Trading and Information Diffusion in Over-the-Counter Markets

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OTC markets

- A large proportion of assets trade over the counter (currencies, bonds, most derivatives, repo agreements)
- OTC markets have been at the core of the 2008 financial crisis.

In OTC structures:

- trading is bilateral
- through persistent links
- at dispersed prices
- in highly concentrated markets (intermediation)
A dealer network (municipal bonds)

Source: Li and Schurhoff (2012)
In this paper:

- a novel approach to model OTC markets:
  - demand functions in a network, private information
  - naturally consistent with stylized facts (bilateral trades through persistent links, dispersed prices, profitable intermediation)

1. theory focus: How much information is diffused by trades in over-the-counter markets?
In this paper:

- a novel approach to model OTC markets:
  - demand functions in a network, private information
  - naturally consistent with stylized facts (bilateral trades through persistent links, dispersed prices, profitable intermediation)

1. theory focus: How much information is diffused by trades in over-the-counter markets?

- answer: information diffusion is “effective but not efficient”
  - each price partially (in common value limit, fully) incorporates the private information of far away agents after a single round
  - but too much reliance on private information → limited informativeness of prices
  - not from price-manipulation, profit motive, but decentralization → learning externality
2. applied focus:

- normal times: predictions on the connection of transaction cost/price dispersion/volume/position
- distressed markets: narratives vs evidence?
  - less support for adverse selection and other informational stories
  - more support for counterparty risk (no trade with specific dealers)
Set up

• *n* risk-neutral *strategic* dealers trade a risky asset in zero net supply with uncertain value in a one shot game
  
  • Dealers’ values are interdependent
    
    \[ \theta_i \sim N(0, \sigma^2_\theta) \]
    \[ \text{cov}(\theta_i, \theta_j) = \rho \sigma^2_\theta, \rho \in (0,1) \]
  
  • Dealers are privately informed about their valuation
    
    \[ s_i = \theta_i + \varepsilon_i, \text{ s.t. } \varepsilon_i \sim \text{IID } N(0, \sigma^2_{\varepsilon_i}) \]
  
  • Groups of costumers (possibly heterogenous *β*)
    
    \[ U(y) = \frac{1}{2\beta} y^2 \quad \beta < 0 \]
  
  • until here: Vives (2012) (Kyle(1989) with this structure)
The key idea for modeling OTC trades

- any network, $g$ of the dealers describing potential trading partners
- each dealer $i$, understanding her price effect given others’ strategies, forms a best response trading strategy:
  - a map from the signal space to the space of generalized demand functions, a continuous function $Q_i : R^{m_i} \rightarrow R^{m_i}$
  - expected payoff for dealer $i$ with signal $s_i$ corresponding to the strategy profile $\{Q_i(s_i; p_{g_i})\}_{i \in \{1, \ldots, n\}}$ is

$$E \left[ \sum_{j \in g_i} Q_i^j(s_i; p_{g_i})(\theta_i - p_{ij}) | s_i \right]$$

where $p_{ij}$ element of the bilateral clearing price vector, $\mathbf{p}$ determined by $\{Q_i(s_i; p_{g_i})\}_{i \in \{1, \ldots, n\}}$
e.g. a linear generalized demand function in a circle of $n$, for dealer 2:

$$Q_2^1(s_2, p_{12}, p_{23}) = b_2^1 s_2 + c_2^1 p_{23} + c_{12}^1 p_{12}$$
$$Q_2^3(s_2, p_{12}, p_{23}) = b_2^3 s_2 + c_2^3 p_{23} + c_{12}^3 p_{12}$$

⇒ interconnected system of generalized demand curves:
- each depends on a different but overlapping set of prices
- not restricted to be linear, but we search for linear equilibrium
- coefficients of $i$ best responds to those of $j \in g_i$ and so on
- fixed point in coefficients is the equilibrium

complex structure, but:
- turns out: with our specification this is solvable for any network
- can think of as reduced form: the steady state of a realistic, dynamic bargaining protocol
Market clearing

