Supplementary Material

Supplement to "Trade clustering and power laws in financial markets"

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This technical appendix provides derivations omitted in the main paper.

Verification for the signal examples

Example 1: A linear distribution Consider a signal *X* that follows

$$f_n^H(x) = \frac{1}{2} + \epsilon_n x$$
 and $f^L(x) = \frac{1}{2}$, $-1 \le x \le 1$,

where $\epsilon_n = n^{-\xi}/3$ and $0 < \xi < 1$. In this section, we show that this signal satisfies Assumptions 1, 2, and 3.

Clearly, the densities are strictly positive and continuously differentiable. The likelihood ratio satisfies MLRP because

$$\ell_n(x) = \frac{f_n^H(x)}{f^L(x)} = 1 + 2\epsilon_n x$$

is strictly increasing in *x*. Moreover, $\ell_n(x) \to 1$ as $n \to \infty$ uniformly in $x \in [-1, 1]$, satisfying Assumption 2. The cumulative distributions are

$$F_n^H(x) = \int_{-1}^x \frac{1}{2} + \epsilon_n z \, dz = \frac{x+1}{2} + \frac{x^2 - 1}{2} \epsilon_n$$
$$F^L(x) = \int_{-1}^x \frac{1}{2} \, dz = \frac{x+1}{2}.$$

Hence, $\lambda_n(x) = 1 + (x - 1)\epsilon_n$. This implies $\lambda''_n(x) = 0$, satisfying Assumption 3.

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Finally, we investigate Assumption 1. We note that

$$\lim_{x \to 1} \log\left(\frac{\Lambda_n(x)}{\lambda_n(x)}\right) = \log\left(\frac{f_n^H(1)}{f^L(1)}\right) = \log(1 + 2\epsilon_n) = O(\epsilon_n).$$

Thus, to show that the signal satisfies Assumption 1, it suffices to show that $\log(\Lambda_n(x)/\lambda_n(x))$ is decreasing in $x \in [-1, 1]$. We have

$$\frac{d}{dx}\log\left(\frac{\Lambda_n(x)}{\lambda_n(x)}\right) = \frac{d}{dx}\left[\log\left(\frac{1}{F_n^H(x)} - 1\right) - \log\left(\frac{1}{F^L(x)} - 1\right)\right]$$
$$= \frac{1}{1 - F^L(x)}\frac{f^L(x)}{F^L(x)} - \frac{1}{1 - F_n^H(x)}\frac{f_n^H(x)}{F_n^H(x)}$$
$$= \frac{(1 - F_n^H(x))F_n^H(x)f^L(x) - (1 - F^L(x))F^L(x)f_n^H(x)}{(1 - F^L(x))F^L(x)(1 - F_n^H(x))F_n^H(x)}.$$

The denominator is positive. We inspect the numerator to find it negative:

$$\begin{split} &\left(1 - \frac{x+1}{2} - \frac{x^2 - 1}{2}\epsilon_n\right) \left(\frac{x+1}{2} + \frac{x^2 - 1}{2}\epsilon_n\right) \left(\frac{1}{2}\right) - \left(1 - \frac{x+1}{2}\right) \left(\frac{x+1}{2}\right) \left(\frac{1}{2} + x\epsilon_n\right) \\ &= \frac{(1 - x - (x^2 - 1)\epsilon_n)((x+1) + (x^2 - 1)\epsilon_n) - (1 - x)(x+1)(1 + 2x\epsilon_n)}{8} \\ &= \frac{x+1}{8} \left[(1 - x - (x^2 - 1)\epsilon_n)(1 + (x - 1)\epsilon_n) - (1 - x)(1 + 2x\epsilon_n) \right] \\ &= \frac{(x+1)(1 - x)}{8} \left[(1 + (1 + x)\epsilon_n)(1 + (x - 1)\epsilon_n) - (1 + 2x\epsilon_n) \right] \\ &= \frac{(x+1)(1 - x)}{8} \left[(1 + x)\epsilon_n(1 + (x - 1)\epsilon_n) - (x + 1)\epsilon_n \right] \\ &= -\frac{(x+1)^2(1 - x)^2\epsilon_n^2}{8} < 0. \end{split}$$

Hence, $\log(\Lambda_n(x)/\lambda_n(x))$ is bounded from below by $\log(1 + 2\epsilon_n)$. Thus, Assumption 1 is satisfied.

