Market Making

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Market maker

- Who are they: players who post bid and ask quotes and thus supply liquidity in Forex, OTC, US futures markets.
- Obligations: to post quotes, limit on spread, minimum on quantity, reporting requirements.
- Privileges: right to post quotes, information about order flow and book, lower or no fees paid to the exchange.
- In some markets, they are the only one who can post two-way quotes (hence, quote-driven market). Examples: Nasdaq(pre-1997), FX(phone), Bonds(phone), derivatives.
- Now many exchanges have mixed/hybrid market structures: auction(order-driven) + market makers. Examples: London, NYSE, Nasdaq.

Market maker

- Revenue: bid-ask spread (buy low sell high).
- Cost (key issues they care about):
  1. Inventory cost: risk when holding inventory between purchase and sale
  2. Adverse selection: permanent price shift (against MM) due to trading with informed counterparties.
  3. How do MM fund?
     1. Collateralized financing: there is a margin requirement.
  4. However, they are subject to regulatory requirements. e.g. SEC "net capital rule".
- When the market is competitive: the bid-ask spread is the only compensation for inventory costs and adverse selection costs.

Market making business in investment banks

- Category 1: agency business (not on risk to the client)
  - Brokerage service.
  - Put orders into the algorithms on behalf of their clients.
  - 80% of investment banking trading business.
- Category 2: risk business (on risk to the client)
  - Dealer/market making.
  - 20% of investment banking trading business.

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Market Liquidity, capital constraint and inventory risk

- Traditionally, inventory models without capital constraints: liquidity (bid-ask spread) is not affected by the market maker's inventory positions with some exceptions.
- However, the assumption is not valid.
- In general, we want to understand how market liquidity is affected by both the capital constraint and inventory risk.

Market makers' ability to make markets depends on their funding ability [Brunnermeier and Pedersen, 2009]

They proposed a theoretical model that explains empirically documented feature of market liquidity. They found that market maker's funding liquidity:

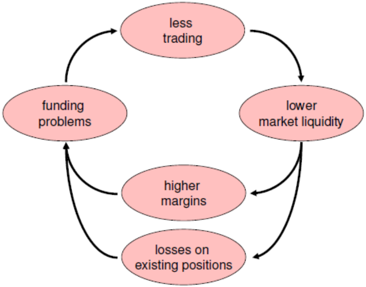
1. can suddenly dry up (fragile) during crisis.
2. has commonality across securities.
3. is related to volatility ("flight to quality").
4. experiences "flight to liquidity" events (from less liquid assets to liquid assets, leading to further crisis)
5. comoves with the market.

Some prelims in the paper

- Market liquidity: difference between the transaction price and the fundamental value.
- Funding liquidity: a dealer's scarcity (or shadow cost) of capital/funding constraint.

Liquidity and margin spirals

When there is a crisis (shock), prices of security decrease => less borrowing power => less trading activities => lower market liquidity



The main reason is the "mark to market" rule [Adrian and Shin, 2010]

Assume there is a target leverage ratio. If price of the security increases by 1%, then the dealer will have more borrowing power. It can borrow and buy more securities to maintain the leverage level.

Assets	Liabilities
Securities 100	Equity, 10
	Debt, 90

=>

Assets	Liabilities
Securities 101	Equity, 11
	Debt, 90

=>

Assets	Liabilities
Securities 110	Equity, 11
	Debt, 99

Conversely, if the price decreases. The dealer will have to sell some securities and repay part of its debt.

Assets	Liabilities
Securities 109	Equity, 10
	Debt, 99

=>

Assets	Liabilities
Securities 100	Equity, 10
	Debt, 90

So, anything that has an impact on market makers' funding capability => their ability to provide liquidity => market liquidity

e.g.

1. Inventory level.
2. Ceiling of the capital constraint.
3. Market volatility.

The larger the inventory positions (long or short), market makers are less likely to take on more inventory => less attractive (two-way) quotes.

- This is supported by empirical evidence [Comerton-Forde et al., 2010].
- At the market level, revenues associated with inventories held overnight forecast future liquidity (non-linear effects) => consistent with the previous theoretical models.
- At the specialist firm level, same conclusions hold [Comerton-Forde et al., 2010, Coughenour and Saad, 2004].

Ceiling of the capital constraint

- The sensitivity of liquidity to inventories and revenues is greater for specialist-owned firms compared to corporate-owned specialist firms due to less access to capital.
- If there is a shock directly to market makers' capital constraint, the liquidity of those assigned stocks becomes less sensitive (e.g. M&A events of market makers Comerton-Forde et al. [2010]).

