## Dimensional Analysis, Leverage Neutrality, and Market Microstructure Invariance

Albert S. Kyle

Anna A. Obizhaeva

University of Maryland

New Economic School

Summer School, Moscow August 2019

## **Big Questions**

We think of trading a stock as playing a trading game: Long-term traders buy and sell shares to implement "bets," and intermediaries with short-term strategies-market makers, high frequency traders, and other arbitragers-clear markets.

- Can we derive quantitative predictions about microstructure variables? Is there a simple empirical measure of liquidity and how can theoretical liquidity parameters, like market impact coefficient λ, be implemented empirically?
- Trading games look different across assets that different in terms of their trading activity: dollar trading volume, volatility etc. Are there any fundamental (universal) laws in financial markets as in physics?

## **Answers: Use General Principles**

- Trading games look different across assets only at first sight! They are similar if one looks through invariance lenses.
- Invariance implies a simple measure of liquidity as function of volume V · P and returns volatility σ<sup>2</sup>:

$$L = \left(\frac{m^2 \cdot P \cdot V}{C \cdot \sigma^2}\right)^{1/3}$$

where constants  $m^2 = 0.25$  and C = 2000.

- Liquidity L can be mapped to permanent price impact λ, temporary price impact κ, funding and trading liquidity etc.
- Theoretical dynamic models can link liquidity *L* to resiliency of prices  $\rho$  and error variance of prices  $\Sigma$ .

## A General Picture

The scaling laws can be derived using different approaches:

- "Market Microstructure Invariance: Empirical Hypotheses" (Ecma, 2016): Empirical conjectures and tests.
- "Market Microstructure Invariance: A Dynamic Equilibrium Model": Dynamic equilibrium model of speculative trading in which liquidity constrained investors seek to profit from trading on signals with invariant cost.
- "Adverse Selection and Liquidity: From Theory to Practice": A meta-model.
- This paper: Physicists' approach, apply dimensional analysis (consistency of units, Buckingham  $\pi$ -theorem)

# APPROACH I: DIMENSIONAL ANALYSIS AND LEVERAGE NEUTRALITY

Derivation of Invariance for Physicists

## Overview

This paper combines dimensional analysis, leverage neutrality, and a principle of invariance to derive scaling laws.

- Scaling laws relate transaction costs functions, bid-ask spreads, bet sizes, number of bets, and other financial variables in terms of dollar trading volume and volatility.
- These laws are tested using a data set of trades in the Russian and U.S. stock markets and find a strong support in the data.
- These scaling laws provide useful metrics for risk managers and traders; scientific benchmarks for evaluating issues related to high frequency trading, market crashes, and liquidity measurement; and guidelines for designing policies.

## **Dimensional Analysis**

Physics researchers obtain powerful results by using dimensional analysis to reduce the dimensionality of problems (the size and number of molecules in a mole of gas, the size of the explosive energy, turbulence).

- **Physics:** fundamental units of mass, distance, and time & conservation laws based on laws of physics.
- Finance: fundamental units of time, currency, and shares & conservation laws based on no-arbitrage restrictions.

### **Oscillation of a Pendulum?**

Suppose the time of oscillation T of a pendulum T = f(M, L, g).

$$[T] = s \qquad \text{and} \qquad \begin{array}{l} [M] = kg \\ [L] = m \\ [g] = m/s^2. \end{array}$$

Buckingham  $\pi$  theorem: Rescaled T is a function of N-3 rescaled dimensionless variables

$$T = \sqrt{\frac{L}{g}} \cdot f(\text{dimensionless variables}) = \sqrt{\frac{L}{g}} \cdot f(\cdot) = \sqrt{\frac{L}{g}} \cdot \text{const.}$$

The law of conservation of energy implies that  $const = 2\pi$ .

If 
$$T = f(M, L, g, x_1, x_2)$$
, then  $T = \sqrt{\frac{L}{g}} \cdot f(\text{scaled x1, scaled x2})$ .

#### How Big was the Bomb?

The first atomic blast, the Trinity Test in New Mexico in 1945, had an explosive yield of about 20 kilotons, but this value was secret.

Based on photographs of the Trinity Test released by the US Army in 1947 and dimensional analysis, Taylor guessed the size E from

$$R = \left(\frac{E \cdot t^2}{\rho}\right)^{1/5},$$

where R is radius, E is energy, t is time,  $\rho$  is density of air.

$$[R] = m \qquad \text{and} \qquad [E] = kg \cdot m^2/s^2$$
$$[t] = s$$
$$[\rho] = kg/m^3.$$

#### **Dimensional Analysis and Finance**

In financial markets, institutional investors trade by implementing speculative "bets" which move prices. A bet is a decision to buy or sell a quantity of institutional size.

