

# An Introduction to Market Microstructure Invariance

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# Overview

Our goal is to explain how **order size**, **order frequency**, **market efficiency and trading costs** vary across time and stocks.

- We propose **market microstructure invariance** that generates predictions concerning variations of these variables.
- We develop a meta-model suggesting that invariance is ultimately related to granularity of information flow.
- Invariance relationships are tested using a data set of portfolio transitions and find a strong support in the data.
- Invariance implies simple formulas for order size, order frequency, market efficiency, market impact, and bid-ask spread as functions of observable volume and volatility.

## Preview of Results: Bet Sizes

Our estimates imply that bets  $|\tilde{X}|/V$  are approximately distributed as **a log-normal** with the log-variance of 2.53 and the number of bets per day  $\gamma$  is defined as ( $W = V \cdot P \cdot \sigma$ ),

$$\ln \gamma = \ln 85 + \frac{2}{3} \ln \left[ \frac{W}{(0.02)(40)(10^6)} \right].$$

$$\ln \left[ \frac{|\tilde{X}|}{V} \right] \approx -5.71 - \frac{2}{3} \cdot \ln \left[ \frac{W}{(0.02)(40)(10^6)} \right] + \sqrt{2.53} \cdot N(0, 1)$$

For a benchmark stock, there are 85 bets with the median size of 0.33% of daily volume. Buys and sells are symmetric.

## Preview of Results: Transaction Costs

Our estimates imply two simple formulas for expected trading costs for any order of  $X$  shares and for any security. The linear and square-root specifications are:

$$C(X) = \left( \frac{W}{(0.02)(40)(10^6)} \right)^{-1/3} \frac{\sigma}{0.02} \left( \frac{2.50}{10^4} \cdot \frac{X}{0.01V} \left[ \frac{W}{(0.02)(40)(10^6)} \right]^{2/3} + \frac{8.21}{10^4} \right).$$

$$C(X) = \left( \frac{W}{(0.02)(40)(10^6)} \right)^{-1/3} \frac{\sigma}{0.02} \left( \frac{12.08}{10^4} \cdot \sqrt{\frac{X}{0.01V} \left[ \frac{W}{(0.02)(40)(10^6)} \right]^{2/3}} + \frac{2.08}{10^4} \right).$$

# A Structural Model

We outline a dynamic infinite-horizon model of trading, from which various invariance relationships are derived results.

- **Informed traders** face given costs of acquiring information of given precision, then place informed bets which incorporate a given fraction of the information into prices.
- **Noise traders** place bets which turn over a constant fraction of the stocks float, mimicking the size distribution of bets placed by informed trades.
- **Market makers** offer a residual demand curve of constant slope, lose money from being “run over” by informed bets, but make up the losses from trading costs imposed on informed and noise traders.

# Fundamental Value

- The unobserved “fundamental value” of the asset follows an exponential martingale:

$$F(t) := \exp[\sigma_F \cdot B(t) - \frac{1}{2} \cdot \sigma_F^2 \cdot t],$$

where  $B(t)$  follows standardized Brownian motion with  $\text{var}\{B(t + \Delta t) - B(t)\} = \Delta t$ .  $F(t)$  follows a martingale.

# Market Prices

- The price changes as informed traders and noise traders arrive in the market and anonymously place bets.
- Risk neutral market makers set the market price  $P(t)$  as the conditional expectation of the fundamental value  $F(t)$  given a history of the “bet flow”.
- $\bar{B}(t)$  is the market’s conditional expectation of  $B(t)$  based on observing the history of prices; the error  $B(t) - \bar{B}(t)$  has a normal distribution with variance denoted  $\Sigma(t)/\sigma_F^2$ .
- The price is the best estimate of fundamental value; the price has a martingale property:

