Information Asymmetries, Volatility, Liquidity, and the Tobin Tax

by Danilova and Julliard

Discussion

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Main Contribution and Outline of Discussion

• Main contribution of the paper (Abstract):

“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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  – Trading costs
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  – Optimal trading decisions: trade/no trade + trading amount

• Optimal trading decisions generate implications for
  – Stochastic volatility, liquidity, trading volume

• Cost of trading $\implies$ trading choices $\implies$ Tobin tax implications
Model (Schematics)

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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_t^M; \quad B_t(v) = \frac{q}{q + \delta} \left(1 - \beta v^{\frac{q+\delta}{1-q}}\right)^+ Z_t^M
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• As \( q \) increases (more noise), A/B functions become steeper.
  
  – More noise \( \implies \) less information \( \implies \) more risk
Figure 2: Ask and Bid equilibrium prices for different shares \((q)\) of uninformed traders.

- As \(q\) increases (more noise), A/B functions become steeper.
  - More noise \(\implies\) less information \(\implies\) more risk

- Bid/Ask functions move over time, as

\[
    z_i^M = (1 - q) \z_i + q z_{i-1}^M
\]

\(Prob. \ I\) Last Trade Valuation \(Prob. \ U\)
Model (Schematics)

- Four price frequencies

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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.
• 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?
Comments – 3

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• How about other models with predictions on trading and volatility
  – Differences of opinion models
    * Variation in differences of opinion $\Rightarrow$ trading and volatility
  – Heterogeneous preferences models
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- What is unique about this setting?
  - It must be the time scale. Other theories $\implies$ persistent volatility.
  - This paper $\implies$ high frequency: Even ultra-low frequency must be intraday, I think.
• 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?
Comments – 5

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  – This is a “reverse engineering” assumption.
  – Normally, fundamental economic structure (preferences, information, etc) is defined, and everything else is derived.
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- 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”?