Trading is costly; bets tend to move market prices.

Dimensional analysis can be used to find formulas for the number of bets, their average size, market depth, transaction costs, etc.

## Market Microstructure Variables

Easy-to-observe quantities include price, volume, and volatility:

 $\begin{array}{l} {\sf Price} = P_{jt} = 40.00 \ {\sf dollars/share} \\ {\sf Trading \ Volume} = V_{jt} = 1.00 \ {\sf million \ shares/day} \\ {\sf Returns \ Volatility} = \sigma_{jt} = 0.02/{\sf day}^{1/2} \end{array}$ 

Hard-to-measure quantities that vary greatly across assets and time include bet size, number of bets, and the price impact coefficient:

Size of Bet =  $Q_{jt} = 10\,000$  shares Number of Bets =  $\gamma_{jt} = 100/\text{day}$ Execution Horizon =  $H_{jt} = 1$  day Price Change per Bet =  $\Delta P_{jt} = 0.04 = \text{ dollars/share}$ Price Impact Coefficient =  $\lambda_{jt} = 5 \times 10^{-5} \text{dollars/share}^2$ Price Error =  $\Sigma_{jt}^{1/2} = \text{var}^{1/2} \{\log\left(\frac{F_{jt}}{P_{jt}}\right)\} = \log(2) (\text{dimensionless})$ 

Price Resiliency =  $ho_{jt} = 0.0040/{
m day}$ 

#### **Transaction Costs**

Transaction costs are usually also hard to measure.

Price Impact =  $\Delta P_{it} = 0.04$  dollars/share

Price impact cost  $G_{jt}$  as fraction of value traded:

$$G_{jt} = rac{\Delta P_{jt}}{P_{jt}} = rac{\Delta P_{jt} \cdot Q_{jt}}{P_{jt} \cdot Q_{jt}} = 10$$
 basis points

Price impact cost in dollars:

Dollar Price Impact Cost =  $\Delta P_{jt} \cdot Q_{jt} = 400$  dollars

Avg Dollar Cost per Bet C:

$$C = E_Q \{ \Delta P_{jt} \cdot Q_{jt} \}.$$

## **Dimensional Analysis and Finance**

Basic idea: Use dimensional analysis like a physicist (units consistency, Buckingham  $\pi$  Theorem):

- "Guess" correct functional form, i.e, correct list of explanatory variables.
  - Warning: Incorrect guess may lead to nonsense.
- Reduce dimensionality of problem by factoring out units, making remaining parameters dimensionless.
- Add restriction of "leverage neutrality" (Modigliani-Miller Theorem) to reduce dimensionality further. The cost of exchanging cash is zero. Dollar market impact cost of exchanging a risky bundle of assets is the same for any positive or negative amount of cash-equivalent assets included with the bundle.
- Make empirically motivated invariance assumption.

## Dimensional Analysis Approach: Example of $\gamma$

I. Assume that the variable of interest—the number of bets  $\gamma_{jt}$ —is determined by some unknown functions  $f_{\gamma}$ , which take share volume  $V_{jt}$ , share price  $P_{jt}$ , returns volatility  $\sigma_{jt}$ , and expected dollar costs C as their arguments:

$$\gamma_{jt} = f_{\gamma}(V_{jt}, P_{jt}, \sigma_{jt}^2, C),$$

II. Reduce the dimensionality by applying dimensional analysis:

$$[\gamma_{jt}] = 1/day$$
 and  $[\sigma_{jt}^2] = 1/day$   
 $[\gamma_{jt}] = 1/day$   $[V_{jt}] = shares/day$   
 $[P_{jt}] = dollars/share$   
 $[C] = dollars.$ 

$$\gamma_{jt} = \sigma_{jt}^2 \cdot g_{\gamma} \left( C \cdot \frac{\sigma_{jt}^2}{V_{jt} \cdot P_{jt}} \right) \sim \sigma_{jt}^2 \cdot \left( \frac{C \cdot \sigma_{jt}^2}{V_{jt} \cdot P_{jt}} \right)^{\alpha_{\gamma}}.$$

## Example Cont'd: Leverage Neutrality

III. Impose a leverage neutrality restriction:

Exchanging cash-equivalent assets incurs zero cost. Exchanging risky securities is costly. The economic cost of trading bundles of risky securities and cash-equivalent assets is the same for any positive or negative amount of cash-equivalent assets included into a bundle.