A Linear Bayesian Nash equilibrium of the OTC game is a vector of linear trading strategies solving the problem

$$\max \{ Q^j_i(s_i, p_{g_i}) \}_{j \in g_i} E \left[ \sum_{j \in g_i} Q^j_i(s_i, p_{g_i}) (\theta_i - p_{ij}) \right]$$

where $p_{ij}$ is determined by

$$Q^i_i(s_i, p_{g_i}) + Q^j_j(s_j, p_{g_j}) + \beta^i_{ij} p_{ij} + \beta^j_{ij} p_{ij} = 0$$

(customers: purely technical role, $\beta_{ij} \equiv (\beta^i_{ij} + \beta^j_{ij}) \to 0$ do not change prices, beliefs, $\frac{q^i_i}{\beta_{ij}}$ or relative positions)
Finding the equilibrium

- given normal information structure: can search for Linear Bayesian Nash equilibrium
- Separation
  1. Finding beliefs by a simpler auxiliary game: the conditional-guessing game.

\[ e_i = E(\theta_i \mid s_i, p_{gi}) \]

2. Given the beliefs, each quantity in OTC game is implied by FOCs and market clearing as

\[ q^j_i = t_i (e_i - p_{ij}) \]

\[ p_{i,j} = \frac{t_i e_i + t_j e_j + (-\beta_{ij}) 0}{t_i + t_j + (-\beta_{ij})} \]

with \( t_i \) trading intensity of \( i \) (potentially differing across neighbors)
Example 1: 3 in a line, signals
Example 1: 3 in a line, prices and quantities
Example 1: 3 in a line, quantities

\[ 3.8\left(E(\theta_L \mid -2, p_L) - p_L\right) \]

\[ t_L = t_C \left(1 - \frac{\partial E(\theta_C \mid \cdot)}{\partial p_L}\right) - \beta \]
Example 1: 3 in a line, profits when $\theta_i = 0$
Beliefs: The conditional-guessing game

- Same information, same network ⇒ same posterior beliefs as in OTC game
- Dealers do not trade, do not maximize profit: guessing their value given their links guesses:

\[
\max_{\mathcal{E}_i(s_i, e_{g_i})} -E\left((\theta_i - e_i)^2\right)
\]

where \(\mathcal{E}_i(s_i, e_{g_i})\) is a conditional guessing function mapping \(\mathbb{R}^{m_i} \rightarrow \mathbb{R}\) and \(e_i\) is given by the fixed point of

\[
\left[e_i = \mathcal{E}_i(s_i, e_{g_i})\right]_i^N.
\]

- strategies: functions
- fixed point condition is like market clearing
• solution:

1. conjecture that every guess is a linear combination of the \(n\)-signals
   \[e_i = v_1^i s_1 + ... + v_n^i s_n = v_i^T s\]

2. given the conjectures, form the conditional expectations
   \[E_i(s_i, e_{g_i}) = E(\theta_i|s_i, e_{g_i}) = v_i'^T s\]
   and find the coefficients of each \(s_i\)

3. find the fixed point in coefficients
• Key results:
  • equilibrium in conditional-guessing game exists for any network
  • for any connected network: each $v_i^j > 0$
  • available information is fully revealed in any network in the common value limit $\rho \to 1$ or complete network
• (also: signals of agents farther away tend to get smaller weights)
• to see why: think of self-map as an iterated algorithm mapping $v_i^n$ to $v_i^{n+1}$ by

$$e_i^{n+1} = E(\theta_i|s_i, e_{g_i}^n)$$

• (might not converge from every point in every network)
Iterated algorithm, circle of 11
Iterated algorithm, circle of 11
Iterated algorithm, circle of 11

Graph showing the weight on each signal for three different round-1 guesses: 6 (blue), 5 (red), and 7 (green). The x-axis represents the index of the signal, and the y-axis represents the weight on each signal.
Iterated algorithm, circle of 11
Iterated algorithm, circle of 11

The graph shows the weight on each signal over the index of signal. The lines represent different rounds and guesses. For example, the round-1 guess of 6 is shown by a purple line, and the round-2 guess of 5 is shown by a red dashed line.
Iterated algorithm, circle of 11
Iterated algorithm, circle of 11

Round-5 guess of 6
• Is information diffusion constrained efficient when $\rho < 1$?

