Informed Traders and Dealers in the FX Forward Market

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The FX forward market:

- 2019 BIS estimates: 54 tn EUR notional outstanding in FX forwards, compared to 7 tn for equity linked OTC derivatives.
- FX forwards are still traded OTC in **two-tiered** markets despite large trading volume and homogeneous contracts.

Why a two-tiered market structure?

- Demand for **immediacy** in the presence of infrequent and large customer order flow (Grossman-Miller (1988), Grossman (1992)).
- Absence of **anonymity** can alleviate **adverse selection** (Seppi (1990), Benveniste, Markus, Wilhelm (1992), Lee and Wang (2019), Glode and Opp (2016)).
- **Dealers** prevent All-to-All trading (Managed Fund Association (2015)).
D2D order imbalance predicts FX rate (Evans and Lyons (2002), Payne (2003)).

→ private information in D2D? (see also Bjonnes, Osler and Rime (2008))

D2C markups don’t seem related to trade’s likely information content:
- Volume discounts (large trades get smaller markups).
- Smaller markups for financial than non-financial firms.
  (Bjonnes, Kathiziotis and Osler (2016), Osler, Mende, Menkhoff (2016))

→ price discrimination in D2C on basis of ‘sophistication’ rather than adverse selection? Strategic dealing hypothesis?

D2C order imbalance predicts FX rates (Evans and Lyons (2005), Evans and Rime (2016), Menkhoff, Sarno, Schmeling, Schrimpf (2016)).

Evidence above based on trades from one specific dealer typically over short time window and high frequency.
**European Market Infrastructure Regulation ~ Dodd-Frank**

- requires since March 2013 reporting of all derivatives trading to a data repository.

→ **European Systemic Risk Board** provides transaction level information on all trades and counterparties

- We focus on EUR/USD FX forward trades in EU.

- Analyze individual traders’ activity over time as well as D2C and D2D networks.

**Questions:**

- Is there evidence of informed trading in D2C FX-trading?
- How does it affect D2C markups across dealers?
- Does D2C order flow predict future FX rates?
- Who are the informed traders and dealers?
- What is the nature of their information?
- What are network implications of informed trading for the D2C and D2D markets?
Summary of Results

- Large dispersion in clients’ 1-day PI and Mkps:
  - Both non-financial and funds have large and significant 1-day PI and face high Mkps (with non-fi > funds).
  - Insurance & Pension fund have negative PI and pay lowest Mkps.
  - Governments and Central Banks have no significant PI.

- Skill seems persistent in that high-PI clients in first sub-period tend to remain high-PI in second period:
  - Frequent traders display persistence in 1-minute PI across sub-periods.
  - Non-‘HFT’ display persistence in 1-day PI across sub-periods

- Mkps positively related to PI, suggesting some role for adverse selection.

- Individual dealers’ client order flow predicts future FX Rate changes.

- Define informedness of a dealer by the predictive power of her clients order flow (regression $R^2$):
  - Informed traders are more likely to trade with informed dealers.
  - Informed traders and dealers have fewer counterparties.
Related literature

1. **Trading costs in two-tiered OTC markets**
   - Due to search frictions: Hau, Hoffmann, Langfield, Timmer (2019).
   - Due to risk-sharing of liquidity mis-match: Gallien, Kassibrakis, Malamud, Teguia (2020).

2. **Information leakage and dealer informedness**
   - Hagstromer and Menkveld (2019), Li and Song (2019).

3. **Determinants of FX price movements**

4. **Network structure of OTC markets**

5. **Why do we have OTC markets?**
EMIR data:
- Similar to Dodd-Frank in US, EMIR aims at promoting more transparency.
- Each derivatives transaction needs to be reported to “trade repository.”
- The data from all trade repositories are accessible at the ECB.
- Unique feature: Identities of traders and dealers.
- We focus on EUR/USD forward transactions from May 2018 to April 2019.