$$\begin{array}{ll} \gamma_{jt} \to \gamma_{jt}, & P_{jt} \to P_{jt} \cdot A, \\ V_{jt} \to V_{jt}, & \sigma_{jt} \to \sigma_{jt} \cdot A^{-1}, \\ C \to C, & P_{jt} \cdot \sigma \to P_{jt} \cdot \sigma_{jt}. \end{array}$$

This restriction implies that  $\alpha_{\gamma} = -2/3$ .

$$\gamma_{jt} \sim \sigma_{jt}^2 \cdot \left(\frac{C \cdot \sigma_{jt}^2}{V_{jt} \cdot P_{jt}}\right)^{\alpha_{\gamma}} \Rightarrow \gamma_{jt} \sim \sigma_{jt}^2 \cdot \left(\frac{C \cdot \sigma_{jt}^2}{V_{jt} \cdot P_{jt}}\right)^{-2/3}$$

## Example Cont'd: Invariance

IV. Impose invariance restriction:

Average dollar cost C is hard to observe. Suppose C is approximately constant across assets and time, perhaps due to equilibrium in allocating resources and skills across markets. Then,

$$\gamma_{jt} \sim \sigma_{jt}^2 \cdot \left(\frac{\mathcal{C} \cdot \sigma_{jt}^2}{V_{jt} \cdot P_{jt}}\right)^{-2/3} \quad \Rightarrow \quad \gamma_{jt} \sim \left(\sigma_{jt} \cdot V_{jt} \cdot P_{jt}\right)^{2/3}$$

In terms of liquidity measure 
$$L_{jt} = \left(\frac{m^2 \cdot P_{jt} \cdot V_{jt}}{C \cdot \sigma_{jt}^2}\right)^{1/3}$$
, we get

$$\gamma_{jt} \sim \sigma_{jt}^2 \cdot L_{jt}^2$$

#### **Russian Data**

- One-minute data from the Moscow Exchange for January–December 2015 provided by Interfax Ltd.
- 50 Russian stocks in the RTS index as of June 15, 2015.
- The Russian stock market is centralized with all trading implemented in a consolidated limit-order book.
- Small tick and lot sizes.

## U.S. Data

- One-minute data from the Trades and Quotes (TAQ) dataset for January-December 2015.
- 500 U.S. stocks in the S&P 500 index as of June 15, 2015.
- The U.S. stock market is fragmented, and securities are traded simultaneously at dozens of exchanges.
- Tick size of one cent, and lot sizes of 100 shares.

#### **Tests for Number of Trades**

Let  $N_{jt}$  denote the number of trades. Suppose

 $N_{jt} \sim \gamma_{jt}$ 

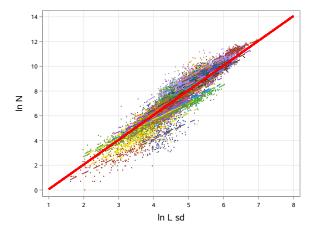
Then, from prediction

$$\gamma_{jt} \sim \sigma_{jt}^2 \cdot L_{jt}^2,$$

we get

$$\log(N_{jt}) = \text{const} + \mathbf{2} \cdot \log(\sigma_{jt} L_{jt}).$$

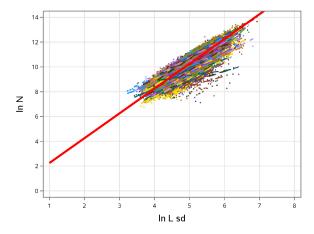
#### Number of Trades: Results for Russian Data



In aggregate sample, the slope is close to 2! R-square is 0.882.

$$\log(N_{jt}) = -3.085 + \mathbf{2.239} \cdot \log(\sigma_{jt}L_{jt})$$

#### Number of Trades: Results for U.S. Data



In aggregate sample, the slope is close to 2! R-square is 0.702.

$$\log(N_{jt}) = 1.005 + 1.842 \cdot \log(\sigma_{jt}L_{jt})$$

#### **Dimensional Analysis: Transaction Costs**

Let  $G_{jt}$  denote the price impact cost as a fraction of the value traded  $Q_{jt} \cdot P_{jt}$ . The price impact  $G_{jt}$  is dimensionless, e.g. in basis points, and it is a function of

$$G_{jt} := \frac{\Delta P_{jt}(Q_{jt})}{P_{jt}} = g(Q_{jt}; P_{jt}, V_{jt}, \sigma_{jt}^2, C).$$

- bet size  $Q_{jt}$  in units of shares,
- stock price P<sub>it</sub> in units of dollars per share,
- share volume V<sub>it</sub> in units of shares-per-day,
- volatility  $\sigma_{it}^2$  in units of per-day,
- bet cost C in units of dollars.

