, \tau_i=t}}_{M's \text{ "future" valuation}} \quad (2)$$

$$B_t(v^-) (1 + \delta) = \sum_{i=1}^{\infty} \mathbf{1}_{\{i=1+L_{t-}\}} \mathbb{E} \left[e^{D_T} | \tilde{\mathcal{H}}_i^M, N_{\tau_i} = L_{\tau_i} \right] \Big|_{\tilde{v}_i=-v^-, \tau_i=t} \quad (3)$$

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Market Maker's optimisation problem

- M sets time t bid and ask prices as a functions of the order size v :

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Equilibrium: Definition

Definition (Equilibrium)

A market equilibrium is a set of policy functions $A_t(v^+)$, $B_t(v^-)$ satisfying regularity conditions and $v_i(A_{\theta_i}(v^+), B_{\theta_i}(v^-))$ such that:

- 1 $A_t(v^+)$ and $B_t(v^-)$ solve the market maker optimisation problem $\forall v, t$;
- 2 $v_i(A_{\theta_i}(v^+), B_{\theta_i}(v^-))$ solves the trader's problem.

Equilibrium: Bid and Ask functions

Proposition (Optimal ask and bid functions)

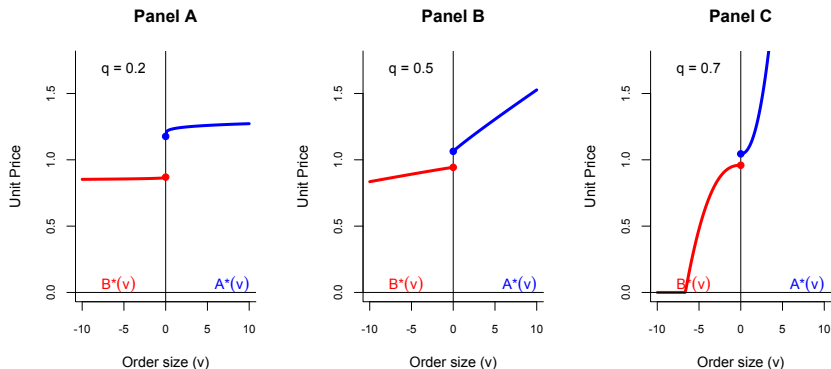
Suppose assumptions A1-A4 are satisfied. Then there exist optimal ask, $A_t(v^+)$, and bid, $B_t(v^-)$, prices that satisfy conditions C1-C5, and the market maker's optimality conditions. Moreover, optimal $A_t(v)$ and $B_t(v)$ have the following forms:

$$A_t^*(v) = \frac{q}{q-\delta} \left(1 + \alpha v^{\frac{q-\delta}{1-q}} \right) \underbrace{\sum_{i=0}^{\infty} \mathbf{1}_{\{i=L_{t-}+1\}} Z_{\tau_{i-1}}^M}_{M\text{'s "current" valuation}} \quad (4)$$

$$B_t^*(v) = \begin{cases} \frac{q}{q+\delta} \left(1 - \beta v^{\frac{q+\delta}{1-q}} \right) \sum_{i=0}^{\infty} \mathbf{1}_{\{i=L_{t-}+1\}} Z_{\tau_{i-1}}^M & \text{if } \beta v^{\frac{q+\delta}{1-q}} \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

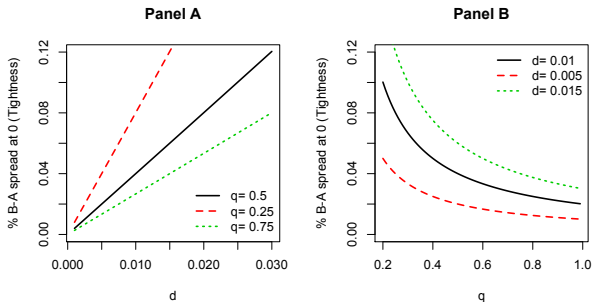
where α and β are strictly positive arbitrary constants, and $Z_t^M := \mathbb{E} \left[e^{D\tau} \mid \mathcal{G}_t^M, N_t = L_t \right]$ denotes the market maker valuation.

Equilibrium: Bid and Ask functions cont'd



- order book interpretation (M analogy).
- flexible parametrisation and empirically promising.