Other data:
- Thomson Reuters Tick History: Bid and ask quotes on EUR/USD forwards at the level of microseconds.
- ORBIS: types of traders, information on parent companies and subsidiaries.
Summary statistics

<table>
<thead>
<tr>
<th>trader type</th>
<th># traders</th>
<th>avg. notional</th>
<th>CPs/month</th>
<th>trades/month</th>
<th>avg. maturity</th>
</tr>
</thead>
<tbody>
<tr>
<td>CENTRAL BANK</td>
<td>45</td>
<td>35,013,323</td>
<td>5</td>
<td>41</td>
<td>24</td>
</tr>
<tr>
<td>EMPTY</td>
<td>14,215</td>
<td>13,395,139</td>
<td>3</td>
<td>144</td>
<td>42</td>
</tr>
<tr>
<td>FUND</td>
<td>11,055</td>
<td>10,155,767</td>
<td>4</td>
<td>1,190</td>
<td>38</td>
</tr>
<tr>
<td>GOVERNMENT</td>
<td>94</td>
<td>41,151,354</td>
<td>13</td>
<td>1,118</td>
<td>43</td>
</tr>
<tr>
<td>INSURANCE &amp; PENSION</td>
<td>524</td>
<td>66,889,994</td>
<td>10</td>
<td>406</td>
<td>36</td>
</tr>
<tr>
<td>NON-FINANCIAL</td>
<td>6,739</td>
<td>9,458,687</td>
<td>7</td>
<td>1,349</td>
<td>59</td>
</tr>
</tbody>
</table>

- Dispersion in trade sizes and number of counterparties.
- Funds and non-financials trade smaller notionals and have fewer counterparties.
Markups and price impact

The benchmark mid-price:
- Look at the best bid and ask prices from TRTH database for each second and for each fixed tenor (overnight, 1W, ..., 1 year).
- Define midpoint as the benchmark price for that second and tenor.
- Interpolate prices linearly between tenors to get benchmark prices for individual transactions.

Markups:
- For buys: transaction price – benchmark price
- For sells: benchmark price – transaction price

Price impact:
- Change in the benchmark price over next minute/day multiplied by +1 for buys and -1 for sells
- Noisy: $PI_{it} = \mu_i + \varepsilon_{it}$,
  → Sort traders on their trade frequency and form 30 groups (each accounting for 1/30th of all trades) to generate significant ‘spread’ in average $\mu_i$ in first half of sample in order to test for persistence in second-half of sample.
### Markups and price impact (in bps)

<table>
<thead>
<tr>
<th>trader type</th>
<th>1-day impact</th>
<th>1-minute impact</th>
<th>Markups</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>t-stat</td>
<td>mean</td>
</tr>
<tr>
<td>CENTRAL BANK</td>
<td>-0.133</td>
<td>-0.21</td>
<td>0.0326</td>
</tr>
<tr>
<td>EMPTY</td>
<td>0.224</td>
<td>3.39</td>
<td>0.0106</td>
</tr>
<tr>
<td>FUND</td>
<td>0.189</td>
<td>4.99</td>
<td>0.0110</td>
</tr>
<tr>
<td>GOVERNMENT</td>
<td>-0.070</td>
<td>-0.24</td>
<td>0.0564</td>
</tr>
<tr>
<td>INSURANCE &amp; PENSION</td>
<td>-0.763</td>
<td>-4.71</td>
<td>0.0216</td>
</tr>
<tr>
<td>NON-FINANCIAL</td>
<td>1.174</td>
<td>19.03</td>
<td>0.0133</td>
</tr>
</tbody>
</table>

- Average markups line up with average price impact.
- 1-day PI highest for non-financials who pay highest markup.
- Evidence for ‘price-discrimination’ of non-financials mostly driven by 1-mn horizon.

→ Dealer horizon?
Persistence of price impact

- Circle size: average notional/trade
- Stronger persistence on daily frequency
  - left: coefficient = 0.33 (0.14), $R^2 = 0.17$
  - right: coefficient = 0.34 (0.14), $R^2 = 0.24$
Persistence of 1-minute price impact

- Circle size: average notional/trade
- Persistence in 1-minute price impact is driven by ‘HFT’ traders (more than 10 trades per day)
  - left: coefficient=0.37 (0.13), $R^2=0.15$
  - right: coefficient=-0.01 (0.16), $R^2=0.00$
Persistence of 1-day price impact

Circle size: average notional/trade

Non-HFT seem to have a longer trading horizon.