#### **Dimensional Analysis**

Since the value of  $G_{jt} := g(Q_{jt}, P_{jt}, V_{jt}, \sigma_{jt}^2, C)$  is dimensionless, consistency of units implies that it cannot depend on the dimensional quantities  $P_{jt}$ ,  $Q_{jt}$ , and  $\sigma_{jt}^2$ .

Thus, *dimensional analysis* implies that the function g() can be further simplified by writing it as function of two dimensionless variables.

 $G_{jt} = P_{jt}^{0} \cdot Q_{jt}^{0} \cdot (\sigma_{jt}^{2})^{0} \cdot f(\text{two dimensionless variables})$ = f(two dimensionless variables).

## **Dimensional Analysis**

There are three sets of distinct units and five dimensional quantities— $Q_{jt}$ ,  $P_{jt}$ ,  $V_{jt}$ ,  $\sigma_{jt}^2$ , C.

Form two independent dimensionless quantities:

$$L_{jt} := \left(\frac{m^2 \cdot P_{jt} \cdot V_{jt}}{\sigma_{jt}^2 \cdot C}\right)^{1/3}, \qquad Z_{jt} := \frac{P_{jt} \cdot Q_{jt}}{L_{jt} \cdot C},$$

where  $m^2$  is a dimensionless scaling constant.

Thus, dimensional analysis implies that the function g can be further simplified by writing it as  $g(L_{jt}, Z_{jt})$ .

$$G_{jt} := g(L_{jt}, Z_{jt}).$$

#### Leverage Neutrality

The cost of exchanging cash is zero. Adding cash/riskless debt to a risky asset or changing margin requirements must not affect economic costs and trading.

If (A-1)P dollars of cash or debt is added to  $P_{jt}$ , then

$$\begin{array}{ll} P_{jt} \rightarrow P_{jt} \cdot A & \qquad L_{jt} \rightarrow L_{jt} \cdot A \\ \sigma_{jt}^2 \rightarrow \sigma_{jt}^2 \cdot A^{-2} & \qquad Z_{jt} \rightarrow Z_{jt} \\ Q_{jt} \rightarrow Q_{jt} & \qquad C \rightarrow C \\ V_{jt} \rightarrow V_{jt} & \qquad G_{jt} \rightarrow G_{jt} \cdot A^{-1} \end{array}$$

The dollar costs  $G_{jt} \cdot Q_{jt} \cdot P_{jt}$  are the same, but dollar bet size  $Q_{jt} \cdot P_{jt}$  changes.  $1/L_{jt}$  has the same leverage scaling as  $G_{jt}$ .

#### Leverage Neutrality

Percentage cost  $G_{jt}$  of executing a bet of  $Q_{jt}$  shares changes by a factor  $A^{-1}$ , since dollar cost did not change but dollar value changed. Leverage neutrality implies that

$$g(A \cdot L_{jt}, Z_{jt}) = A^{-1} \cdot g(L_{jt}, Z_{jt}).$$

If 
$$A = L_{jt}^{-1}$$
, then  $g(L_{jt}, Z_{jt}) = L_{jt}^{-1} \cdot g(1, Z_{jt})$ .

Define  $f(Z_{jt}) := g(1, Z_{jt})$  and get a very **important formula**:

$$G_{jt} = g(L_{jt}, Z_{jt}) = \frac{1}{L_{jt}} \cdot f(Z_{jt}).$$

#### **Transaction Costs Model**

A general specification for transaction costs functions consistent with the scaling implied by dimensional analysis and leverage neutrality:

$$g(Q_{jt}, P_{jt}, V_{jt}, \sigma_{jt}^2, C) = \left(\frac{\sigma_{jt}^2 \cdot C}{m^2 \cdot P_{jt} \cdot V_{jt}}\right)^{1/3} \cdot f\left(\left(\frac{\sigma_{jt}^2 \cdot C}{m^2 \cdot P_{jt} \cdot V_{jt}}\right)^{1/3} \cdot \frac{P_{jt} \cdot Q_{jt}}{C}\right)$$

It is consistent with different assumptions about the shape of the function f.

## Market Microstructure Invariance

Extra assumptions are necessary to make our predictions operational.

- Three of the quantities—asset price  $P_{jt}$ , trading volume  $V_{jt}$ , and return volatility  $\sigma_{jt}$ —can be observed directly or readily estimated from public data feeds.
- $Q_{jt}$  is a characteristic of a bet privately known to a trader.
- **Invariance:** the dollar value of C and the dimensionless scaling parameter  $m^2$  are the same!