Liquidity: Tightness

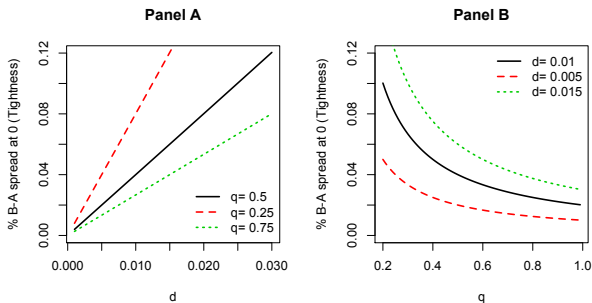


$$\% \text{ Bid-Ask spread at } 0 = \frac{2q\delta}{q^2 - \delta^2}$$

- B-A \uparrow in adverse selection $(1 - q)$ and trading cost (δ)
 $\Rightarrow M$ uses the spread to recoup both type of costs.
- mutually reinforcing effects

Data: $(1 - q)$ & δ explain 86%-100% of the spread (e.g. Stoll (1989), George, Kaul and Nimalendran (1991), Huang and Stoll (1996))

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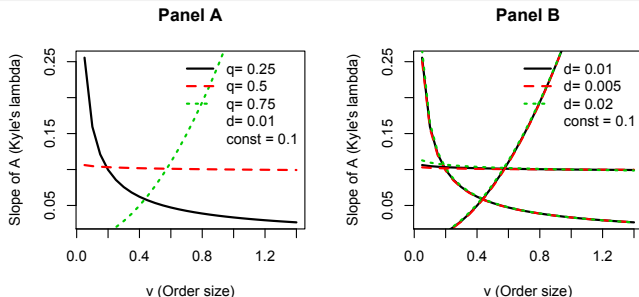
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Liquidity: Depth



Slope of the Ask schedule, normalised by M's valuation: $\frac{q}{1-q} \alpha(v^+) \frac{2q-\delta-1}{1-q}$.

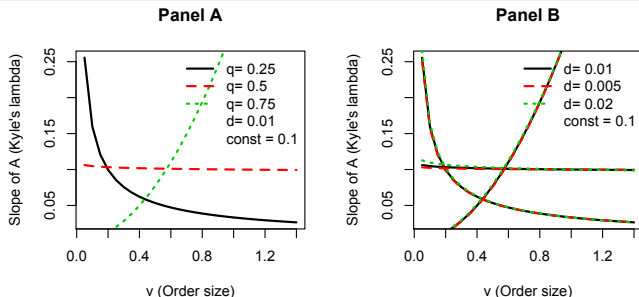
High q: price more likely to deviate substantially from fundamental \Rightarrow M's potential losses from trading with I are large \Rightarrow **Depth \downarrow in v**

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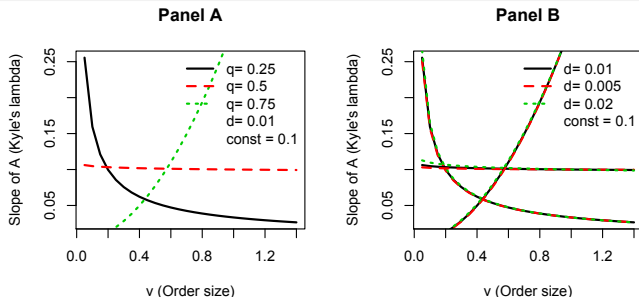
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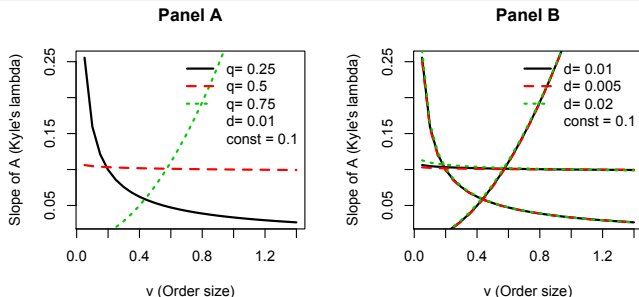
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High Frequency Price Process

- Since trades happen either at ask or bid, we can characterise the price process for any volume process:

$$\log \frac{P_{t+s}}{P_t} = \sum_{i=L_t}^{L_{t+s}} \{ \log (1 + \xi_i |V_{\tau_i} - V_{\tau_{i-1}}|^{\gamma_i}) + \log c_{1,i} + \log c_{2,i-1} \} . \quad (6)$$

where ξ_i , γ_i , $c_{1,i}$ and $c_{2,i}$ are known functions of δ , q , and whether trades are at ask or bid (the latter is a binomial r. v.).

