Information Asymmetries, Volatility, Liquidity, and the Tobin Tax

by Danilova and Julliard

Discussion

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Main Contribution and Outline of Discussion

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  "Information asymmetries and trading costs, in a financial market model with dynamic information, generate a self-exciting equilibrium price process with stochastic volatility, even if news have constant volatility."

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- Optimal trading decisions generate implications for
  - Stochastic volatility, liquidity, trading volume

- Cost of trading $\Longrightarrow$ trading choices $\Longrightarrow$ Tobin tax implications

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- Market maker can partially invert the trading strategy, estimate fundamentals, and set bid / ask prices as functions of trade size

$$A_t(v) = \frac{q}{q-\delta}\left(1-\alpha v^{\frac{q-\delta}{1-q}}\right) Z^M_{t-}; \quad B_t(v) = \frac{q}{q+\delta}\left(1-\beta v^{\frac{q+\delta}{1-q}}\right)^+ Z^M_{t-}$$

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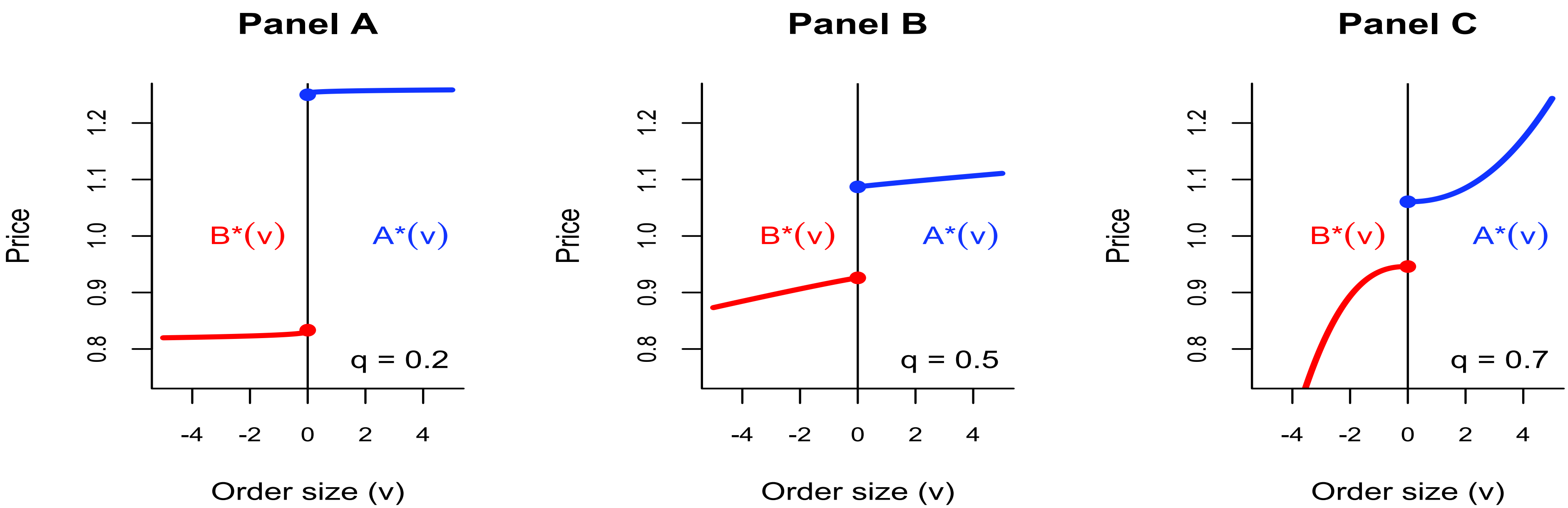

Figure 2: Ask and Bid equilibrium prices for different shares (q) of uninformed traders.