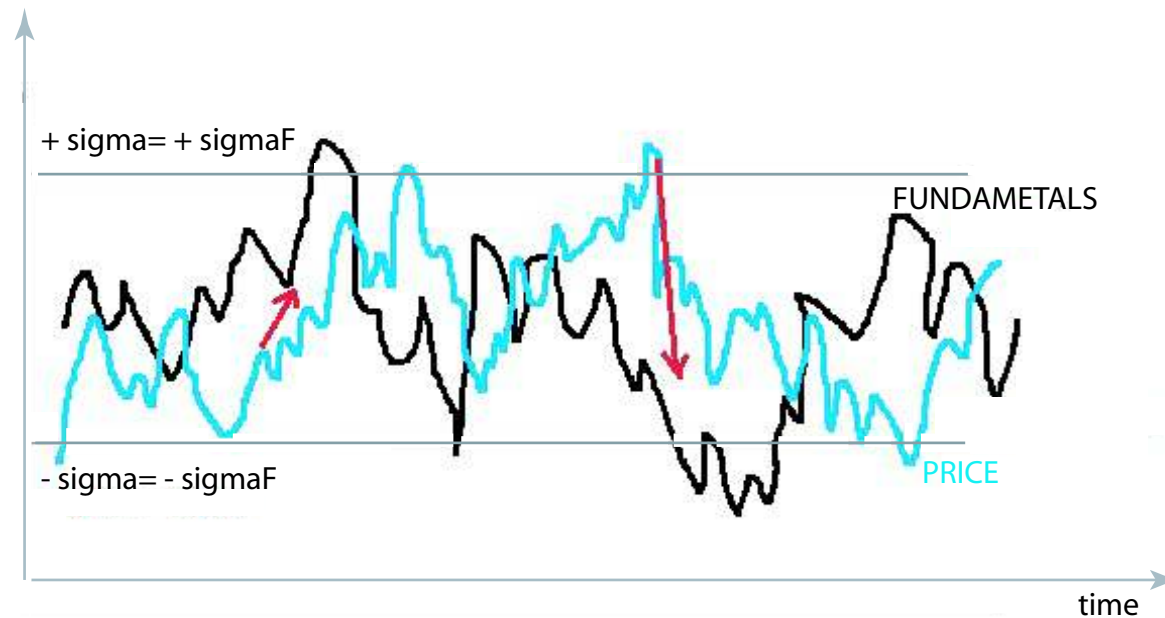
$$P(t) = \exp[\sigma_F \cdot \bar{B}(t) + \frac{1}{2} \cdot \Sigma(t) - \frac{1}{2} \cdot \sigma_F^2 \cdot t].$$

# Pricing Accuracy

- Pricing accuracy is defined as  $\Sigma(t) = \text{var}\{\log[F(t)/P(t)]\}$ ; market is more efficient when  $\Sigma^{1/2}$  is smaller.
- $\Sigma^{-1/2}$  is Fischer Black's measure of market efficiency: He conjectures *“almost all markets are efficient” in the sense that “price is within a factor 2 of value” at least 90% of the time.*



# Pricing Accuracy - Intuition



- Pricing accuracy is defined as  $\Sigma(t) = \text{var}\{\log[F(t)/P(t)]\}$ ; the market is more efficient when  $\Sigma^{1/2}$  is smaller.
- Fama says a market is “efficient” if all information is appropriately reflected in price (prices follow a martingale), even if very little information is available and prices are not very accurate, i.e.,  $\Sigma^{1/2}$  is large.

# Pricing Accuracy

- $\Sigma^{-1/2}$  is Fischer Black's measure of market efficiency: He conjectures *“almost all markets are efficient” in the sense that “price is within a factor 2 of value” at least 90% of the time.* In mathematical terms,  $\Sigma^{1/2} = \ln(2)/1.64 = 0.42$ .
- In time units,  $\Sigma/\sigma^2$  is the number of years by which the informational content of prices lags behind fundamental value, e.g., if  $\sigma = 0.35$  and  $\Sigma^{1/2} = \ln(2)/1.64$ , then prices are about  $(\ln(2)/1.64)^2/0.35^2 \approx 1.50$  years “behind” fundamental value.

# Informed Traders

- Informed traders arrive randomly in the market at rate  $\gamma_I(t)$ .
- Each informed trader observes one private signal  $\tilde{i}(t)$  and places one and only one bet, which is executed by trading with market makers.

$$\tilde{i}(t) := \tau^{1/2} \cdot \Sigma(t)^{-1/2} \cdot \sigma_F \cdot [B(t) - \bar{B}(t)] + \tilde{Z}_I(t),$$

where  $\tau$  measures the precision of the signal and  $\tilde{Z}_I(t) \sim N(0, 1)$ .  $\text{var}\{\tilde{i}(t)\} = 1 + \tau \approx 1$ .