⇒ consistent with non-lin model of Gallant, Rossi, and Tauchen (1992) (Tauchen-Pitts (1983), Epps-Epps (1976), Clark (1973), etc.)

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Equilibrium: Volume

Theorem

Suppose Assumptions A1-A4 are satisfied. For strictly positive constants α and β , there is a unique market equilibrium, $A_t^*(v)$, $B_t^*(v)$, v_i^* , where $A_t^*(v)$ and $B_t^*(v)$ are given, respectively, by equations (4) and (5), and

$$v_i^* = \begin{cases} \left[\frac{1-q}{\alpha(1-\delta)} \left(\frac{q-\delta}{q} \frac{z_i}{z_i^M} - 1 \right) \right]^{\frac{1-q}{q-\delta}} & \text{if } \frac{q}{q-\delta} z_i^M < z_i, \\ - \left[\frac{1-q}{\beta(1+\delta)} \left(1 - \frac{q+\delta}{q} \frac{z_i}{z_i^M} \right) \right]^{\frac{1-q}{q+\delta}} & \text{if } z_i < \frac{q}{q+\delta} z_i^M, \\ 0 & \text{if } \frac{q}{q+\delta} z_i^M \leq z_i \leq \frac{q}{q-\delta} z_i^M \end{cases}$$

where $z_i^M := Z_{\theta_i}^M$

From fundamentals to price process

Lemma (price process as map of fundamentals)

Suppose that Assumptions A1-A5 are satisfied and the market is at the equilibrium. Then the *trading times* are defined recursively ($\tau_0 = 0$)

$$\tau_i = \inf \{ \theta_j > \tau_{i-1} : \log z_j - \log \tilde{p}_{i-1} \notin (b(c_{2,i-1}), a(c_{2,i-1})) \},$$

where $a(x) = \log\left(\frac{qx}{q-\delta}\right)$ and $b(x) = \log\left(\frac{qx}{q+\delta}\right)$, and *prices* are

$$\tilde{p}_0 = e^{D_0 + (\mu + \frac{1}{2}\sigma^2)T}, \quad \tilde{p}_i = \frac{1}{c_{2,i}} [(1-q)z_i + q\tilde{p}_{i-1}c_{2,i-1}], \quad (7)$$

$$c_{2,i} = \begin{cases} 1 - \delta & \text{if } \log \tilde{z}_i - \log \tilde{p}_{i-1} > a(c_{2,i-1}) \text{ and } i > 0 \\ 1 + \delta & \text{if } \log \tilde{z}_i - \log \tilde{p}_{i-1} < b(c_{2,i-1}) \text{ and } i > 0 \\ 1, & \text{if } i = 0 \end{cases}$$

The process Z (Shadow Price)

- The (de-meaned) log shadow valuation of the i -th agent is:

$$d_i^{tr} = \begin{cases} \log z_i - \left(\mu + \frac{\sigma^2}{2} \right) (T - \theta_i) & \forall i \geq 1 \\ D_0 & i = 0 \end{cases}, \quad D_t^{tr} = \sum_{i=0}^{\infty} \mathbf{1}_{\{i=N_t\}} d_i^{tr}.$$

- The (conditional) distribution of this process is (Lemma 3):

$$\mathbb{P}[d_i^{tr} \leq x | \mathcal{H}_{i-1}, \theta_i] = \sum_{j=1}^{i-1} (1-q) q^{i-1-j} \mathbb{P}[d_j^{tr} + \varepsilon_{i,j} \leq x | d_j^{tr}, \Delta_{i,j}] + q^{i-1} \mathbb{P}[d_0^{tr} + \varepsilon_{i,0} \leq x | d_0^{tr}, \Delta_{i,0}]$$

where $\Delta_{i,j} := \theta_i - \theta_j$, $\varepsilon_{i,j} := \mu \Delta_{i,j} + \sigma \sqrt{\Delta_{i,j}} \eta_{i,j}$, and $\eta_{i,j} \sim N(0, 1)$ is independent of d_j^{tr} and $\Delta_{i,j}$ for all $j < i$.