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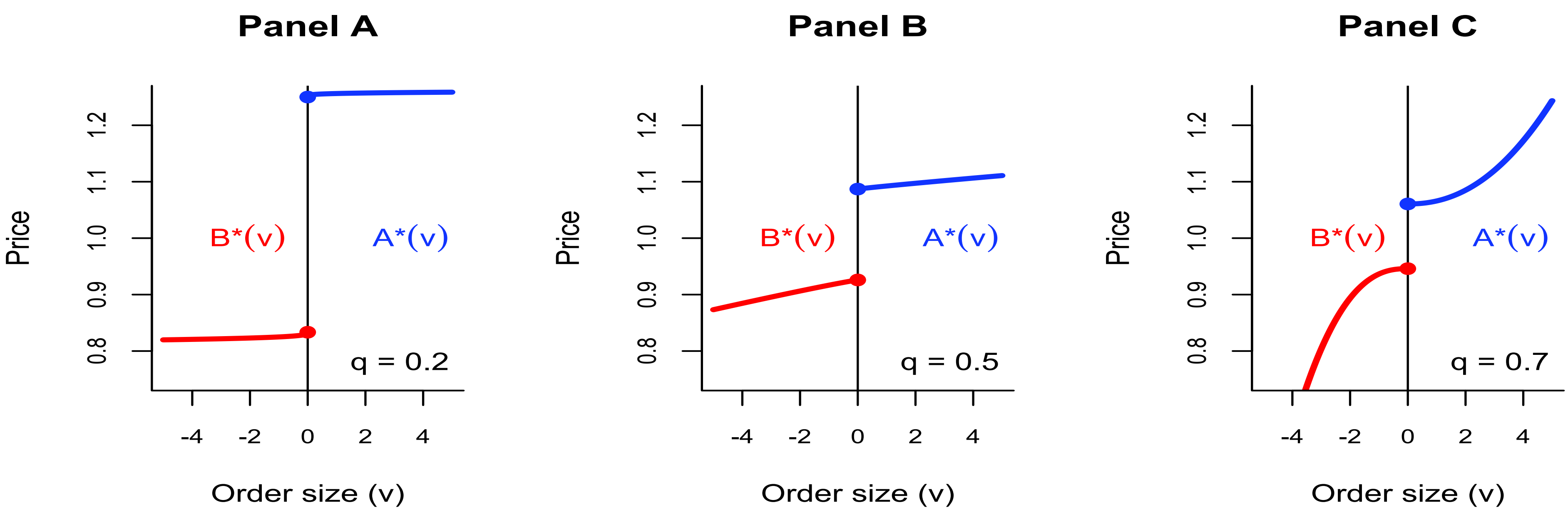

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- Bid/Ask functions move over time, as

$$z_i^M = \underbrace{(1-q)}_{\text{Prob. } I} \underbrace{z_i}_{\text{Last Trade Valuation}} + \underbrace{q}_{\text{Prob. } U} z_{i-1}^M$$