• planner’s problem:

$$\max \left\{ \mathbb{E}_i(s_i,e_{g_i}) \right\}_{i=1...n} - E \sum_i \left( (\theta_i - e_i)^2 \right)$$

• *No. Planner would put less weight on own signal.
  • individual distorts average signal towards her own: closer to her own value, but makes learning harder for others
  • a learning externality
Weights of signals in equilibrium guesses
Dealers’ excess weight on private signal in simulated data

- 500 simulated, connected Erdos-Renyi networks \((p = 0.5)\), 11 dealers each
Dealers’ excess weight on private signal in simulated data

- 500 simulated, connected Erdos-Renyi networks \( (p = 0.5) \), 11 dealers each
- largest for center in star, smallest in almost complete

Ordinary Least-squares Estimates
Dependent Variable = overweighting
R-squared = 0.2523
Rbar-squared = 0.2517
Nobs, Nvars = 5500, 5

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Equivalence of beliefs

- both directions:
  1. in any linear equilibrium of OTC game the vector with elements $e_i = E(\theta_i \mid s_i, p_{gi})$ is an equilibrium expectation vector in the conditional guessing game.
  2. based on equilibrium in conditional guessing game (+ some conditions) we can construct an equilibrium of the OTC game
- extra conditions ensuring that $N$ expectations can be transformed to $M \geq N$ prices (no counterexamples found)
key observation behind argument:

if others follow linear strategies, best response:

\[ q_j^i = -t_i (E(\theta_i | s_i, p_{g_i}) - p_{ji}) \]

by market clearing, price informationally equivalent to posterior of \( j \).

Guessing value conditional on prices is essentially the same as guessing value conditional on neighbors’ guesses
Consequences for OTC game:

- all available information is revealed if
  1. centralized market (Vives, 2012)
  2. OTC game with complete network
  3. OTC game in any network in the common value limit $\rho \to 1$

- profit motive does not affect information diffusion, but learning externality does:
  - when $\rho \leq 1$ each dealer’s signal is incorporated to each price, but prices do not maximize revealed information for given network
Dynamic Foundations

- One shot game is an abstraction: we think of this as reduced from for dynamic price discovery process
- Assuming an auctioneer finding the fixed-point would be against the idea of modeling decentralized markets
- Is it a good abstraction?
Dynamic Foundations

• One shot game is an abstraction: we think of this as reduced from for dynamic price discovery process
• Assuming an auctioneer finding the fixed-point would be against the idea of modeling decentralized markets
• Is it a good abstraction?
• we construct the dynamic protocol which implements our equilibrium without the need of an auctioneer
A Dynamic Protocol

a day of trading with two groups at the trading desk:

- quants:
  - in each morning come up with trading strategy
    - a bargaining rule: how to response to counterparties’ quotes
    - a quantity rule: how much to trade at a given vector of prices
  - both comes from equilibrium coefficients of the generalized demand function: needs only network structure and joint distribution (but not realization)
• traders: trade during the day by protocol:
  1. receive the signal
  2. to each counterparty tell a price
  3. in next round receive a price back from each counterparty
  4. feed own signal and received prices through bargaining rule: new price
  5. repeat this till update is minimal for everyone: then all trades at those prices and by quantity rule (which will clear all markets)
we show that if