# Informed Traders

- An informed trader updates his estimate of  $B(t)$  from  $\bar{B}(t)$  to  $\bar{B}(t) + \Delta\bar{B}_I(t)$ . Assuming  $\tau$  is small,

$$\Delta\bar{B}_I(t) \approx \tau^{1/2} \cdot \Sigma(t)^{1/2} / \sigma_F \cdot \tilde{i}(t).$$

- If the signal value were to be fully incorporated into prices, then the dollar price change would be equal to

$$E\{F(t) - P(t) \mid \Delta\bar{B}_I(t)\} \approx P(t) \cdot \sigma_F \cdot \Delta\bar{B}_I(t).$$

- Only a fraction  $\theta$  of the “fully revealing” impact is incorporated into prices ( $\lambda(t)$  is price impact), i.e.,

$$\tilde{Q}(t) = \theta \cdot \lambda(t)^{-1} \cdot P(t) \cdot \sigma_F \cdot \Delta\bar{B}_I(t).$$

# Profits of Informed Traders

- An informed trader's expected “paper trading” profits are

$$\bar{\pi}_I(t) := E\{[F(t) - P(t)] \cdot \tilde{Q}(t)\} = \frac{\theta \cdot P(t)^2 \cdot \sigma_F^2 \cdot E\{\Delta \bar{B}_I(t)^2\}}{\lambda(t)}.$$

- His expected profits net of costs conditional on  $\Delta \bar{B}_I(t)$  are

$$E\{[F(t) - P(t)] \cdot \tilde{Q}(t) - \lambda(t) \tilde{Q}(t)^2\} = \frac{\theta(1 - \theta)P(t)^2\sigma_F^2 \cdot \Delta \bar{B}_I(t)^2}{\lambda(t)}.$$

- $\theta = 1/2$  maximizes the expected profits of the risk-neutral informed trader. We assume  $0 < \theta < 1$  to accommodate possibility of informed traders being risk averse and information can be leaked.

# Noise Traders

- Noise traders arrive at an endogenously determined rate  $\gamma_U(t)$ .
- Each noise trader places one bet which mimics the size distribution of an informed bet, even though it contains no information, i.e.,  $\tilde{i}(t) = \tilde{Z}_U(t) \sim N(0, 1 + \tau) \approx N(0, 1)$ .
- Noise traders turn over a constant fraction  $\eta$  of shares outstanding  $N$ . The expected share volume  $V(t)$  and total number of bets per day  $\gamma(t) := \gamma_I(t) + \gamma_U(t)$  satisfy

$$\gamma_U(t) \cdot E\{|\tilde{Q}(t)|\} = \eta \cdot N, \quad \gamma(t) \cdot E\{|\tilde{Q}(t)|\} = V(t).$$

