

Private Information Distributions in Securities Markets

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- How can we use theory and the price and/or order flow data to measure private information?
- In Back, Crotty, Li (2018), we develop and estimate a structural model of informed trading to address this question.

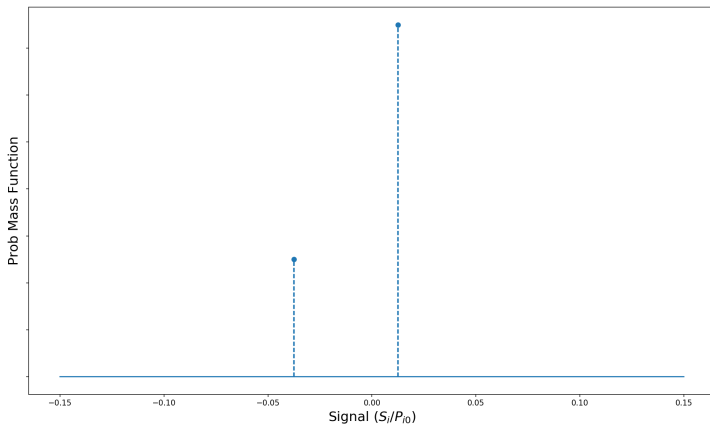
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 - A problem: information asymmetry is generally unobservable.
- How can we use theory and the price and/or order flow data to measure private information?
- In Back, Crotty, Li (2018), we develop and estimate a structural model of informed trading to address this question.
- Unexplored question: **From what distribution is private information drawn?**

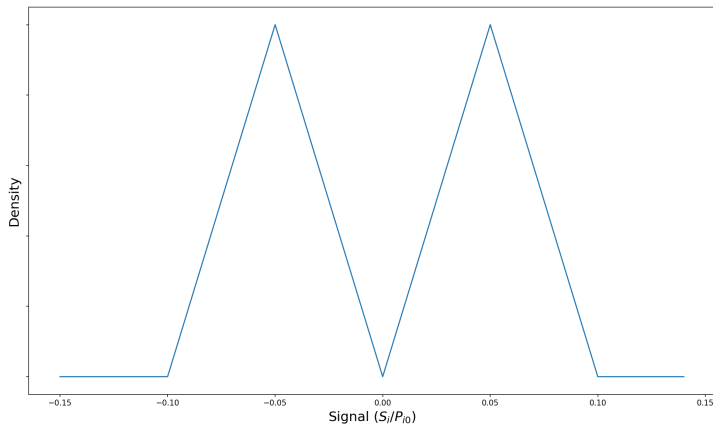
Back, Crotty, Li (2018)

- We develop a structural model of informed trading and an estimation procedure to identify information asymmetry.
 - Continuous-time Kyle model with uncertain information event and magnitude
 - Propose ML estimation that allows use of intraday observations
 - Estimation utilizes the joint distribution of returns and order flows
- For computational reasons, BCL (2018) makes simplifying assumption that signal is binary in order to facilitate estimation.