Intuition:

- Last I arrival has all the relevant info
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Changing Frequency & Time Changes

Arrival intensity $\rightarrow \infty$ ("business time") \Rightarrow valuation of i -th arrival
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 B-A bounds + The map from D^{tr} to P is continuous (Lem. 5) \Rightarrow
 Price $\xrightarrow{\mathcal{L}}$ on trade time (Thm. 7) \Rightarrow Calendar time dist. = time
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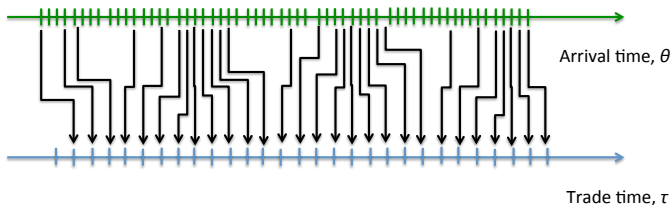
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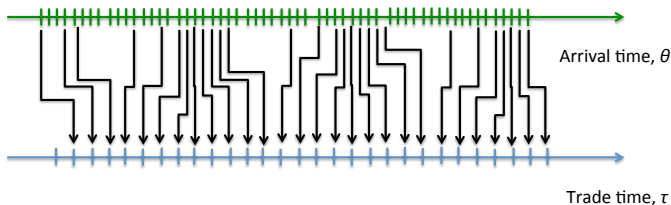
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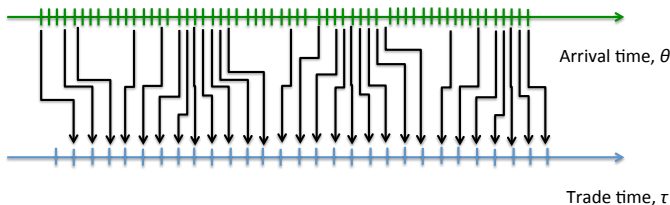
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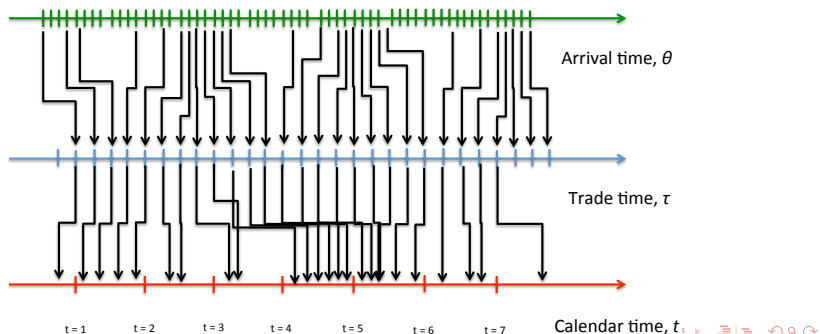
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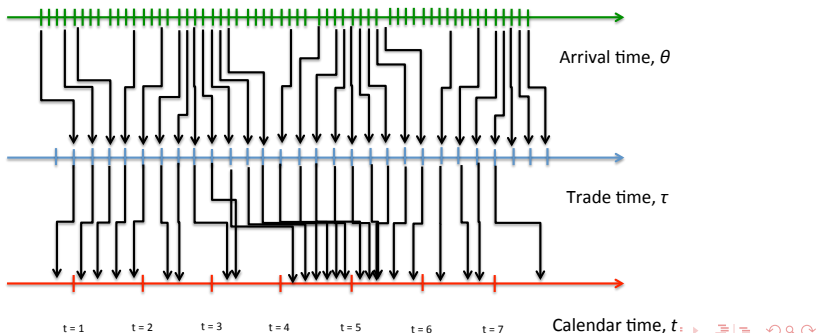
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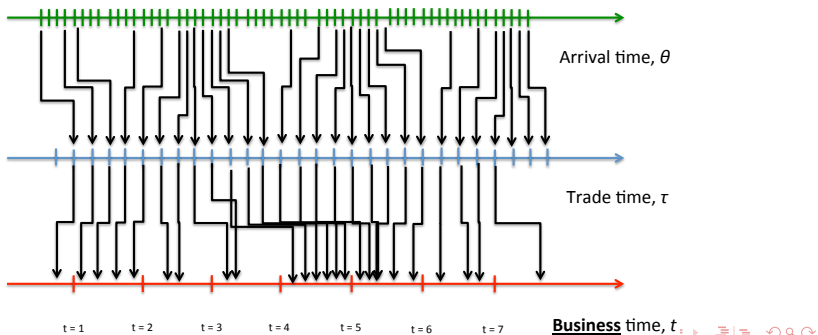
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 B-A bounds + The map from D^{tr} to P is continuous (Lem. 5) \Rightarrow
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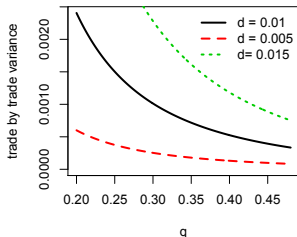
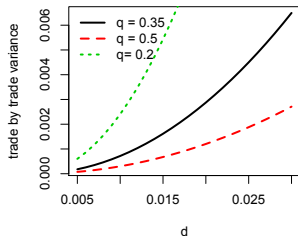