Example 2: An exponential signal Consider a signal *X* that follows an exponential distribution with

$$f^{H}(x) = \frac{\mu e^{-\mu x}}{1 - e^{-\mu}}$$
 and $f_{n}^{L}(x) = \frac{(\mu + \epsilon_{n})e^{-(\mu + \epsilon_{n})x}}{1 - e^{-(\mu + \epsilon_{n})}}, \quad 0 \le x \le 1,$

where $\epsilon_n = \delta_{\epsilon} n^{-\xi}$ is a positive sequence, and $\delta_{\epsilon} > 0$, $\mu > 2$, and $\xi \in (0, 1)$ are constants. In this section, we show that this signal satisfies Assumptions 1, 2, and 3.

The signal has the monotone increasing likelihood ratio $\ell_n(x) = (\mu/(1 - e^{-\mu}))((1 - e^{-(\mu + \epsilon_n)})/(\mu + \epsilon_n))e^{\epsilon_n x}$. Thus, the signal satisfies all the properties assumed in Section 2.2. In particular, f_n^s is continuously differentiable and strictly positive over common bounded support \mathcal{X} and satisfies MLRP ($\ell'_n(x) > 0$) for any $x \in \mathcal{X}$. Moreover, ℓ_n converges to 1 uniformly on \mathcal{X} and, therefore, satisfies Assumption 2.

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Next we show that the signal satisfies Assumption 1. We have

$$\begin{split} F^{H}(x) &= \frac{1 - e^{-\mu x}}{1 - e^{-\mu}}, \qquad 1 - F^{H}(x) = \frac{e^{-\mu x} - e^{-\mu}}{1 - e^{-\mu}} \\ F^{L}_{n}(x) &= \frac{1 - e^{-(\mu + \epsilon_{n})x}}{1 - e^{-(\mu + \epsilon_{n})}}, \qquad 1 - F^{L}_{n}(x) = \frac{e^{-(\mu + \epsilon_{n})x} - e^{-(\mu + \epsilon_{n})}}{1 - e^{-(\mu + \epsilon_{n})}}, \end{split}$$

 $\Lambda_n = (1 - F^H)/(1 - F_n^L)$, and $\lambda_n = F^H/F_n^L$. Let $\delta_n := \log(\Lambda_n/\lambda_n)$. Then

$$\delta_n(x, \epsilon_n) = \log\left(\frac{e^{-\mu x} - e^{-\mu}}{e^{-(\mu + \epsilon_n)x} - e^{-(\mu + \epsilon_n)}} \frac{1 - e^{-(\mu + \epsilon_n)x}}{1 - e^{-\mu x}}\right)$$
$$= \log\left(\frac{e^{(\mu + \epsilon_n)x} - 1}{e^{\mu x} - 1}\right) - \log\left(\frac{e^{(\mu + \epsilon_n)(x-1)} - 1}{e^{\mu(x-1)} - 1}\right)$$

Note that δ_n is an analytic function of ϵ_n and converges to 0 as $\epsilon_n \to 0$ for any $x \in \mathcal{X}$. Thus, the first-order Taylor expansion of δ_n around $\epsilon_n = 0$ yields

$$\delta_n(x,\epsilon_n) = \left(\frac{xe^{\mu x}}{e^{\mu x} - 1} - \frac{(x-1)e^{\mu(x-1)}}{e^{\mu(x-1)} - 1}\right)\epsilon_n + O(\epsilon_n^2)$$
$$= \left(h(x) - h(x-1)\right)\epsilon_n + O(\epsilon_n^2), \tag{*}$$

where $h(x) := x/(1 - e^{-\mu x})$. We note that h(x) is strictly increasing in x:

$$h'(x) = \frac{1 - e^{-\mu x} - \mu x e^{-\mu x}}{\left(1 - e^{-\mu x}\right)^2} > 0.$$

The inequality holds since $1 - e^{-y} - ye^{-y} > 0$ for any $y \neq 0$ and also since h'(0) = 1/2 by l'Hôpital's rule. Hence, h(x) - h(x-1) is bounded below by a positive number uniformly on \mathcal{X} .