# Transaction Costs

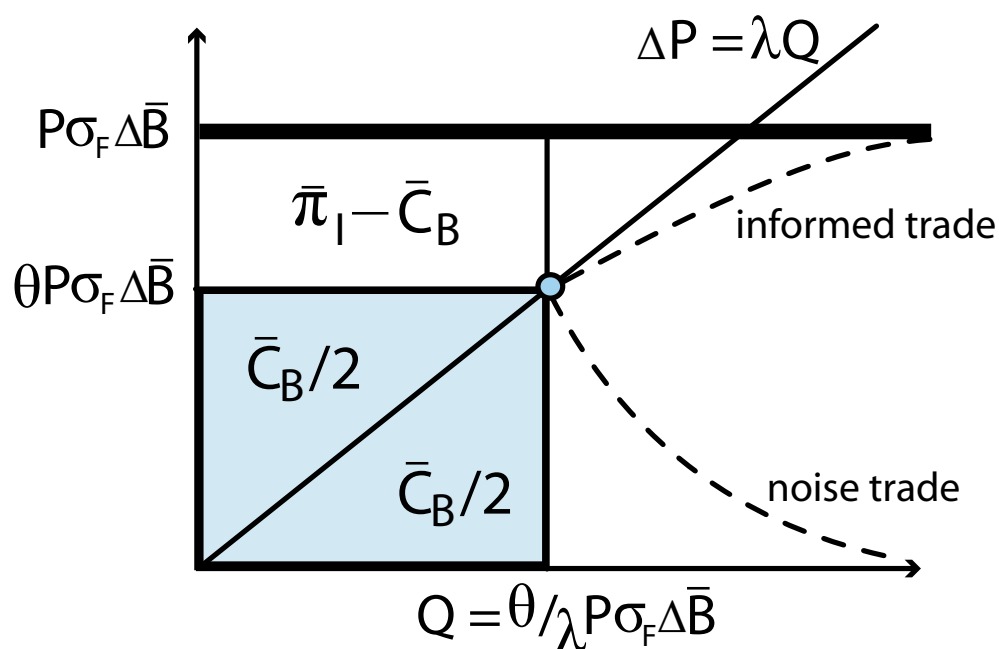
- Both informed traders and noise traders incur transactions costs. The unconditional expected costs are

$$\bar{C}_B(t) := \lambda(t) \cdot E\{\tilde{Q}(t)^2\} = \frac{\theta^2 \cdot P(t)^2 \cdot \sigma_F^2 \cdot E\{\Delta \bar{B}(t)^2\}}{\lambda(t)}.$$

- Illiquidity  $1/L(t)$  is defined as the expected cost of executing a bet in basis points:

$$1/L(t) := \bar{C}_B(t)/E\{|P(t) \cdot \tilde{Q}(t)|\}.$$

# Break-Even Conditions - Intuition



There is price continuation after an informed trade and mean reversion after a noise trade. The losses on trading with informed traders are equal to total gains on trading with noise traders,  $\gamma_I \cdot (\bar{\pi}_I - \bar{C}_B) = \gamma_U \cdot \bar{C}_B$ .



# Break-Even Condition For Market Maker

- The equilibrium level of costs must allow market makers to break even.
- The expected dollar price impact costs that market makers expect to collect from all traders must be equal to the expected dollar paper trading profits of informed traders:

$$(\gamma_I(t) + \gamma_U(t)) \cdot \bar{C}_B(t) = \gamma_I \cdot \bar{\pi}_I(t).$$

# Break-Even Condition for Informed Traders

- The break-even condition for informed traders yields the rate at which informed traders place bets  $\gamma_I(t)$ .
- The expected paper trading profits from trading on a signal  $\bar{\pi}_I(t)$  must equal the sum of expected transaction costs  $\bar{C}_B(t)$  and the exogenously constant cost of acquiring private information denoted  $c_I$ :

$$\bar{\pi}_I(t) = \bar{C}_B(t) + c_I.$$

# Market Makers and Market Efficiency

- Zero-profit, risk neutral, competitive market makers set prices such that the price impact of anonymous trades reveals on average the information in the order flow. The average impact of a bet must satisfy

$$\lambda(t) \cdot \tilde{Q}(t) = \frac{\gamma_I(t)}{\gamma_I(t) + \gamma_U(t)} \cdot \lambda(t) \cdot \tilde{Q}(t) \cdot \frac{1}{\theta} + \frac{\gamma_U(t)}{\gamma_I(t) + \gamma_U(t)} \cdot 0.$$

- The ratio of informed traders to noise traders then turns out to be equal to the exogenous constant  $\theta$ . The turnover rate is constant.

$$\frac{\gamma_I(t)}{\gamma_I(t) + \gamma_U(t)} = \theta, \quad V = \eta \cdot N / (1 - \theta).$$

# Diffusion Approximation

- As a result of each bet, market makers update their estimate of  $\bar{B}(t)$  by  $\Delta\bar{B}(t)$ .
- A trade is informed with probability  $\theta$  and, if informed, incorporates a fraction  $\theta$  of its information content into prices, leading to an adjustment in  $\bar{B}(t)$  of

$$\Delta\bar{B}(t) = \theta\tau^{1/2}\Sigma(t)^{1/2}\sigma_F^{-1} \cdot \left( \tau^{1/2}\Sigma(t)^{-1/2}\sigma_F[B(t) - \bar{B}(t)] + \tilde{Z}_I(t) \right)$$