These assumptions are related to bet size and transaction costs invariance hypotheses. Preliminary calibration gives  $C \approx $2,000$  and  $m^2 \approx 0.25$ .

#### **Economic Intuition**

Scale m and define C so that

$$E\{|Z_{jt}|\}=1$$
 and  $C=E\{G_{jt}\cdot|P_{jt}Q_{jt}|\}$ .

The variables  $L_{jt}$  and  $Z_{jt}$  have an intuitive interpretation:

• 
$$\frac{1}{L_{jt}} = \frac{C}{E\{P_{jt} : |\tilde{Q}_{jt}|\}}$$
 is "illiquidity index" measuring average cost.

• 
$$m = \frac{E\{|Q_{jt}|\}}{(E\{Q_{jt}^2\})^{1/2}}$$
 is moment ratio.

#### **Liquidity Index**

The liquidity index  $L_{jt}$  is consistent in terms of units. It is the correct way to construct empirical measure of Kyle's lambda.

$$L_{jt} := \left(\frac{m^2 \cdot P_{jt} \cdot V_{jt}}{\sigma_{jt}^2 \cdot C}\right)^{1/3} \sim \left(\frac{P_{jt} \cdot V_{jt}}{\sigma_{jt}^2}\right)^{1/3}$$

.

## Liquidity Index and Other Variables

Liquidity index  $L_{jt}$  can be linked to many variables, including composition of order flow. More liquid markets are associated with more bets of larger sizes (2-to-1 ratio):

• Bet size 
$$E\{P_{jt} \cdot |\tilde{Q}_{jt}|\} = C \cdot L_{jt}$$
.

• Number of bets per day 
$$\gamma_{jt} = \frac{1}{m^2} \cdot \sigma_{jt}^2 \cdot L_{jt}^2$$
.

Liquidity index  $L_{jt}$  appears in market impact formula:

$$G_{jt}=g(L_{jt},Z_{jt})=rac{1}{L_{jt}}\cdot f(Z_{jt}).$$

#### **Transaction Costs Models**

Suppose  $f(\cdot)$  is a power function of the form  $f(Z_{jt}) = \text{const} \cdot |Z_{jt}|^{\omega}$ .

• A percentage bid-ask spread cost ( $\omega = 0$ ) implies

$$G_{jt} = rac{S_{jt}}{P_{jt}} = \mathrm{const} \cdot rac{1}{L_{jt}}.$$

• A linear market impact cost  $(\omega=1)$  implies

$$G_{jt} = \operatorname{const} \cdot \frac{P_{jt} \cdot |Q_{jt}|}{C \cdot L_{jt}^2}.$$

• A square-root market impact cost (  $\omega=1/2$  ) implies

$$G_{jt} = \operatorname{const} \cdot \sigma_{jt} \cdot \left(\frac{|Q_{jt}|}{V_{jt}}\right)^{1/2}$$

#### Tests for Bid-Ask Spread

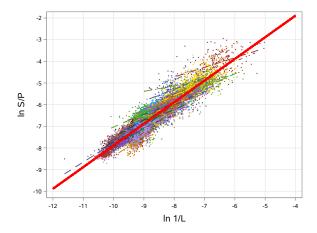
Let  $S_{jt}$  denote the percentage bid-ask spread ( $\omega = 0$ ). Since

$$rac{S_{jt}}{P_{jt}} = const \cdot rac{1}{L_{jt}},$$

we get

$$\log\left(\frac{S_{jt}}{P_{jt}}\right) = \operatorname{const} + \mathbf{1} \cdot \log\left(\frac{1}{L_{jt}}\right).$$

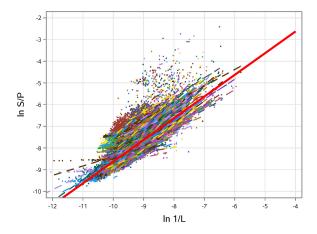
#### Spread: Results for Russian Data



In aggregate sample, the slope is close to 1! R-square is 0.876.

$$\log(S_{jt}/P_{jt}) = 2.093 + 0.998 \cdot \log(1/L_{jt})$$

#### Spread: Results for U.S. Data



In aggregate sample, the slope is close to 1! R-square is 0.450.

$$\log(S_{jt}/P_{jt}) = 1.011 + 0.961 \cdot \log(1/L_{jt})$$

#### Extensions

The empirical implications of dimensional analysis, leverage invariance, and market microstructure invariance can be generalized to incorporate various trading **frictions**.