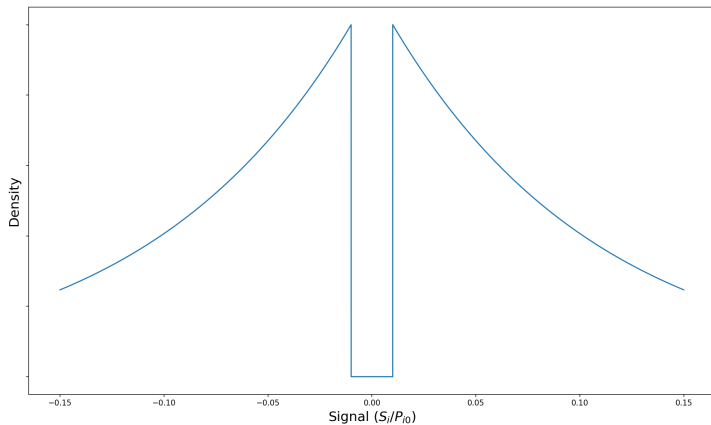
Some possible signal distributions



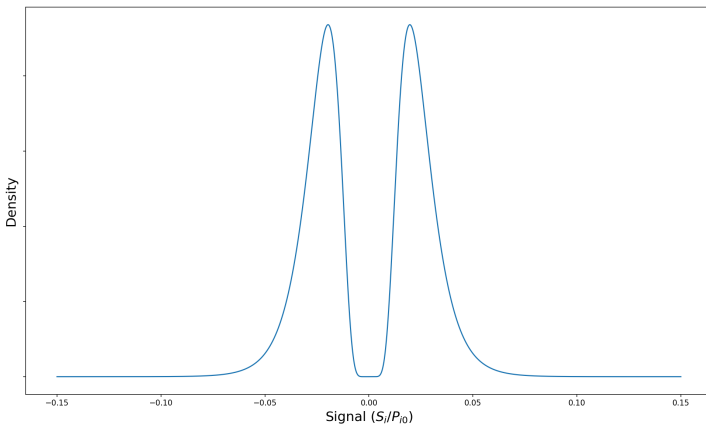
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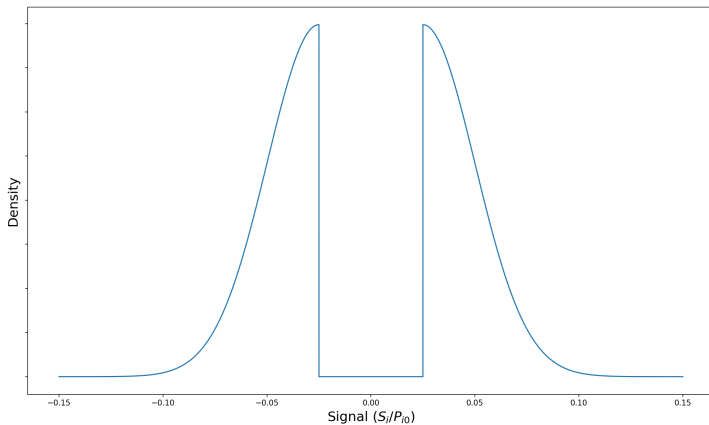
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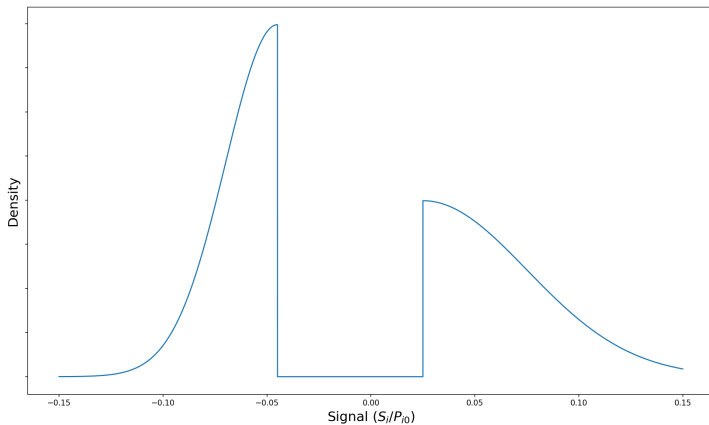
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Research questions

- What types of distributions are private signals drawn from?
- Are these distributions systematically linked to firm characteristics?
- What explains time-series variation in private signals?
- Are private signal distributions related to trading frictions (e.g., short-sale costs)?
- What are the asset-pricing implications of private information distributions?

Computational issues

- Estimating the model for non-binary signals involves optimizing a likelihood function containing numerical integration (in the pricing function).

Signal Type	Computing Time in Python	
	Single Firm-Year	25-yr panel of 2500 firms
Triangular	15 hrs	1,070 yrs
Exponential	7 hrs	500 yrs
Normal	4 hrs	285 yrs
Lognormal	22 hrs	1,570 yrs

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- Continuous-time Kyle model with asset traded on time interval $[0, 1]$
- Liquidity trades: Brownian motion Z with standard deviation σ
- Risk-neutral competitive market makers
- Information event at beginning with probability α
 - If there is an information event, a single trader sees a zero-mean signal S
 - If there is no information event, the trader is still present in the market as a value trader.
- Public information = martingale V

Definition of Equilibrium

- Let $\xi =$ indicator of information event (1 if yes, 0 if no).
- Let $Y = X + Z$ where $X =$ strategic trader's inventory.
- Market makers observe cumulative order imbalances Y and public information V .

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- Strategic trades must be optimal. The strategic trader chooses a rate of trade to maximize expected profits.