- quants design bargaining rule for counter offer of agent $i$ at link with $j$ in round $t$ as

$$p_{ij,t}^i = \frac{t_i e_{i,t} + t_j e_{j,t-1}}{t_i + t_j + (-\beta_{ij})}$$

where $t_i, t_j$ is given by OTC equilibrium

- $e_{i,t} = \tilde{y}_i s_i + \tilde{z}_i e_{g(i),t-1}$ with conditional game equilibrium coefficients

- for each $j \in g(i)$ $e_{j,t-1}$ is deducted from offers $p_{ij,t-1}^j$

- quantity rule is the generalized demand function from OTC game
then

- The equilibrium expectations, prices and quantities in the one-shot OTC game are a steady state of the dynamic protocol.
- Regardless of starting point, protocol converges to the equilibrium of the OTC game.
- Although changing coefficients in each round might be better, conditional on fixed coefficients quants could not do better.
Applications

• given the structure of links and parameters, we get full list of quantities and prices for each link
• ultimately: parameters should be estimated from a sufficiently detailed dataset under different market conditions
• main question: Does stylized facts can be generated by diffused information?
Three types of exercises:

1. transaction level data with ID: connect network characteristics with economic measures: e.g. Which agent creates is with most profit/intermediation?

2. transaction level with no ID: connect economic measures with economic measures thinking of network as unobserved characteristic: e.g. robust connections across cost/price dispersion/quantity/profits

3. focus on special events: e.g. distressed markets which narrative is most consistent with stylized facts under our assumptions?

- methodologically: on realistic network, or simulating random networks and running regressions
Application I: Profit, intermediation and position in network

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Applications II: OTC markets and diffused information

- empirical papers on various markets: corporate bond, municipal bond, CDS, overnight interbank loans, repo
- limited data-availability on the transaction level
  - typically prices, size, some indication of counterparty type
  - very few instances with unique identifier of counterparties
- we focus on transaction cost and price dispersion
- a robust fact: markups/cost decline with transaction size
• how to measure cost/spread/mark-up?
  • in empirical literature: % cost of a round-trip trade of given amount compared to mid-quote/fair value
  • in this paper: cost of round-trip for \( i \) trading \( q_i \) with \( j \) when fundamental value \( \theta_i \):

\[
\frac{p_{ij}^B - p_{ij}^S}{q_i \theta_i} = \frac{b_j s_j + \sum_{k \in g_j, k \neq i} c^i_{jk} p_{jk} + q_i}{c^i_{ji} + \beta_{ij} q_i} = \frac{2}{t_i \theta_i}
\]

• think of a ‘panel’ with fixed network, but changing realization of signals at each ‘date’
• because of linearity, constant in quantity for a given trader (dealer-pair fixed effect)
• still can be related to quantity when we cannot control for the given trader
Hypothesis

*In the cross-section of transactions, the percentage cost of the transaction decreases in the size of the transaction.*

Hypothesis

*By conditioning on the characteristics of the participating dealers in a bilateral transaction, the negative relationship between the transaction’s size and its cost gets weaker.*
• two dimensions of price variability:
  • price volatility: ‘time-series’ dimension for dealer-pair, diagonal of $\Sigma_p$
  • price dispersion: ‘cross-section’ dimension, off-diagonal of $\Sigma_p$ or $|R_p|$
  • price volatility is larger when agents trade more
  • price dispersion is smaller among agents’ who are better informed (have more connections) as their posterior is closer
  • better informed also trade larger quantities
Hypothesis

Price volatility is larger in those transactions in which dealers trade larger quantities.

Hypothesis

Price dispersion is smaller across those transactions in which dealers trade larger quantities.
Example 2: 2-level core-periphery
Information precision, $\sigma_0^2/\sigma_\epsilon^2$ vs. price dispersion by trade-type.

Information precision, $\sigma_0^2/\sigma_\epsilon^2$ vs. spread by trade-type.

Information precision, $\sigma_0^2/\sigma_\epsilon^2$ vs. gross volume by trade-type.