Market volatility

- Two market crashes: 1987 and 2008. Market makers basically stopped quoting prices => liquidity evaporation => market crash.
- "By the end of trading on October 19, [1987] thirteen [NYSE specialist] units had no buying power" - SEC (1988) [Brunnermeier and Pedersen, 2009].
- When markets are (very) volatile:
  1. High margins (borrowing costs).
  2. Direct impact on the returns of the inventory positions.
- Market volatility can predict market makers' return from providing liquidity [Nagel, 2012].

Proxy

- Market Liquidity: quoted bid-ask spread, effective bid-ask spread [Comerton-Forde et al., 2010] (mid-price vs. actual transaction price).
- Market maker's revenue:
    - difference in buying and selling prices for all round-trip transactions + overnight and daily P/L on inventories. [Comerton-Forde et al., 2010].
    - expected return of the reversal strategy (buy stocks that went down, sell stocks that went up) [Nagel, 2012].
- Market volatility: VIX index of the implied vol of S&P500 [Nagel, 2012]; realized variance[Comerton-Forde et al., 2010].

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Market maker research: from a design perspective

- The aforementioned view is on ***why:*** based on specific patterns we observed, mostly at a market level, we intend to understand why specific patterns occur.
- Another view is on ***how:*** how should some known issues be addressed when designing market maker agents.
- This is often (formally) referred as the optimal control modelling/agent-based modelling.
- It's becoming popular due to algo-trading/high frequency trading and recent progress in machine learning/artificial intelligence.
- The two views are not mutually exclusive:
  1. e.g. you may study adverse selection from both views.
  2. Theoretical modelling of the first view often requires a virtual agent.

Optimal control modelling

The goal is to find optimal pricing strategy, given certain assumptions and one or more target problems.

- The role of inventory risk in determining the optimal pricing strategy for a market maker:
  1. Amihud and Mendelson [1980], Garman [1976] (both on JFE)
  2. Avellaneda and Stoikov [2008], Guéant et al. [2013]
- The role of adverse selection risk arising from informed traders in the market.
  1. Glosten and Milgrom [1985], Kyle [1985], etc.

Optimal control modelling

Assumptions:

- One single market maker => lack of competitiveness.
- Specific distributions of order arrivals and prices.

Why:

- Techniques used to derive analytical solutions: stochastic optimal control techniques.
- Without certain assumptions, analytical solutions do not exist.

Similar problems arise in agent-based modelling research where the goal is to find market equilibrium (fixed point) Ganesh et al. [2019].

(Some) challenges in market making modelling research

- Market is dynamic: we need to design robust systems in a dynamic context.
- There are more than one underlying asset/asset classes.
- It is hard to model even a single agent:
  - PnL (objective function): spread PnL, Inventory level, hedging cost
  - Bid/ask price (order placing strategy).
  - Internalization: *skewness* in prices to attract trades that offset inventory level.
  - etc.

(Some) challenges in market making modelling research

- Let alone there are multiple players in the market (multi-agent problem):
  - More than 2 players, humans and robots, higher order of beliefs.
  - The market consists of both traders and other market makers.
  - Each market maker has different risk preferences.
  - Each market maker can impose different level(s) of impact on the market.
- Limit order book modelling: we need a financial market simulator to evaluate algorithms.
  - At any point of time during the simulation, we need at least the following:
    - ★ Top 5/10 best buy/sell prices.
    - ★ Corresponding volume.

(Some) proposed solutions to challenges

Many of the above issues can be modelled in a single framework: (deep) reinforcement learning.

- Spooner et al. [2018]: realistic, data-driven simulation of a limited order book (basically they used real data to reconstruct the limited order book) using a basket of 10 equities across 5 venues and a mixture of sectors.
- Ganesh et al. [2019]: single asset, multiple agents (mixed with algo-traders, conventional market making algorithms and reinforcement learning algorithms) with partial observable order information in a competitive context.
- Guéant and Manziuk [2019]: determine the optimal bid and ask quotes for a large universe of corporate bonds (address the curse of dimensionality).

Why is it different now? Super-human performance in many (sophisticated) games

Figure: Atari games (Nature 2013) [Mnih et al., 2013]

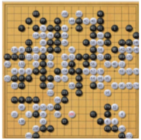

Figure: Board games (Nature, 2016) [Silver et al., 2016]

Figure: Poker (Science, 2019) [Brown and Sandholm, 2019]

Figure: RTS games (Nature, 2019) [Vinyals et al., 2017]

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