Trade-by-trade Volatility (at Med. Frequency)

Corollary (Volatility of the Limiting Price Process)

The conditional variance on the trade time scale, for $i > 1$, is:

$$\text{Var} \left(\frac{\tilde{p}_i}{\tilde{p}_{i-1}} \mid \mathcal{F}_{\tau_{i-1}}^W \right) = \frac{\delta^2(1 - q^2)}{q^2 - \delta^2}.$$



↑ in adverse selection and δ (cf. Hau (2006), Jones-Seguin (1997), Umlauf (1993))

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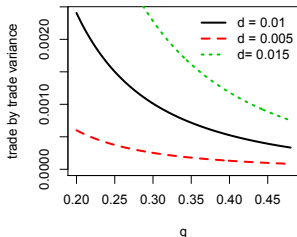
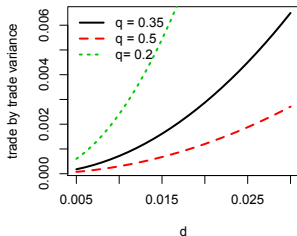
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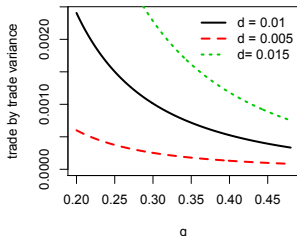
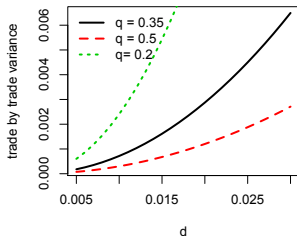
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Low & Ultra-Low Frequency Price Distribution

Proposition (Low & Ultra-Low Frequency Price Distribution)

$$\frac{\log \frac{P_t}{P_s} - \frac{\sigma^2}{2}(s-t)}{\sqrt{L_t^P - L_s^P}} \xrightarrow[t-s \rightarrow \infty]{d} \mathcal{N}\left(0, \sigma^2 \mu_\tau\right), \quad (8)$$

where μ_τ is the expected time between trades. And at Ultra-low frequency

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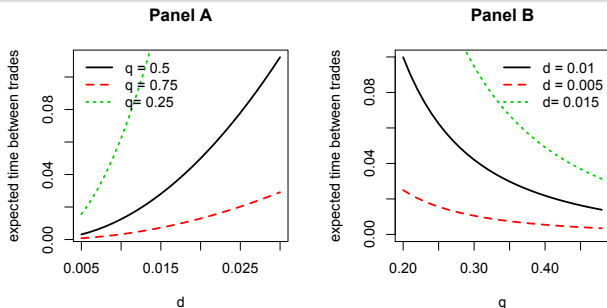
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Expected time between trades (μ_T)

