Discussion of “The Conduits of Price Discovery: A Machine Learning Approach” by Kwan, Philip, and Shkilko

Vincent Bogousslavsky

Boston College

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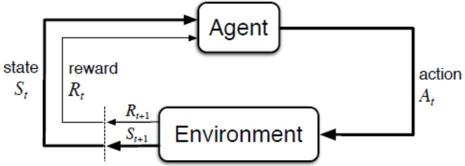
Overview

This paper uses a reinforcement learning approach (Philip (2020)) to study the determinants of price discovery

- The methodology allows for nonlinearities and multiple conditioning variables, which can be problematic in standard VARs
- The most important conditioning variable is “the state of the order book” (depth imbalance)
- The results are consistent with predictions from recent models that emphasize the role of limit orders for price discovery

Reinforcement learning approach



Source: Sutton and Barto (2020)

$$v^*(s) = \max_{\pi} E\left[\sum_{k=0}^{\infty} \gamma_t R_{t+k+1} \middle| S_t = s\right]$$

$$q^*(s, a) = R(s, a) + E\left[\gamma \max_{a'} q^*(S_{t+1}, a') \middle| S_t = s, A_t = a\right]$$

Contrary to the stochastic control approach (e.g., Bertsimas and Lo (1998)), we are not specifying an exogenous price process

Reinforcement learning approach to estimate permanent price impact (Philip (2020))

- Consider a market with two possible actions (buy and sell) and two possible states (high volatility, low volatility)
- What is the permanent price impact of buying in the high volatility state?

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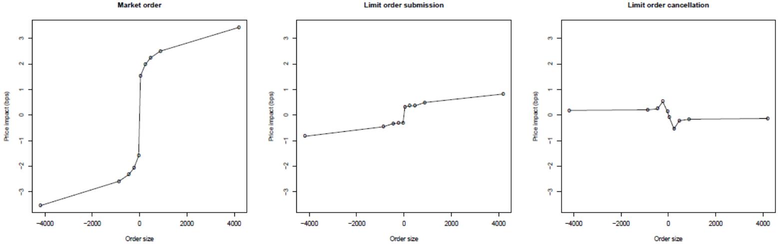
$$
\begin{aligned}
q(\sigma_{\mathrm{H}}, \mathrm{buy}) = & R(\sigma_{\mathrm{H}}, \mathrm{buy}) \\
& + \mathit{Prob}((\sigma_{\mathrm{H}}, \mathrm{buy}), (\sigma_{\mathrm{H}}, \mathrm{buy}))\gamma q(\sigma_{\mathrm{H}}, \mathrm{buy}) \\
& + \mathit{Prob}((\sigma_{\mathrm{H}}, \mathrm{buy}), (\sigma_{\mathrm{H}}, \mathrm{sell}))\gamma q(\sigma_{\mathrm{H}}, \mathrm{sell}) \\
& + \mathit{Prob}((\sigma_{\mathrm{H}}, \mathrm{buy}), (\sigma_{\mathrm{L}}, \mathrm{buy}))\gamma q(\sigma_{\mathrm{L}}, \mathrm{buy}) \\
& + \mathit{Prob}((\sigma_{\mathrm{H}}, \mathrm{buy}), (\sigma_{\mathrm{L}}, \mathrm{sell}))\gamma q(\sigma_{\mathrm{L}}, \mathrm{sell})
\end{aligned}
$$

How to estimate the parameters?

Unconditional evidence

3 orders $\times$ 2 buy/sell $\times$ 5 sizes $=$ 30 actions



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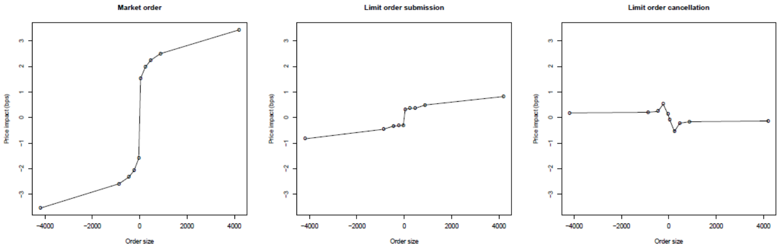
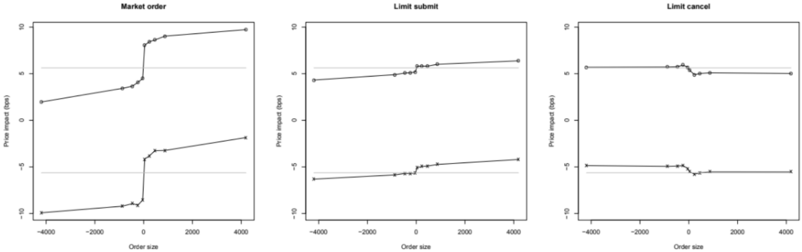


- Market orders contribute 53.87% to price discovery
- The paper argues that results are complementary to Brogaard, Hendershott, and Riordan (2019)
  - This argument suggests that the RL methodology is “better” mostly because it can handle many more variables rather than because of nonlinearities
  - Does a linear VAR give the same results?

Conditional evidence (depth imbalance)



"Consistent with Ricco, Rindi, and Seppi (2020), even a large market buy order may have a negative effect on prices if the limit order book imbalance is negative."

- My interpretation: the state of the order book predicts returns; e.g., Cao et al. (2009); Cont et al. (2014); Stoikov (2018)
- Low probability states and bias-variance trade-off?

Link with theory

- Why not systematically test the predictions of Ricco, Rindi, and Seppi (2020) and other recent models?
  - Low volatility vs high volatility
  - Market orders executed at inside vs outside prices
  - Non-Markovian learning? Standing limit order book is a sufficient statistic for prior order history?

- Time effects
  - Quite a few papers examine time-of-day effects in price impact (Hasbrouck (1991), . . ., Yueshen and Zhang (2020))
  - Perhaps focus on the market/limit order distinction

Overview

Well-written and interesting paper

My suggestions:

- Emphasize differences relative to standard VARs
- Develop the economic intuition and the relation to existing work for the depth imbalance results and time-of-day effect
- Perhaps a more systematic link with theory would help