Information precision, $\sigma_0^2/\sigma_\epsilon^2$ vs. price volatility by trade-type.
Effective spread and volume

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<td></td>
<td>(7.5731)</td>
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Effective spread, risk and volume

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<td>(9.787)</td>
<td>(7.8767)</td>
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<td>-0.0003***</td>
<td>0.145***</td>
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<td>(-32.509)</td>
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### Application II.: Stylized facts

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<td>Repo</td>
<td>MBS</td>
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<td>/</td>
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<td><strong>Price impact</strong></td>
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<td><strong>Volume</strong></td>
<td>$\leftrightarrow, \downarrow$</td>
<td>$\leftrightarrow$</td>
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- **Price dispersion**: determinant of the covariance-matrix or correlation matrix
- **Trading volume**: expected gross (or net) quantity traded by each dealer over all of her links
- **Price impact**: $-\frac{1}{c'_{ij} + c''_{ij}}$ the slope of inverse demand curve customer faces (inversely related to volume)
Model and narratives

1. larger uncertainty around a crisis: $\sigma_\theta^2 \uparrow$
2. more idiosyncratic elements, larger role of differences in probability and value of bail-outs, early liquidation, etc: $\rho \downarrow$
3. larger adverse selection, some institutions have relative advantage of valuating the securities: a increase of some dealers’ $\sigma_\epsilon^2$
4. increased counterparty risk, some institutions consider others too risky to trade with: drop of links

- 1 and 2: symmetric, 3 and 4: asymmetric
More uncertainty

- \( R_p \): price dispersion
- \( \sigma^2 \): variance of fundamental

- \( \text{star} \)
- \( \text{circle} \)
- \( \text{star (center)} \)
- \( \text{star (periphery)} \)
- \( \text{circle} \)
More idiosyncratic valuations
Adverse selection vs. counterparty risk
• information stories seems to be bad candidates
  • intuition: in this model, adverse selection (worry that others trade a lot, because they know something relevant) is the limiting force of volume ⇒ agents trade less when they want to learn from others ⇒ then their posteriors are more correlated ⇒ price dispersion is small
  • adverse selection is large when $\rho, \sigma^2_\epsilon$ large or $\sigma^2_\theta$ small (same as in centralized model)
  • counterparty risk works: less opportunities to trade, less opportunities to learn from prices
• asymmetric information does not limit trade
• suppose we give marginally more precise information to one of the counterparties ⇒
  1. more informed is less worried about adverse selection: c.p. trades with higher slope
  2. less informed is more worried about adverse selection: c.p. trades with lower slope
    slopes are complements ⇒ equilibrium intensities might go either way
  3. more information in total, more precise estimates of private values, more gains from trade

• numerically we find [3.] to dominate
Literature

- demand curves in an arbitrary structure of partially segmented set of markets, risk-sharing instead of learning: Malamud and Rostek (2013)
Example: Entire network of dealers

The figure illustrates the network structure of dealers in the municipal bond market in terms of the order flow between the dealers. Each node represents a dealer firm. Each arrow represents directed order flow between a pair of dealers.

Panel A: Order flow among most active dealers

Panel B: Order flow in entire network
Conclusion

- A model of strategic information diffusion in over-the-counter markets
  - dealers are strategic, and can decide to buy a certain quantity at a given price from one counterparty and sell a different quantity at a different price to another.
- The equilibrium price in each transaction partially aggregates the private information of all agents in the economy
  - privately fully revealing in the common value limit
  - otherwise there is a systematic distortion (too much information on own signal) limiting information revelation
    - not from profit motive, but from network structure + imperfect correlation of values
• **predictions:**
  1. larger transaction size - smaller % cost
     • all from across dealers (for given dealer-pair relationship disappears)
  2. price dispersion negatively, volatility positively related to transaction size
• **Model can distinguish between various mechanisms affecting OTC markets in dire economic conditions**
  • support for counterparty risk as opposed to adverse selection
• a strategy for dealer $i$: a map from the signal space to the space of generalized demand functions, a continuous function $Q_i : \mathbb{R}^{m_i} \rightarrow \mathbb{R}^{m_i}$