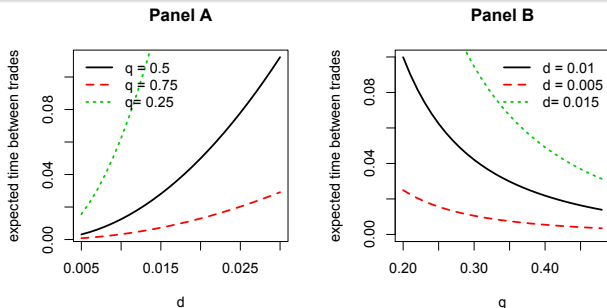


$$\mu_T := \frac{2}{\sigma^2} \left[\log \frac{q - \delta}{q(1 - \delta)} + \frac{(q + \delta)(1 + \delta)}{2(q + \delta^2)} \log \frac{(1 - \delta)(q + \delta)}{(1 + \delta)(q - \delta)} \right]$$

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Liquidity: Resilience

- on the trade time scale, the M's valuation evolves as

$$\tilde{z}_i^M = (1 - q) \tilde{z}_i + q \tilde{z}_{i-1}^M. \quad (10)$$

(i.e. an AR(1)) where \tilde{z}_i is the valuation of the i -th trader.

Hence: half-life (reciprocal of resilience) on the calendar time scale:

$$\underbrace{\frac{\ln 1/2}{\ln q}}_{\text{trade-by-trade half-life}} \times \underbrace{\mu_\tau}_{\text{expected time between trades}}$$

w.r.t. δ : same properties as $\mu_\tau \Rightarrow \uparrow$ in δ (consistent with Umlauf (1993)):
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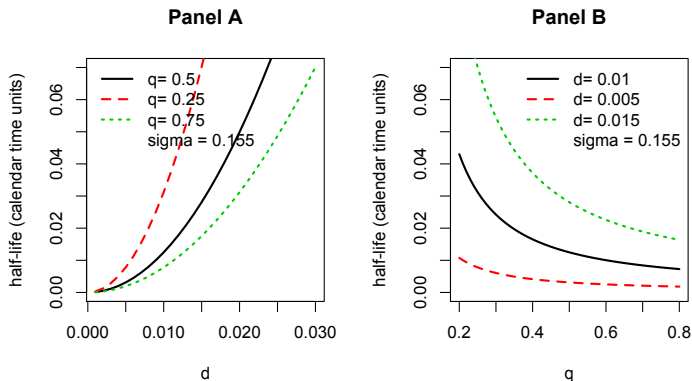
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Resilience: calendar time half-life of M's update



negative effects of trade cost (δ) and adverse selection ($1 - q$) on resilience mutually reinforce

Conclusion

A simple and tractable equilibrium framework that:

- 1 can rationalise a very large set of empirical findings about financial market volatility and returns at different frequencies, including joint volatility spikes and liquidity dry-ups.
- 2 identifies the equilibrium determinants of the 3 main liquidity dimensions, and can rationalise related empirical findings.
- 3 delivers policy relevant (and empirically consistent) predictions about the Tobin Tax.
- 4 can be structurally estimated to pin down asset specific measures of: adverse selection, frictions to trade, liquidity, fundamental vol etc. \Rightarrow empirical follow up.
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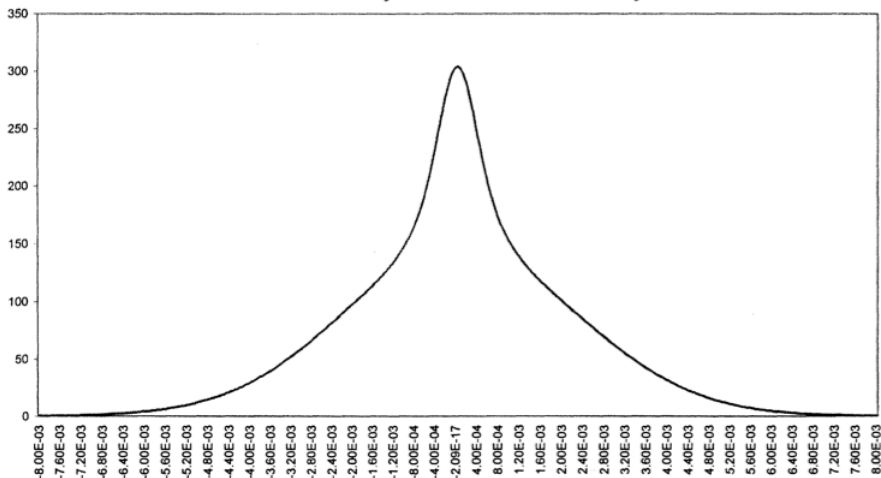
Appendix