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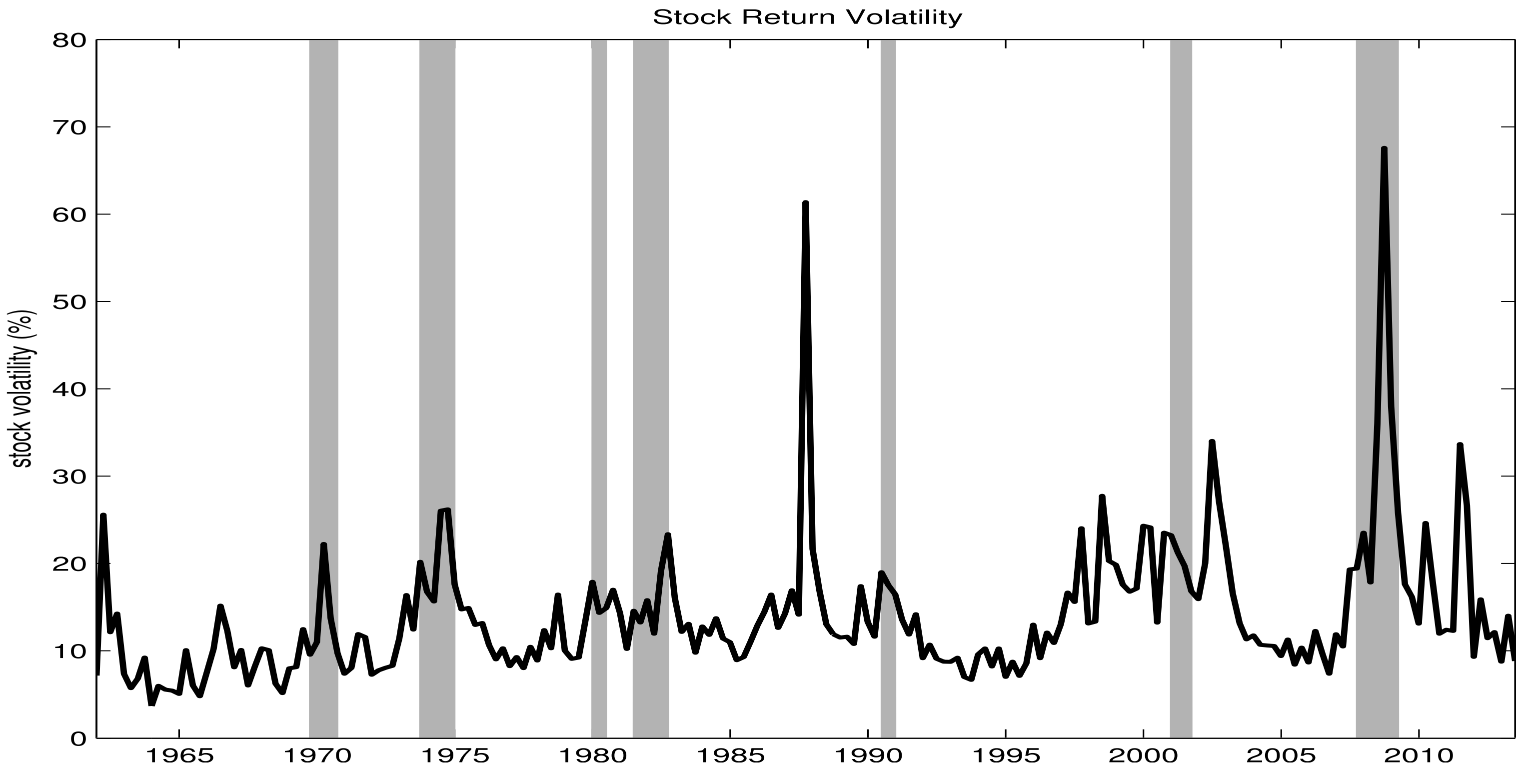
- Distinction between 3 and 4 is not clear.
  – Both stem from same limiting argument, but different scaling.
    * Low frequency considers time-varying numbers of trades?
    * Wouldn't the limiting number of trades over a given interval be the same?

Comments – 1

- Paper as it stands is a tour-de-force
- It is quite well written, considering the amount of math involved
- Message is a bit unfocused (see below), and in fact, it is not clear exactly what the paper tries to explain.
- However, it seems to me it is onto something interesting.
  - Combination of market microstructure with dynamics and learning is interesting
  - Implications about cross-section could be intriguing, if developed further
  - The results on the limit as number of trades goes to infinity are quite interesting, although at the moment they quite a bit unclear still.

