Discussion of "FX Trading and the Exchange Rate Disconnect" by Martin Evans

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Microstructure approach to exchange rates

- Importance of order flow for exchange rate dynamics (Evans and Lyons (2002))
 - Daily order flow explains 63% (40%) of daily changes in DM-\$ (yen-\$) whereas the change in one-day interest rate differential explains only 0-1% (sample: May-Aug 1996)
 - Contemporaneous return-order flow relation strong in all asset classes (e.g., 28% R² for equity market daily return (Chordia et al. (2002)))
- Is order flow related to fundamentals or due to transitory liquidity effects?
- Does order flow have predictive power for future returns?

This paper

- Microstructure model of limit order book trading is developed to disentangle liquidity and information channels
- VAR system (motivated by the model) is estimated using EUR/USD intraday data
 - 2003-2015 data from an electronic LOB platform (EBS)
 - *Variables:* order flow; volume; depth balance; total depth; spread; change in log midpoint
- ⇒ One type of shocks drives 87% of the 1-60mn variations in FX prices
- ⇒ FX movements are connected to interest rate differentials via trading flows

Overview

Useful and interesting to use LOB information over a long sample to understand FX movements

- Fundamental information in the model
- VAR system and VAR-model 'disconnect'
- Exchange rate disconnect empirical results

Model

Traders do not observe the depth of the order book

• At time *t*, traders submit limit orders:

$$p_t^{\text{bid}} = \mu_t - \frac{1}{2}\delta + \beta E_t d_t^{\text{buy}}$$
$$p_t^{\text{ask}} = \mu_t + \frac{1}{2}\delta - \beta E_t d_t^{\text{sell}}$$

• At time t^* , all traders receive signals about depth and depth balance, but only market traders can submit orders at an expected trade price = $(1 - \omega)p_t^{\text{bid/ask}} + \omega E_t^* p_{t+1}^{\text{bid/ask}}$ (ω does not depend on expected depth)

Where does fundamental information come from?

At t + 1, traders update their estimate of fundamental value:

$$\mu_{t+1} = \mu_t + \underbrace{n_{t+1}}_{\text{news shock}} + \underbrace{\lambda(\textit{fl} w_{t+1} - \textit{E}_t \textit{fl} w_{t+1})}_{\text{price impact}}$$

- Unexpected order flow is informed, but market traders don't update μ_t after receiving the balance/depth signals (equ. (2))
- The (fundamental) information must then come from outside the model (order flow shocks)
- But then limit traders should condition on the signals (*E*^{*}_t) to compute the expected flow since the balance/depth signals are *not* informative about fundamentals

Insights from the model



- Depth balance is mean-reverting (inventory management), which generates return/order flow predictability
- Order book (balance) shocks have a *permanent* price impact due to the above

The idea that order book shocks contribute to price discovery makes sense and is empirically supported in other markets:

- Fleming, Mizrach, and Nguyen (2018); Brogaard, Hendershott, and Riordan (2019)
- Important! But not clear in the current model

VAR system

Ordering: order flow, volume, balance, depth, spread, Δp

- It makes sense to allow order book innovations to affect prices contemporaneously
- Except that price shocks are allowed to affect order flow (and depth balance) *contemporaneously*

Departure from standard MM setup that deserves an in-depth discussion and robustness checks

Disconnect between model and VAR

Long-run restrictions: balance (+ depth, spread) shocks do **not** have a permanent impact

Balance shocks in the VAR vs. balance shocks in the model

Explain better why the Δp innovation is interpreted as a balance shock (and not the balance innovation itself)

• Balance innovations do not account for the variance of the order flow and price change... Do we even need them?

Empirical results

The "order flow" innovation accounts for \approx 87% of the variance of Δp over horizons of 1-60mn

$$\mathsf{flw}_t pprox a(L)v_t^1 + b(L)v_t^6$$

 $\Delta p_t pprox c(L)v_t^1 + d(L)v_t^6$

Innovation components aggregated at the daily level

Sample	Variable	Specification				
		I: $flow_t^1$		II: $flow_t^6$		
A: 2003-20 (3388 obs)	$\begin{array}{c} 15\\ \Delta(i^{(yr)} - i^{*(yr)}) \end{array}$	-3.995**** (0.613)	-3.964*** (0.602)	$0.276 \\ (0.673)$	$\begin{array}{c} 0.356\\ (0.660) \end{array}$	
	lag	no	yes	no	yes	
	\overline{R}^2	0.038	0.041	0.000	0.072	

flw¹ component sign. related to interest rate differentials

Empirical results (2)

dependent variable: Δp_t



- Last 2 columns: instrument Δp^1 with Δi
- Δ*p_t* is mostly driven by *v*¹, hence any variable correlated with Δ*p_t* is likely to be correlated with *v*¹
 - Δ*i* is correlated with v¹ and not with v⁶ (already in the previous table)
- Regressing flw¹ on ∆*i* yields low R² (previous table); maybe try other variables to benchmark the results

Misc. comments/suggestions

- Prices may be more sensitive to order flow at specific times of the day
 - Might be useful to get more intuition: inventory vs. information effects (Madhavan, Richardson, and Roomans (1997))
- More details on the institutional setting (traders do not observe the depth of the limit order book) would help
- Robustness to share-weighted measures (avoid price effects)

• $\frac{1}{2}\delta$ in (2)?

Conclusion

Interesting paper, I learned a lot reading it

- Clarify the role of fundamental information in the model
- Motivate better the empirical specification (price shocks affect order flow contemporaneously, no permanent impact of order book events)
- Importance of order book variables is not crystal-clear from the empirical results: what if we drop these variables?
- My view: more focus on the VAR and other empirical results, less on the model
 - How surprising is it that the order flow innovation is correlated with the interest rate differential?