#### **Generalized Transaction Costs Formula**

Add the execution horizon  $T_{jt}$  (in units of time), the tick size  $K_{jt}^{MIN}$  (in dollars per share), and the lot size  $Q_{jt}^{MIN}$  (in shares).

Re-scale variables to make them dimensionless and leverage neutral using the four variables  $P_{jt}$ ,  $V_{jt}$ ,  $\sigma_{it}^2$ , and C:

• 
$$\frac{|Q_{jt}|}{T_{jt}} \rightarrow \frac{|Q_{jt}|}{V_{jt} \cdot T_{jt}}$$
,

• 
$$K_{jt}^{MIN} o K_{jt}^{MIN} \cdot \frac{L_{jt}}{P_{jt}}$$

• 
$$Q_{jt}^{MIN} 
ightarrow Q_{jt}^{MIN} \cdot rac{\sigma_{jt}^2 \cdot L_{jt}^2}{V_{jt}}.$$

#### **Generalized Transaction Costs Formula**

$$G_{jt} = \frac{1}{L_{jt}} \cdot f\left(\frac{P_{jt} \cdot Q_{jt}}{C \cdot L_{jt}}; \frac{|Q_{jt}|}{V_{jt} \cdot T_{jt}}, \frac{K_{jt}^{MIN} \cdot L_{jt}}{P_{jt}}, \frac{Q_{jt}^{MIN} \cdot \sigma_{jt}^2 \cdot L_{jt}^2}{V_{jt}}\right).$$

#### **Optimal Execution Horizon**

Suppose the optimal execution horizon  $T_{jt}^*$  for an order of  $Q_{jt}$  shares depends on  $P_{jt}$ ,  $V_{jt}$ ,  $\sigma_{jt}^2$ , C,  $K_{jt}^{MIN}$ , and  $Q_{jt}^{MIN}$ .

Since  $|Q_{jt}|/(V_{jt} \cdot T_{jt}^*)$  is dimensionless and leverage neutral, the same logic implies:

$$\frac{|Q_{jt}|}{V_{jt} \cdot T_{jt}^*} = h^* \left( \frac{P_{jt} \cdot Q_{jt}}{C \cdot L_{jt}}, \frac{K_{jt}^{MIN} \cdot L_{jt}}{P_{jt}}, \frac{Q_{jt}^{MIN} \cdot \sigma_{jt}^2 \cdot L_{jt}^2}{V_{jt}} \right)$$

If tick size and lot size do not affect execution horizon,  $|Q_{jt}|/(V_{jt} \cdot T_{jt}^*)$  depends only on  $Z_{jt} := P_{jt} \cdot Q_{jt}/(C \cdot L_{jt})$ . .

# **Optimal Tick Size and Lot Size**

Setting optimal tick size and minimum lot size is of interest for exchange officials and regulators.

Let  $K_{jt}^{MIN*}$  and  $Q_{jt}^{MIN*}$  denote optimal tick size and optimal minimum lot size, respectively.

#### **Optimal Tick Size and Lot Size**

Since the scaled optimal quantities  $K_{jt}^{MIN*} \cdot L_{jt}/P_{jt}$  and  $Q_{jt}^{MIN*} \cdot L_{jt}^2 \cdot \sigma_{jt}^2/V_{jt}$  are dimensionless and leverage neutral, the scaling laws for these market frictions are

$$\mathcal{K}_{jt}^{MIN*} = \operatorname{const} \cdot \frac{P_{jt}}{L_{jt}}, \qquad Q_{jt}^{MIN*} = \operatorname{const} \cdot \frac{V_{jt}}{L_{jt}^2 \cdot \sigma_{jt}^2}.$$

#### General Formula for Bid-Ask Spread

Here is a formula for bid-ask spread for the market with frictions:

$$\frac{S_{jt}}{P_{jt}} = \frac{1}{L_{jt}} \cdot s\left(\frac{K_{jt}^{MIN} \cdot L_{jt}}{P_{jt}}, \frac{Q_{jt}^{MIN} \cdot \sigma_{jt}^2 \cdot L_{jt}^2}{V_{jt}}\right)$$

If tick size and minimum lot size have no influence on quoted bid-ask spreads, then the the relationship simplifies to  $S_{jt}/P_{jt} \sim 1/L_{jt}$ .