• expected payoff for dealer $i$ with signal $s_i$ corresponding to the strategy profile $\{Q_i(s_i; p_{gi})\}_{i \in \{1,...,n\}}$ is

$$E \left[ \sum_{j \in g_i} Q^i_j(s_i; p_{gi}) (\theta_i - p_{ij}) | s_i \right]$$

where $p_{ij}$ are the elements of the bilateral clearing price vector $\mathbf{p}$ defined by the smallest element of the set

$$\tilde{\mathcal{P}} \left( \{Q_i(s_i; p_{gi})\}_{i,s} \right) \equiv \{ \mathbf{p} \mid Q^i_j(s_i; p_{gi}) + Q^j_i(s_j; p_{gj}) + \beta_{ij}p_{ij} = 0, \forall ij \in g \}$$

by lexicographical ordering, if $\tilde{\mathcal{P}}$ is non-empty.

• If empty, let $\mathbf{p}$ be the infinity vector and define all dealers’ payoff to be zero.
No linear equilibrium without customers

- consider centralized market and 2 agents: \( q_i = bs_i + c_i p \) and customer with slope \( \beta \)
- think of 1 adjusting quantity with \( c_1 \) as a response to the slope of 2’s inverse demand \( 1/c_2 \)
- f.o.c.: \( c_1 = (c_2 + \beta)(1 - \frac{\partial E(\theta_1 | s_1, p)}{\partial p}) \)
- more sharper the price response (smaller \( c_2 \)), the smaller the quantity (smaller \( c_1 \))
- a \( \beta > 0 \) gives an upper bound on the price response \( \rightarrow \) finite \( c_1, c_2 \)
- when \( \beta = 0 \) best-response iteration pushes \( c_1 = c_2 = 0 \)
- but that cannot be an equilibrium because inelastic demand curves cannot clear the market for any realization of signals
Let $\bar{y}_i$ and $\bar{z}_{ij}$ the coefficients of signals and observed guesses in an equilibrium in the conditional-guessing game. Then whenever $\rho < 1$ and the following system

\begin{align*}
\frac{y_i}{\left(1 - \sum_{k \in g_i} z_{ik} \frac{2-z_{ki}}{4-z_{ik}z_{ki}}\right)} &= \bar{y}_i \\
\frac{z_{ij}}{\left(1 - \sum_{k \in g_i} z_{ik} \frac{2-z_{ki}}{4-z_{ik}z_{ki}}\right)} &= \bar{z}_{ij}, \forall j \in g_i
\end{align*}

admits a solution for each $i \in \{1, \ldots, n\}$ such that $z_{ij} \in (0, 2)$, we have an equilibrium of the given form, where

\[ t_{ij}^i = -\frac{2-z_{ji}}{z_{ij} + z_{ji} - z_{ij}z_{ji}} \beta_{ij} \]
Concentration and Intermediation (CDS markets)

Total CDS Notional/Trading Assets by Trading Asset Size

Top 25 HC in Derivatives

Source: Atkeson, Eisfeldt & Weill (2012)
Concentration and Intermediation (CDS markets)

Figure 3 plots net to gross notional for the top 25 bank holding companies in derivatives according to the OCC quarterly report on bank trading and derivatives activities third quarter 2011. Data are from bank holding companies' FR Y-9C filing from Q3 2011. Trading assets in thousands. Empty bars denote zero gross CDS notional.

Figure 4 plots the fraction of purchased credit derivatives from Q2 2009 to Q4 2011 that could be counted as a guarantee for regulatory purposes for the larger vs. the smaller top 25 bank holding companies in derivatives. Data are from bank holding companies' FR Y-9C filings. Size is measured by trading assets.

Source: Atkeson, Eisfeldt & Weill (2012)