- A trade is uninformed with probability  $1 - \theta$  and, if uninformed, adds noise to  $\bar{B}(t)$  of

$$\Delta\bar{B}(t) = \theta\tau^{1/2}\Sigma(t)^{1/2}\sigma_F^{-1} \cdot \tilde{Z}_U(t).$$

# Diffusion Approximation

- When the arrival rate of bets  $\gamma(t)$  per day is sufficiently large, the diffusion approximation for the dynamics of the estimate  $\bar{B}(t)$  can be written as

$$d\bar{B}(t) = \gamma(t) \cdot \theta^2 \cdot \tau \cdot [B(t) - \bar{B}(t)] \cdot dt + \gamma(t)^{1/2} \cdot \theta \cdot \tau^{1/2} \cdot \Sigma(t)^{1/2} \cdot \sigma_F^{-1} \cdot dZ(t).$$

The first term corresponds to the information contained in informed signals which arrive at rate  $\theta \cdot \gamma(t)$ . The second term corresponds to the noise contained in all bets arriving at rate  $\gamma(t)$ .

# Equilibrium Price Process

- Define

$$\sigma(t) := \theta \cdot \tau^{1/2} \cdot \Sigma(t)^{1/2} \cdot \gamma(t)^{1/2}.$$

- By applying Ito's lemma,

$$\frac{dP(t)}{P(t)} = \frac{1}{2} \cdot [\Sigma'(t) - \sigma_F^2 + \sigma(t)^2] \cdot dt + \sigma_F \cdot d\bar{B}(t).$$

- Market efficiency implies that  $P(t)$  must follow a martingale:

$$\frac{d\Sigma(t)}{dt} = \sigma_F^2 - \sigma(t)^2.$$

# Price Process

- Since in the equilibrium,

$$\frac{dP(t)}{P(t)} = \sigma(t) \cdot d\bar{Z}(t).$$

The process  $\bar{Z}(t)$  is a standardized Brownian motion under the market's filtration and  $\sigma(t)$  is the measure of returns volatility.

# Resiliency

- The difference  $B(t) - \bar{B}(t)$  follows the mean-reverting process,

$$d[B(t) - \bar{B}(t)] = -\frac{\sigma(t)^2}{\Sigma(t)} \cdot [B(t) - \bar{B}(t)] \cdot dt + dB(t) - \frac{\sigma(t)}{\sigma_F} \cdot dZ(t).$$

- Market resiliency  $\rho(t)$  be the mean reversion rate at which pricing errors disappear

$$\rho(t) = \frac{\sigma(t)^2}{\Sigma(t)}.$$

Holding returns volatility constant, resiliency is greater in markets with higher pricing accuracy.



# Invariance Theorem - 1

*Assume the cost  $c_I$  of generating a signal is an invariant constant and let  $m := E\{|\tilde{i}(t)|\}$  define an additional invariant constant.*

*Then, the invariance conjectures hold: The dollar risk transferred by a bet per unit of business time is a random variable with an invariant distribution  $\tilde{I}$ , and the expected cost of executing a bet  $\bar{C}_B$  is constant:*

$$\tilde{I}(t) := P(t) \cdot \tilde{Q}(t) \cdot \frac{\sigma(t)}{\gamma(t)^{1/2}} = \bar{C}_B \cdot \tilde{i}(t).$$

$$\bar{C}_B = c_I \cdot \theta / (1 - \theta).$$

# Invariance Theorem -2

*The number of bets per day  $\gamma(t)$ , their size  $\tilde{Q}(t)$ , liquidity  $L(t)$ , pricing accuracy  $\Sigma(t)^{-1/2}$ , and market resiliency  $\rho(t)$  are related to price  $P(t)$ , share volume  $V(t)$ , volatility  $\sigma(t)$ , and trading activity  $W(t) = P(t) \cdot V(t) \cdot \sigma(t)$  by the following invariance relationships:*

$$\gamma(t) = \left( \frac{\lambda(t) \cdot V(t)}{\sigma(t)P(t)m} \right)^2 = \left( \frac{E\{|\tilde{Q}(t)|\}}{V(t)} \right)^{-1} = \frac{(\sigma(t)L(t))^2}{m^2} = \frac{\sigma(t)^2}{\theta^2 \tau \Sigma(t)} = \frac{\rho(t)}{\theta^2 \tau} = \left( \frac{W(t)}{m \bar{C}_B} \right)^{2/3}.$$