#### **General Formula for Trading Patterns**

Here are general formulas for trade sizes  $\tilde{X}_{jt}$  and number of trades  $N_{jt}$ :

$$\operatorname{Prob}\left\{\frac{P_{jt} \cdot \tilde{X}_{jt}}{C \cdot L_{jt}} < z\right\} = F_{jt}^{Q}\left(z, \frac{K_{jt}^{MIN} \cdot L_{jt}}{P_{jt}}, \frac{Q_{jt}^{MIN} \cdot \sigma_{jt}^{2} \cdot L_{jt}^{2}}{V_{jt}}\right).$$
$$N_{jt} = \sigma_{jt}^{2} \cdot L_{jt}^{2} \cdot f\left(\frac{K_{jt}^{MIN} \cdot L_{jt}}{P_{jt}}, \frac{Q_{jt}^{MIN} \cdot \sigma_{jt}^{2} \cdot L_{jt}^{2}}{V_{jt}}\right).$$

#### **Dimensional Analysis Looks Simple Ex Post**

Suppose the variables of interest are functions of share volume  $V_{jt}$ , share price  $P_{jt}$ , returns volatility  $\sigma_{jt}$  (NOT dollar costs C)

$$\gamma_{jt} = f_{\gamma}(V_{jt}, P_{jt}, \sigma_{jt}^2),$$

Then, we get empirically implausible prediction, also being inconsistent with leverage neutrality principle:

$$\gamma_{jt} \sim \sigma_{jt}^2$$

Similar analysis for G results in the Barra sqrt model,  $G \sim \sigma \cdot \frac{Q}{V}$ . Theory has to provide guidance on which arguments have to be used.

# Conclusions

There is a growing empirical evidence that the scaling laws discussed above match patterns in financial data, at least approximately.

Future research:

- Checking the validity of invariance predictions in other samples,
- Improving the accuracy of estimates and the triangulation of proportionality constants.

# APPROACH II: META-MODEL Derivation of Invariance for Econo-physicists

#### References

These slides are based on the following paper:

- Kyle and Obizhaeva, "Adverse Selection and Liquidity: From Theory to Practice".
- Kyle and Obizhaeva, "The Market Impact Puzzle".

#### Meta Model

Basic idea: Write down some simple generic equations that are likely to be valid in most theoretical models:

- Orders add up to trading volume;
- Order flow creates returns volatility;
- Each bet moves prices.

Can we derive invariance formulas from these equations? Yes.

#### Meta-Model

Suppose power function price impact for a bet  $Q: \Delta P = \lambda \cdot Q^{\beta}$ . Define  $\gamma =$  number of bets per day. Now assume three-equation "meta-model":

$$V = \gamma \cdot E[|Q|] \qquad (\text{Definition of volume})$$
  
$$\sigma^{2} = \gamma \cdot E\left[\left(\frac{\Delta P}{P}\right)^{2}\right] \qquad (\text{Bets generate all volatility}),$$
  
$$E\{(\Delta P)^{2}\} = \lambda^{2} \cdot E\left[|Q|^{2\beta}\right] \qquad (\text{Volatility from one bet}).$$

Three easy-to-measure quantities: V,  $\sigma$ , P. We have five unknown hard-to-measure quantities:

$$\gamma, \quad E\left[|Q|\right], \quad E\left[|Q|^{2\beta}\right], \quad E\left[(\Delta P)^2\right], \quad \lambda.$$

and only three log-linear constraints, so we need more equations.

# **Empirical Motivation for Invariance**

- Emprical Problem: Parameters like bet arrival rate γ and bet size E [|Q|] are hard to measure or estimate.
- Can they be replaced with a parameter that is either easier to estimate or does not vary much across assets?
- Empirical strategy: Introduce a parameter C (dollars), which does not vary (much) across assets and time.
- Use "invariant" parameter C to replace parameter which are hard-to-measure and varying across assets, such as γ or E [|Q|].
- Assume "transactions cost invariance": Ex ante expected dollar cost of a bet is constant (almost?)

$$C = E\left[|Q \cdot \Delta P|\right] = \lambda \cdot E\left[|Q|^{1+\beta}\right].$$

# Augmented Four Equation Meta-Model

Add transactions cost invariance to obtain four equations:

$$V = \gamma \cdot E[|Q|]$$
$$\sigma^{2} = \gamma \cdot E\left[\left(\frac{\Delta P}{P}\right)^{2}\right]$$
$$E\left[(\Delta P)^{2}\right] = \lambda^{2} \cdot E\left[|Q|^{2\beta}\right]$$
$$C = \lambda E\left[|Q|^{1+\beta}\right]$$

(Definition of volume)

(Bets generate all volatility),

(Price Impact of one bet), (Dollar impact cost of a bet).