left: coefficient = 0.20 (0.09), $R^2 = 0.10$

right: coefficient = 0.72 (0.21), $R^2 = 0.38$
### Persistence: regression results

$$PI_2 = \beta_0 + \beta_1 PI_1$$

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3) non-HFT</th>
<th>(4) non-HFT</th>
<th>(5) HFT</th>
<th>(6) HFT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>all</td>
<td>all</td>
<td>non-HFT</td>
<td>non-HFT</td>
<td>HFT</td>
<td>HFT</td>
</tr>
<tr>
<td></td>
<td>1 min</td>
<td>1 day</td>
<td>1 min</td>
<td>1 day</td>
<td>1 min</td>
<td>1 day</td>
</tr>
<tr>
<td>PI1</td>
<td>0.33**</td>
<td>0.34**</td>
<td>-0.01</td>
<td>0.72***</td>
<td>0.37***</td>
<td>0.20**</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.14)</td>
<td>(0.16)</td>
<td>(0.21)</td>
<td>(0.13)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00***</td>
<td>-0.00</td>
<td>-0.00</td>
<td>0.00*</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>N</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>r2</td>
<td>0.17</td>
<td>0.24</td>
<td>0.00</td>
<td>0.38</td>
<td>0.15</td>
<td>0.10</td>
</tr>
</tbody>
</table>

$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Sort traders into two groups based on PI in first quarter of sample

Look at average price impact

Also here, PI seems persistent...
Characterizing informed traders: summary statistics

<table>
<thead>
<tr>
<th></th>
<th>non-HFT</th>
<th>HFT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>neg-PI</td>
<td>high-PI</td>
</tr>
<tr>
<td>notional/trade (EUR)</td>
<td>21.4mn</td>
<td>9.6mn</td>
</tr>
<tr>
<td>counterparties</td>
<td>4.1</td>
<td>1.2</td>
</tr>
<tr>
<td>avg. monthly trades</td>
<td>102.9</td>
<td>3.0</td>
</tr>
<tr>
<td>average maturity (days)</td>
<td>34</td>
<td>61</td>
</tr>
</tbody>
</table>

- high-PI: 3 groups with the highest 2nd-period price impact
- neg-PI: all groups with negative price impact in both periods
- More informed traders trade smaller notionals and have fewer counterparties.

→ Could be consistent with information leakage concerns.
Regression confirm that informed have fewer counterparties and tend to trade smaller notionals.
Are dealers informed?

- Evans and Lyons (2002) show that dealer order flow predicts exchange rate movements.
- Does client order flow predict price changes across dealers?
- Regression of daily 1-week forward rate returns on last 5 trading days’ order imbalance (buys − sells):

\[
\frac{rate_{t+1} - rate_t}{rate_t} = \beta_{0,i} + \beta_{1,i} \text{sum}_{-} \text{Ol}_i + \varepsilon_{it},
\]

→ On average client order imbalances predict FX rate, with significant cross-sectional dispersion across dealers.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.022383</td>
<td>0.000002</td>
<td>0.27981</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>1.72584</td>
<td>0.020974</td>
<td>9.855478</td>
</tr>
</tbody>
</table>
Characterizing informed dealers

- Consider only dealers with $R^2$ below 2% and sufficient trading volume (to insure $R^2$ are meaningful):

<table>
<thead>
<tr>
<th></th>
<th>2.5% &gt; volume &gt; 0.5%</th>
<th>volume &gt; 2.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>uninformed</td>
<td>informed</td>
</tr>
<tr>
<td>% G16</td>
<td>66.6%</td>
<td>16.7%</td>
</tr>
<tr>
<td>dealer’s avg. notional/trade</td>
<td>12.1mn</td>
<td>9.2mn</td>
</tr>
<tr>
<td>D2C counterparties</td>
<td>1399</td>
<td>1288</td>
</tr>
<tr>
<td>D2D counterparties</td>
<td>123</td>
<td>102</td>
</tr>
<tr>
<td>% of total notional D2C volume (in EUR)</td>
<td>5.2%</td>
<td>8.7%</td>
</tr>
</tbody>
</table>

- Informed dealers have fewer (D2D and D2C) counterparties and trade smaller notionals.

→ Distinct from classic centrality/connectedness?
Markups and dealer informedness?