Comments – 2

- Volatility of stock returns is definitely time varying and stochastic



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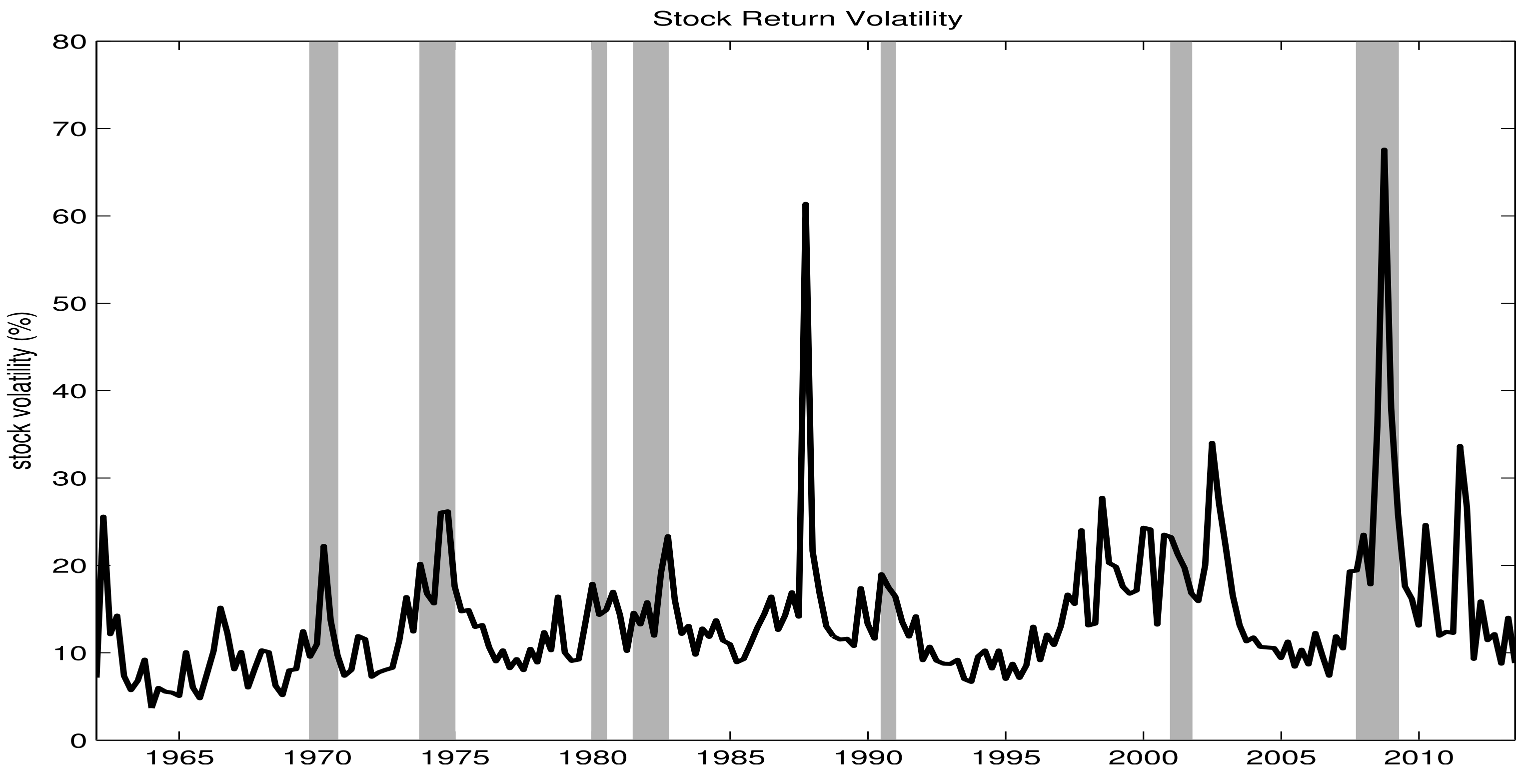

- How much is due to asymmetric information?
- How much of this time variation can this mechanism explain?
- Can we think of the mechanism as an “add-on” of more fundamental variation in volatility?