- 4 Additional Figures
 - Ané and Geman (2000)
 - Bid-Ask Curves

- 5 Notation

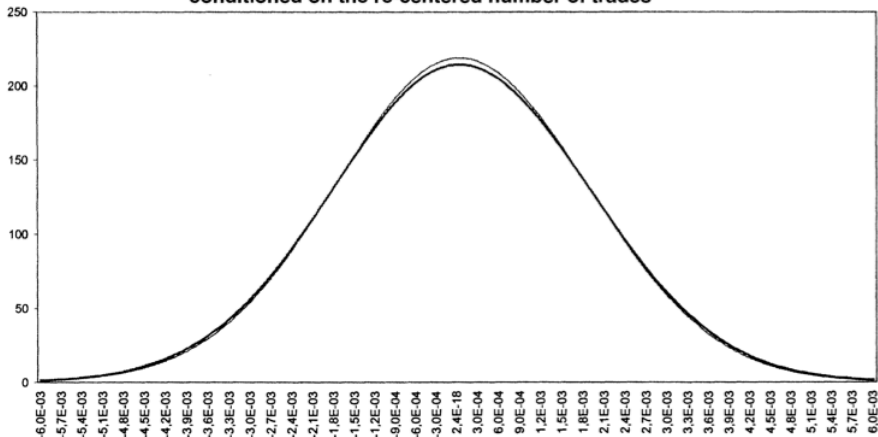
- 6 Extras
 - Time Scales
 - Regularity Conditions
 - Equilibrium Definition

PANEL B. Estimated density of the 10-minute Cisco Systems returns



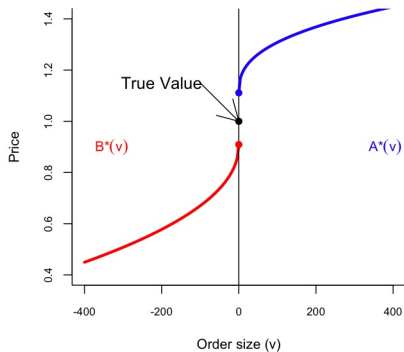
Source: Ané and Geman (2000)

PANEL B. Estimated density of the Cisco Systems 10-minute return conditioned on the re-centered number of trades

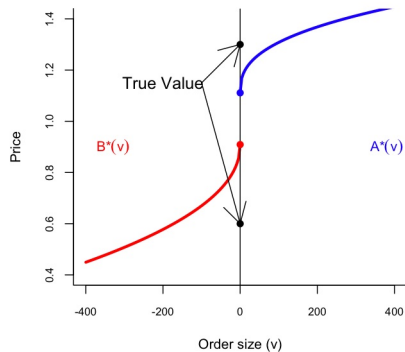


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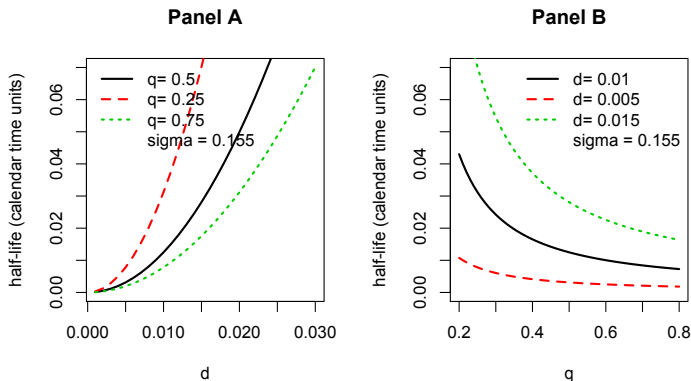
Only uninformed traders trade



Both informed and uninformed traders trade



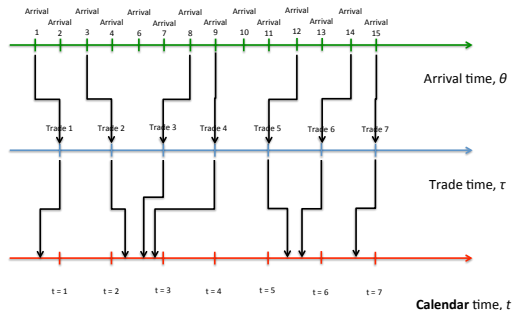
Resilience: calendar time half-life of M's update