Need two invariant moment ratios:

$$m:=rac{E\left[|Q|
ight]\cdot\sqrt{E\left[|Q|^{2eta}
ight]}}{E\left[|Q|^{eta+1}
ight]}, \qquad m_eta:=rac{\left(E\left[|Q|
ight]
ight)^{eta+1}}{E\left[|Q|^{eta+1}
ight]}.$$

Assume six parameters are easy to measure or almost constant:

$$P, V, \sigma, C, m, m_{\beta}.$$

Solve six equations for six hard-to-measure parameters:

$$\gamma, \quad \alpha, \quad E\left[\Delta P^2\right], \quad E\left[|Q|\right], \quad E\left[|Q|^{1+\beta}\right], \quad E\left[|Q|^{2\beta}\right].$$

# Solution with Invariance

Define "illiquidity" 1/L as volume-weighted expected cost:

$$\frac{1}{L} := \frac{C}{E\left[|P \cdot Q|\right]} = \left(\frac{\sigma^2 \cdot C}{m^2 \cdot P \cdot V}\right)^{1/3}$$

Then, expected bet size and number of bets are given by

$$E[|P \cdot Q|] = C \cdot L, \qquad \gamma = \frac{1}{m^2} \cdot \sigma^2 \cdot L^2.$$

Price impact is

$$rac{\Delta P}{P} = rac{1}{L} \cdot m_eta \cdot |Z|^eta, \qquad ext{where} \qquad Z := rac{Q}{E\left[|Q|
ight]} = rac{P \cdot Q}{C \cdot L},$$

If *C*, *m*, and  $m_{\beta}$  are invariant across assets, then we have a universal market impact formula and universal formula for size and number of bets. They require estimation of only these three parameters and  $\beta$ ! All formulas turned out to be the same as in dimensional analysis!

# **Calibration of Constants**

(Preliminary) Calibration of constants: C = \$2,000; if  $\beta = 1$ , then  $m \approx 0.25$  and  $m_{\beta} = m^2$ . If  $\beta = 1/2$ , then  $m_{\beta} = m \approx 0.40$ .

Future research:

- Checking the validity of invariance predictions in other samples,
- Improving the accuracy of estimates and the triangulation of proportionality constants.

# Conclusion

Meta-model derives an empirical formula for liquidity L without an underlying model of adverse selection. This is consistent with mechanical aspects of trading experienced in markets, where information is invisible.

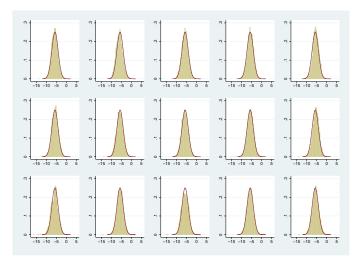
# Conclusion

We need theories based in economics to link meta-model to adverse selection. This enables further link to pricing accuracy, probability of informed trading, and precision of signals.

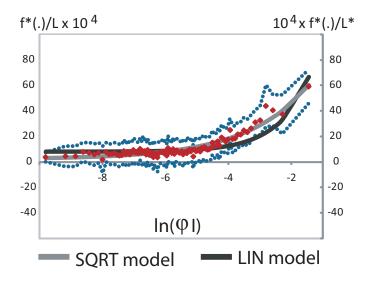
The meta-model and dimensional approach are consistent with theoretical models of both block trading and smooth trading. Theoretical dynamic models link L to resiliency of prices  $\rho$  and error variance of prices  $\Sigma$ .

See Kyle and Obizhaeva "Market Microstructure Invariance: A Dynamic Equilibrium Model".

# Invariant Log-Normality of Portfolio Transition Order Size

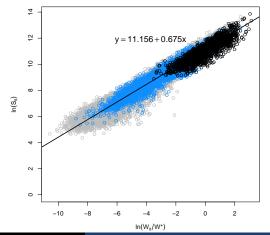


#### Linear versus Square Root Model

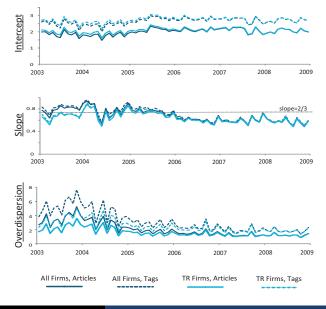


# Switching Points: Korean Data

The fitted line for the regression of the number of switching points on trading activity is  $\ln(S_{it}) = 11.156 + 0.675 \cdot \ln(W_{it}/W^*)$ . The invariance-implied slope is 2/3.



**News Articles** 



Pete Kyle and Anna Obizhaeva

59/60

NYSE TAQ Prints, 1993