Order Imbalances in Equilibrium – Brownian Bridge

- Let F denote the distribution function of the normally distributed variable Z_1 .
- Let G denote the continuous distribution function of the signal S .
- Set $y_L = F^{-1}(\alpha G(0))$ and $y_H = F^{-1}(1 - \alpha + \alpha G(0))$, so

$$\underbrace{\alpha \text{prob}(S \leq 0)}_{\text{Uncond. Prob. of Bad News}} = \text{prob}(Z_1 \leq y_L),$$

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- In equilibrium, final cumulative order flows (Y_1) satisfy:
 - $Y_1 = F^{-1}(\alpha G(S)) < y_L$ when there is a low signal ($\xi S < 0$),
 - $Y_1 = F^{-1}(1 - \alpha + \alpha G(S)) > y_H$ when there is a high signal ($\xi S > 0$),
 - $y_L \leq Y_1 \leq y_H$ when there is no info event ($\xi = 0$).

Order Imbalance Paths in Equilibrium



Equilibrium Trades

- Equilibrium rate of trade depends on t , Y_t , and whether $\xi S < 0$, $\xi S = 0$, or $\xi S > 0$:

$$E[Z_1 - Z_t \mid Z_t = Y_t, \xi S] =$$

$$\begin{cases} F^{-1}(\alpha G(s)) - Y_t & \text{if } \xi S < 0, \\ E[Z_1 \mid Z_t = Y_t, y_L \leq Z_1 \leq y_H] - Y_t & \text{if } \xi = 0, \\ F^{-1}(1 - \alpha + \alpha G(s)) - Y_t & \text{if } \xi S > 0. \end{cases} \quad (1)$$

divided by $1 - t$.

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- Market makers perceive order flows Y as a Brownian motion with zero drift and std deviation σ .

Equilibrium Prices (and a computational challenge)

- Given the history of Y through time t , the equilibrium price is

$$\begin{aligned}
 p(t, Y_t) = & \int_{-\infty}^{y_L} \overbrace{G^{-1}\left(\frac{F(z)}{\alpha}\right)}^{\text{Signal Value}} \overbrace{f(z | t, Y_t)}^{\text{Density of } Z_1 \text{ cond. on } Z_t = Y_t} dz \\
 & + \int_{y_H}^{\infty} G^{-1}\left(\frac{F(z) - 1 + \alpha}{\alpha}\right) f(z | t, Y_t) dz.
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- BCL (2018) makes a simplifying assumption about the signal distribution - signal is either high or low: $L < 0 < H$.
- Simplified pricing function:

$$p(t, Y_t) = L \times \overbrace{N\left(\frac{y_L - Y_t}{\sigma\sqrt{1-t}}\right)}^{\text{Pr(low info | } t, Y_t)} + H \times \overbrace{N\left(\frac{Y_t - y_H}{\sigma\sqrt{1-t}}\right)}^{\text{Pr(high info | } t, Y_t)}.$$

Estimation

- Use the joint distribution of intraday prices and order imbalances.
- Timing assumptions:
 - trading period corresponds to a day.
 - parameters are stable across year.
- The gross return through time t is

$$\frac{P_{it}}{P_{i0}} = \frac{V_{it}}{V_{i0}} + p(t, Y_{it}).$$

- V_{it} is geometric Brownian motion with volatility δ .

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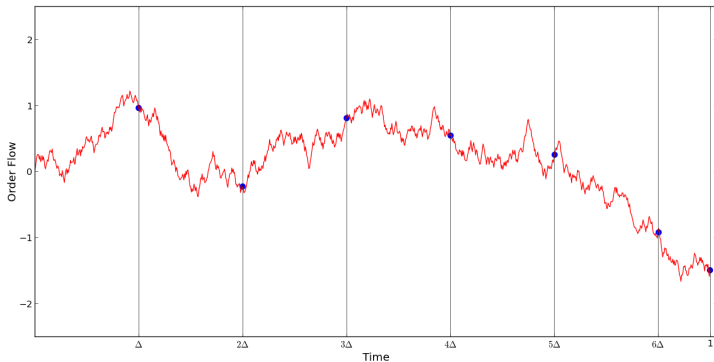
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- Some signal parametrization: BCL (2018) assumes a binary zero-mean signal with magnitude parameter κ such that

$$(H_i - L_i)/P_{i0} = 2\kappa$$

Timing of Observations



- Observe $k + 1$ daily prices (P_{ij}) and order-flows (Y_{ij}) at t_1, \dots, t_{k+1}
 - $t_{k+1} = 1$ being the close
 - Evenly spaced intraday observations: $t_j = j\Delta$ for $\Delta > 0$ and $j \leq k$.