*Arrival Rate — Impact — Bet Size — Liquidity — “Efficiency” — Activity*

*$\tau$  is the precision of a signal,  $\theta$  is the fraction of information  $\tilde{i}(t)$  incorporated by an informed trade. The price follows a martingale with stochastic returns volatility  $\sigma(t) := \theta \cdot \tau^{1/2} \cdot \Sigma(t)^{1/2} \cdot \gamma(t)^{1/2}$ .*

# Proof

The proof is based on the solution of the system of four equations:

- Volume condition:  $\gamma(t) \cdot E\{|\tilde{Q}(t)|\} = V(t)$
- Market resiliency  $\bar{c}_B = \lambda(t) \cdot E\{\tilde{Q}^2(t)\},$
- Volatility condition:  $\gamma(t) \cdot \lambda(t)^2 \cdot E\{\tilde{Q}(t)^2\} = P(t)^2 \cdot \sigma(t)^2,$
- Moments ratio:  $m = \frac{E\{|\tilde{Q}(t)|\}}{[E\{\tilde{Q}(t)^2\}]^{1/2}}.$

One can think of  $\gamma(t)$ ,  $\lambda(t)$ ,  $E\{\tilde{Q}(t)^2\}$ , and  $E\{|\tilde{Q}(t)|\}$  as unknown variables to be solved for in terms of known variables  $V(t)$ ,  $\bar{c}_B$ ,  $P(t)$ , and  $\sigma(t)$ .

## Discussion

- Trading activity  $W(t)$  and its components—prices  $P(t)$ , share volume  $V$ , and returns volatility  $\sigma(t)$ —are a “macroscopic” quantities, which are easy to estimate.
- The bet arrival rate  $\gamma(t)$ , bet size  $\tilde{Q}(t)$ , the average cost of a bet  $1/L(t)$ , pricing accuracy  $\Sigma(t)^{1/2}$ , and resiliency  $\rho(t)$  are “microscopic” quantities, which are difficult to estimate.

Invariance relationships allow to infer microscopic quantities from macroscopic quantities ( $\bar{C}_B$ ,  $m$ , and  $\tau \cdot \theta^2$  are just constants).