The term $O(\epsilon_n^2)$ can be made arbitrarily small (say, a half of the lower bound of $(h(x) - h(x - 1))\epsilon_n$) for large enough *n*. Therefore, applying $\epsilon_n = \delta_{\epsilon} n^{-\xi}$ to (*) above, we see that there exist constants $\delta > 0$ and n_1 such that $\delta_n(x) > \delta n^{-\xi}$ for any $x \in \mathcal{X}$ and for all $n > n_1$. This confirms that the signal satisfies Assumption 1.

Finally, we show that the signal satisfies Assumption 3. Let us write $\mu_L := \mu + \epsilon_n$. For this particular signal, we have

$$\lambda_n(x) = \frac{1 - e^{-\mu_L}}{1 - e^{-\mu}} \frac{1 - e^{-\mu_X}}{1 - e^{-\mu_L x}}$$
$$\lambda'_n(x) = \frac{1 - e^{-\mu_L}}{1 - e^{-\mu}} \frac{\mu e^{-\mu_X} (1 - e^{-\mu_L x}) - \mu_L e^{-\mu_L x} (1 - e^{-\mu_X})}{(1 - e^{-\mu_L x})^2}.$$

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Thus, we have

$$\lambda_{n}^{\prime\prime}(x) = \frac{1 - e^{-\mu_{L}}}{1 - e^{-\mu}} \frac{\left[-\frac{\mu^{2}}{e^{\mu x} - 1} + \frac{\mu_{L}^{2}}{e^{\mu_{L}x} - 1}\right] (1 - e^{-\mu_{L}x}) - 2\mu_{L}e^{-\mu_{L}x} \left[\frac{\mu}{e^{\mu x} - 1} - \frac{\mu_{L}}{e^{\mu_{L}x} - 1}\right]}{(1 - e^{-\mu_{L}x})^{2} (1 - e^{-\mu_{X}})^{-1}}.$$
(**)

Now we have that

$$\frac{d}{d\mu} \left(\frac{\mu}{e^{\mu x} - 1} \right) = \frac{e^{\mu x} - 1 - \mu x e^{\mu x}}{\left(e^{\mu x} - 1 \right)^2}$$

is negative for $\mu x > 0$, because $y - 1 < y \log y$ for any y > 1. Hence, the term

$$-2\mu_L e^{-\mu_L x} \left[\frac{\mu}{e^{\mu x} - 1} - \frac{\mu_L}{e^{\mu_L x} - 1} \right]$$

in (**) is negative since $\mu_L > \mu$. Also, we have

$$\frac{d}{d\mu}\left(\frac{\mu^2}{e^{\mu x}-1}\right) = \frac{2\mu e^{\mu x} \left(1-e^{-\mu x}-\mu x/2\right)}{\left(e^{\mu x}-1\right)^2}.$$

Note that $1 - e^{-y} - y/2$ is strictly negative at y = 2 and decreasing in y for y > 2. Hence, for any fixed $\mu > 2$, there exists an $x_c < 1$ such that the above derivative is negative for any $x \in [x_c, 1]$. Thus, $\left[-\frac{\mu^2}{e^{\mu x}-1} + \frac{\mu_L^2}{e^{\mu L^x}-1}\right](1 - e^{-\mu_L x})$ in (**) is negative in $x \in [x_c, 1]$ for any n, since $\mu_L > \mu$. Hence, there exists an x_c such that, for every n, $\lambda''_n(x) \le 0$ holds for any $x \in [x_c, 1]$. Thus, we verify that the signal satisfies Assumption 3.

Derivation of $\lambda'_n(x_a) = \ell'_n(x_a)/2$ and $\Lambda'_n(x_b) = \ell'_n(x_b)/2$ for (8) and (9)

Using (8), we obtain

$$\lim_{x \to x_a} \lambda'_n(x) = f_n^L(x_a) \lim_{x \to x_a} \frac{\ell_n(x) - \lambda_n(x)}{F_n^L(x)}$$
$$= f_n^L(x_a) \frac{\ell'_n(x_a) - \lambda'_n(x_a)}{f_n^L(x_a)}$$
$$= \ell'_n(x_a) - \lambda'_n(x_a),$$

which implies $\lambda'_n(x_a) = \ell'_n(x_a)/2$.