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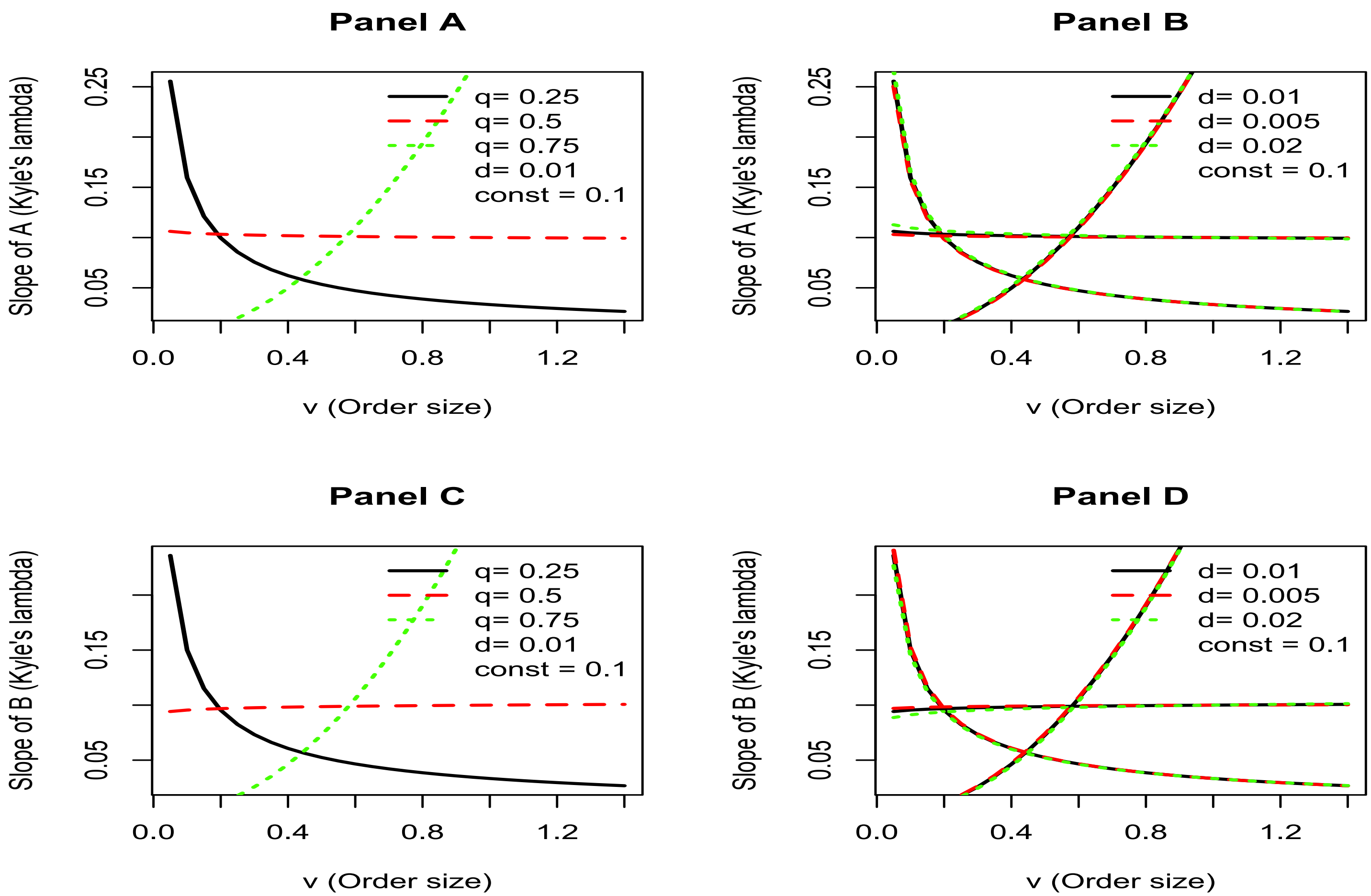
- What is unique about this setting?
  - It must be the time scale. Other theories $\Longrightarrow$ persistent volatility.
  - This paper $\Longrightarrow$ high frequency: Even ultra-low frequency must be intraday, I think.

Comments – 4

- Much of the paper is about the time series volatility.
- Why not focus more on the cross-section?
- How does Kyle lambda depend on information trading?



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- "*[I]t requires that the uninformed traders' valuations of the asset do not excessively deviate from the fundamental value of the asset that is observed by the informed agent.*"
- It seems it is even more than this. Valuations are exactly identical.

Conclusion

- I find the paper intriguing
- I wish I could understand better:
  - Nature of assumptions
  - Message of the paper: What volatility / trading are we talking about?
  - Implications for the cross-section or different types of markets.
- It would help a lot to see a “matching” between the model’s predictions and the data
  - The paper emphasize dynamics, but all plots are “static”
  - How much does this “time-clock change” (from trading time to calendar time) matter for volatility?
  - How close is this to the data, for which we do in fact observe both a “trading scale” and a “calendar scale”?