Day- i likelihood

- The log-likelihood of observing day- i sample is:

$$\mathcal{L}_i = \log \left(f \left(\frac{P_{i1}}{P_{i0}}, \dots, \frac{P_{i,k+1}}{P_{i0}} \mid Y_i \right) f(Y_i) \right)$$

- On each day i , the vector $Y_i = (Y_{i,t_1}, \dots, Y_{i,t_{k+1}})'$ is normally distributed with mean 0 and covariance matrix $\sigma^2 \Delta \Sigma$.

$$\Sigma = \begin{pmatrix} 1 & 1 & \cdots & 1 & 1 \\ 1 & 2 & \cdots & 2 & 2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 2 & \cdots & k & k \\ 1 & 2 & \cdots & k & 1/\Delta \end{pmatrix}.$$

Day- i likelihood

- The density function of $(P_{i1}/P_{i0}, \dots, P_{i,k+1}/P_{i0})$ conditional on Y_i is

$$f(U_{i1}, \dots, U_{i,k+1}) e^{-\sum_{j=1}^{k+1} U_{ij}},$$

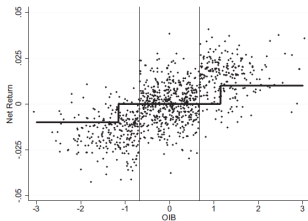
where f denotes the multivariate normal density function with mean vector $-(\delta^2 \Delta / 2) \Gamma$ and covariance matrix $\delta^2 \Delta \Sigma$ and

$$\Gamma = \begin{pmatrix} 1 \\ 2 \\ \vdots \\ k \\ 1/\Delta \end{pmatrix}$$

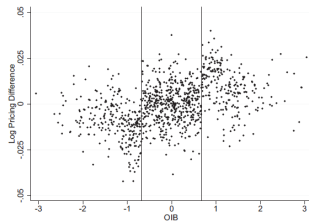
and

$$U_{ij} = \log \left(\frac{P_{ij}}{P_{i0}} - p(t_j, Y_{ij}) \right) \quad (2)$$

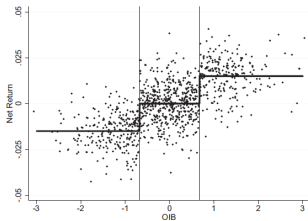
Intuition



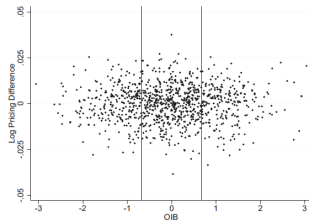
(a) $\hat{\alpha} = 0.25, \hat{\kappa} = 0.01, \hat{p}_L = 0.5$



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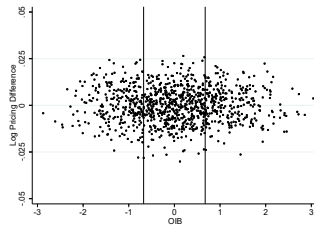
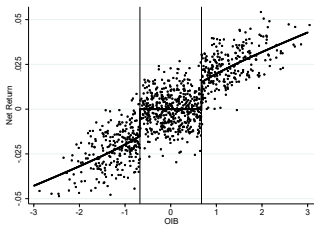


(c) $\hat{\alpha} = 0.50, \hat{\kappa} = 0.015, \hat{p}_L = 0.5$

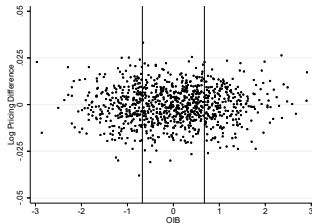
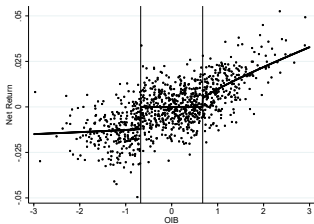
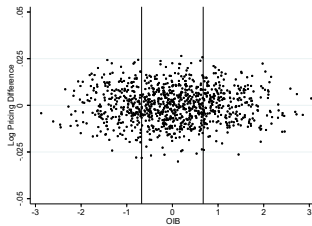
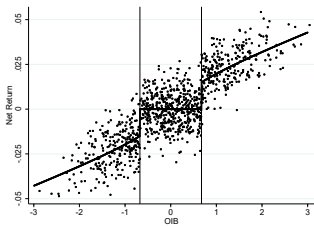


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More general distributions



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- Estimating private information distributions from prices and trading data could provide insights into the information environment in financial markets.

Thanks for your feedback!