Similarly, using (9), we obtain

$$\lim_{x \to x_b} \Lambda'_n(x) = f_n^L(x_b) \lim_{x \to x_b} \frac{\Lambda_n(x) - \ell_n(x)}{1 - F_n^L(x)}$$
$$= f_n^L(x_b) \frac{\Lambda'_n(x_b) - \ell'_n(x_b)}{-f_n^L(x_b)}$$
$$= -(\Lambda'_n(x_b) - \ell'_n(x_b)),$$

which implies $\Lambda'_n(x_b) = \ell'_n(x_b)/2$.

Supplement to Proof of Lemma 2

In this section, we show that the probability of $\Gamma(t)/n$ in (15) exceeding $n^{-\nu_0}$ for some $\nu_0 > 0$ converges to 0 as $n \to \infty$.

From Lemma 1, $K_t \equiv \Gamma(t+1) - \Gamma(1)$ asymptotically follows a Poisson distribution with mean *t*. Combining with inequalities $\sqrt{2\pi}e^{-k}k^{k+0.5} \leq k! \leq e^{1-k}k^{k+0.5}$ for any integer *k*, we obtain

$$\begin{aligned} \Pr(K_t \ge k) &= \sum_{K_t=k}^{\infty} t^{K_t} e^{-t} / K_t ! \\ &= \sum_{s=0}^{\infty} t^{k+s} e^{-t} / (k+s) ! \\ &= t^k e^{-t} \sum_{s=0}^{\infty} \frac{t^s}{s!} \frac{s!}{(k+s)!} \\ &\le t^k e^{-t} \sum_{s=0}^{\infty} \frac{t^s}{s!} \frac{e^{1-s} s^{s+0.5}}{\sqrt{2\pi} e^{-(k+s)} (k+s)^{k+s+0.5}} \\ &= t^k e^{-t} \sum_{s=0}^{\infty} \frac{t^s}{s!} \frac{e^{k+1}}{\sqrt{2\pi} (k+s)^k} \left(\frac{s}{k+s}\right)^{s+0.5} \\ &\le t^k e^{-t} \sum_{s=0}^{\infty} \frac{t^s}{s!} \frac{e^{k+1}}{\sqrt{2\pi} k^k} \\ &= \frac{e}{\sqrt{2\pi}} \left(\frac{te}{k}\right)^k. \end{aligned}$$

Now we consider a region $t \in [0, T]$ and let $k = n^{1-\nu_0}$ for some $\nu_0 \in (0, 1)$. The upper bound of $\Pr(K_T \ge k)$ becomes $(e/\sqrt{2\pi})(n^{\nu_0-1}Te)^{n^{1-\nu_0}}$, which converges to 0 from above as $n \to \infty$. Also note that $\Gamma(t)$ is nondecreasing in t. Thus, the probability of events in which $\Gamma(t)$ exceeds $k = n^{1-\nu_0}$ declines to 0 as $n \to \infty$.

Derivation of (13)

This section derives the asymptotic expression (13) from (12) by applying Stirling's formula $m! \sim \sqrt{2\pi m} (m/e)^m$ as $m \to \infty$.

Substituting Stirling's formula into (12), we obtain

$$\frac{b_o}{m} \frac{e^{-\phi m} (\phi m)^{m-b_o}}{(m-b_o)!} \sim \frac{b_o}{m} \frac{e^{-\phi m + m - b_o} (\phi m)^{m-b_o}}{\sqrt{2\pi (m-b_o)} (m-b_o)^{m-b_o}} = \frac{b_o}{m\sqrt{2\pi (m-b_o)}} e^{-\phi m + m - b_o + (m-b_o)\log\phi} \left(1 - \frac{b_o}{m}\right)^{-m + b_o}$$

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$$\sim rac{b_o(\phi e)^{-b_o}}{m\sqrt{2\pi(m-b_o)}}e^{-(\phi-1-\log\phi)m}e^{b_o} \ \sim rac{b_o\phi^{-b_o}}{\sqrt{2\pi}}rac{e^{-(\phi-1-\log\phi)m}}{m^{1.5}}.$$

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