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Notation

- 3 time scales, hence needs to define variables accordingly



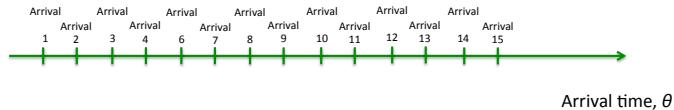
X_t : on calendar time scale

x_i : on arrival time scale i.e. $x_i = X_{\theta_i}$

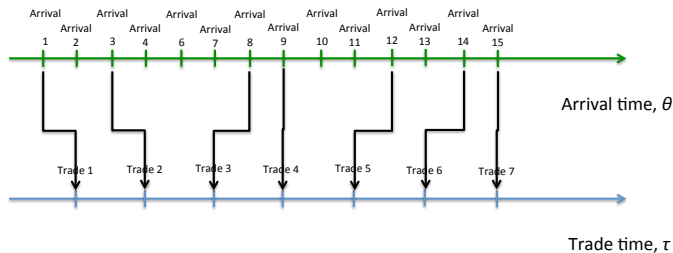
\tilde{x}_i : on number of trade time scale i.e. $\tilde{x}_i = X_{\tau_i}$

Review of Time Scales

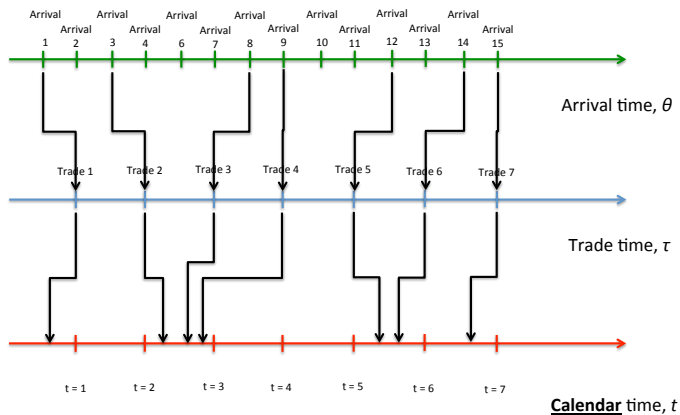
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Regularity Conditions

- C1** For a fixed v , the processes $B_t(v^-)$, $A_t(v^+)$, are *cáglád*
- aka:** M can change prices at any time but the time of trade.
- C2** For a fixed t , $A_t(v^+) : \mathbb{R}_+ \rightarrow \bar{\mathbb{R}}_+ \setminus \{0\}$ is continuous, nondecreasing and $\lim_{v^+ \rightarrow \infty} A_t(v^+) = +\infty$.
- C3** For a fixed t , $B_t(v^-) : \mathbb{R}_+ \rightarrow \bar{\mathbb{R}}_+$ is continuous, nonincreasing and $\lim_{v^- \rightarrow \infty} B_t(v^-) = 0$.
- aka:** no: free disposal, infinite trade size, decreasing price per-share.
- C4** For a fixed t , $A_t(0) \geq B_t(0)$ for all $\omega \in \Omega$.
- C5** For any fixed t , $A_t(\cdot)$ is continuously differentiable, and $B_t(\cdot)$ is continuously differentiable on the set $\{v : B_t(v) > 0\}$
- C6** For a fixed t , $vA_t(v)$ is strictly convex, and $vB_t(v)$ is strictly concave on the set $\{v : B_t(v) > 0\}$
- aka:** C5-C6 ensures strict concavity of traders' problem.

Equilibrium: Definition

Definition (Equilibrium)

A market equilibrium is a set of policy functions $A_t(v^+)$, $B_t(v^-)$ satisfying regularity conditions and $v_i(A_{\theta_i}(v^+), B_{\theta_i}(v^-))$ such that:

- 1 $A_t(v^+)$ and $B_t(v^-)$ solve the market maker optimisation problem $\forall v, t$;
- 2 $v_i(A_{\theta_i}(v^+), B_{\theta_i}(v^-))$ solves the trader's problem.