# Discussion

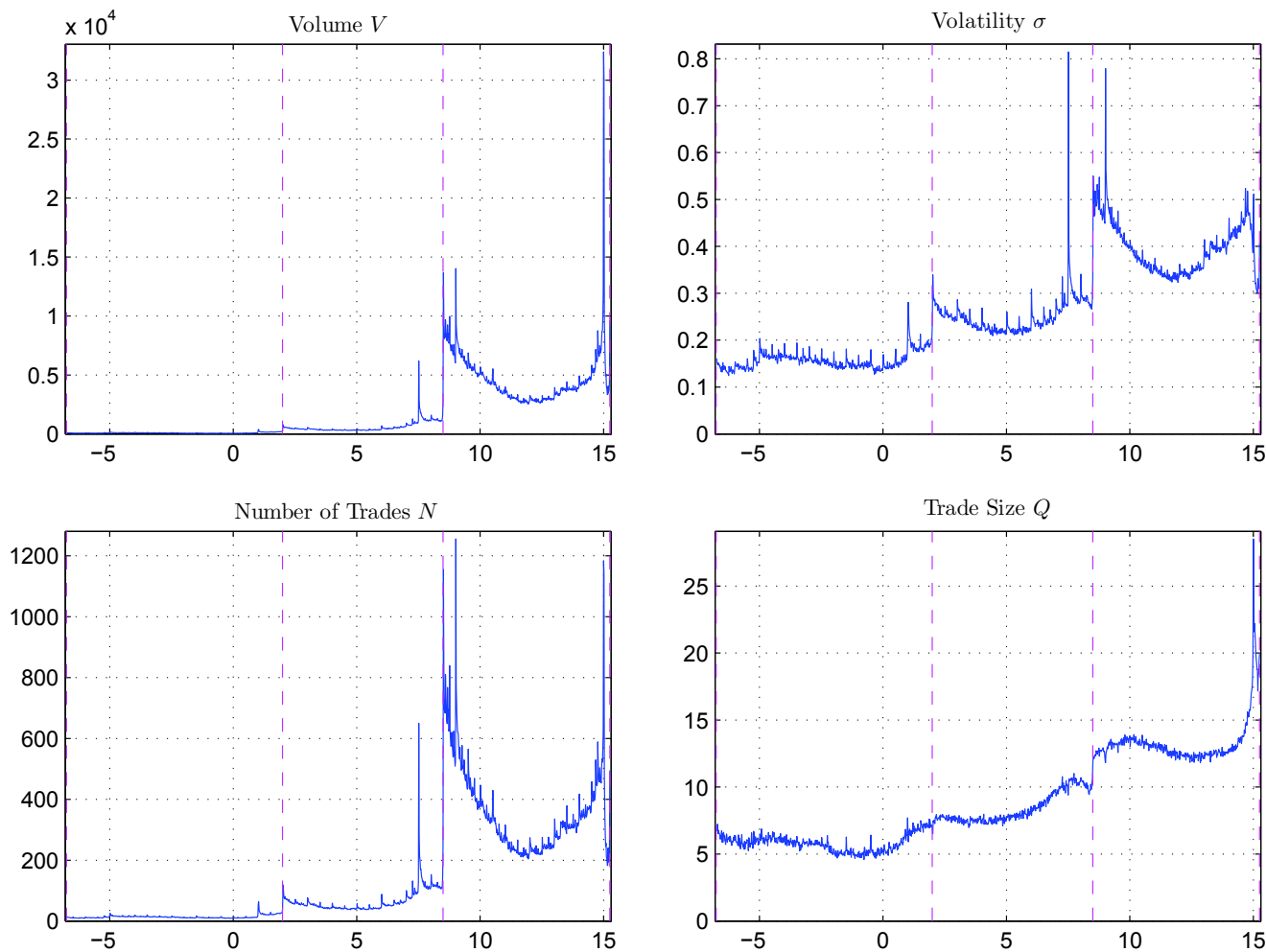
- The assumption that distinct bets result from distinct pieces of private information implies a particular level of granularity for both signals and bets.
- The invariance of bet sizes and their cost rely on the assumption that cost of a private signal  $c_I$  and the shape of the distribution of signals  $m$  are constant ( $c_I$  can be replaced by productivity-adjusted wage of a finance professional).
- The invariance of pricing accuracy and resiliency requires stronger assumptions: the informativeness of a bet  $\tau \cdot \theta^2$  is constant.
- The model is motivated by the time series properties of a single stock as its market capitalization changes, but it can apply cross-sectionally across different securities.

# Robustness of Assumptions

- Our structural model makes numerous restrictive assumptions. The empirical results we are about to describe are not consistent with the “linear-normal” assumptions of the model.
- The size of unsigned bets closely fits a log-normal distribution, not a normal distribution. A linear price impact model predicts market impact costs reasonably well, but a square root model of price predicts impact costs better.
- We conjecture that it should be possible to modify our structural model to accommodate those issues.
- The model is to be interpreted as a “proof of concept” consistent with the interpretation that the invariance hypotheses might apply more generally.

# Intraday Patterns for S&P500 E-mini Futures

Intraday patterns for volume, volatility, number of trades, and average trade size (Andersen, Bondarenko, Kyle, Obizhaeva (2014))



# Intraday Patterns for S&P500 E-mini Futures

Log of number of trades on log trading activity, by day and one-minute time interval (2008-2011). Predicted coeff. is  $2/3$ .

The fitted line is  $\ln(N_{dt}) = -3.7415 + 0.661 \cdot \ln(V_{dt} \cdot P_{dt} \cdot \sigma_{dt})$ .