<table>
<thead>
<tr>
<th></th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>realized 1-day impact × informedness dummy</td>
<td>0.0099**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0043)</td>
<td></td>
</tr>
<tr>
<td>realized 1-day impact × connectedness dummy</td>
<td>-0.0068</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0042)</td>
<td></td>
</tr>
<tr>
<td>realized 1-day impact</td>
<td>0.0091***</td>
<td>0.0171***</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0031)</td>
</tr>
<tr>
<td>realized 1-minute impact</td>
<td>0.0849***</td>
<td>0.0892***</td>
</tr>
<tr>
<td></td>
<td>(0.0330)</td>
<td>(0.0337)</td>
</tr>
<tr>
<td><strong>market conditions:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>volatility</td>
<td>0.7146*</td>
<td>0.7286*</td>
</tr>
<tr>
<td></td>
<td>(0.3640)</td>
<td>(0.3804)</td>
</tr>
<tr>
<td>Smart average 1-day impact group</td>
<td>0.0013</td>
<td>0.0019</td>
</tr>
<tr>
<td></td>
<td>(0.0061)</td>
<td>(0.0064)</td>
</tr>
<tr>
<td><strong>time-varying trader characteristics:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(traders' monthly counterparties)</td>
<td>-0.0139</td>
<td>-0.0145</td>
</tr>
<tr>
<td></td>
<td>(0.0212)</td>
<td>(0.0213)</td>
</tr>
<tr>
<td>log(traders' monthly trades)</td>
<td>0.0269***</td>
<td>0.0276***</td>
</tr>
<tr>
<td></td>
<td>(0.0086)</td>
<td>(0.0086)</td>
</tr>
</tbody>
</table>

- Markup regressions with client-dealer fixed effects (and controls):
  - Markups ‘predict’ a trade’s future realized price impact.
  - Informed dealers are ‘better’ at setting Markups.
  - Informedness more relevant than connectedness for explaining Markups.
- Without client-Dealer fixed effects, we find high-PI clients pay higher markups (price discrimination).
Regressions to ‘predict’ when a trade occurs with an informed dealer (i.e., with a high D2C order-imbalance regression $R^2$):

- Informed traders trade with informed dealers.
- Also when we account for endogeneity:
  1. Determine dealer informedness (R2s) excluding a subset of traders (e.g., financials)
  2. Informed traders from excluded subset trade with informed dealers.
Setup:

- 2 periods, \( N \in \mathbb{N} \) dealers, can trade (1) in D2C and (2) in D2D market, inventory costs.
- Each dealer \( i \) get normally distributed “uninformed” order flow \( x_i \). D2D price \( p_2 \) compensates dealers for holding inventory.
- 1 arbitrageur, can buy/sell quantity \( \alpha > 0 \) in D2C market and offset trade in D2D market, knows price in D2D market.

Results:

- Dealers can forecast D2D prices using their order flow.
- If \( x_i \) is small relative to \( \sum_{j=1}^{N} x_j \) and \( \alpha \to 0 \), one has
  - As \( R^2 \to 1 \), the ask (bid) of dealer \( i \) converges in probability to \( \frac{N}{N+1} p_2 \) if \( p_2 > 0 \) (\( p_2 < 0 \)) and to zero otherwise and the probability that the arbitrageur trades with the dealer goes to 1.
  - If \( R^2 = 0 \), the probability that the arbitrageur trades with the dealer is strictly below 1.
Conclusion: Information and FX price-discovery in D2C?

- Non-financials and funds get charged higher markups that line up with higher 1-day (but not 1-minute) price-impact on average.

- Price-impact seems persistent across trader groups.

- Higher PI traders get charged higher markups.

- Dealers’ client order flow predicts FX rates.

- More informed dealers are ‘better’ at setting markups.

- Informed traders are more likely to trade with informed dealers, to have fewer counterparties, and trade smaller sizes.

→ Different perspective on ‘volume discount,’ ‘price-discrimination,’ and dealer centrality/connectedness measures?
Next steps

- Nature of the client order flow information: does it differ for funds and non-financials?
- Refine classification of dealers and of funds and non-financials (e.g., based on size).
- How does D2C order imbalance compare with D2D order imbalance in predicting FX rates?
- What is dealer horizon? Look at aggregate dealer inventory?
- Further robustness checks (e.g., to deal with possible measurement errors in EMIR time stamps).