Informed Traders and Dealers in the FX Forward Market

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Motivation

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)).

Adverse Selection and FX price discovery?

- D2D order imbalance predicts FX rate
  (Evans and Lyons (2002), Payne (2003)).

$\rightarrow$ 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))

$\rightarrow$ 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.

Research questions

European Market Infrastructure Regulation $\sim$ Dodd-Frank

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

$\rightarrow$ **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.

$\rightarrow$ 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**
   - Evans and Lyons (2002), Payne (2003), Menkhoff et al. (2017).
4. **Network structure of OTC markets**
   - Adverse selection: Babus and Kondor (2018), Collin-Dufresne, Junge, and Trolle (2017), Di Maggio, Franzoni, Kermani, and Sommavilla (2019), Kondor and Pinter (2019).
   - Dealer Centrality and network relationships: Di Maggio, Kermani, and Song (2017), Sambalaibat (2018), and Li and Schürhoff (2019), Hendershott, Li, Livdan, Schuerhoff (2017).
5. **Why do we have OTC markets?**
   - Mitigate costs of adverse selection: Seppi (1990), Lee and Wang (2019), Glode and Opp (2016, 2019).

Data

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

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

- 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: $\textit{transaction price} - \textit{benchmark price}$
- For sells: $\textit{benchmark price} - \textit{transaction price}$

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 μ_i in first half of samplein order to test for persistence in second-half of sample.

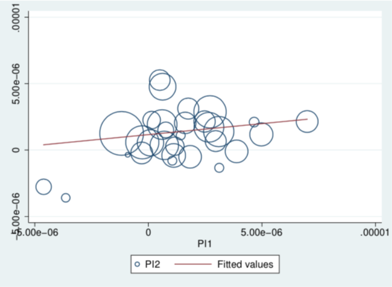
Markups and price impact (in bps)

	1-day impact		1-minute impact		Markups
trader type	mean	t-stat	mean	t-stat	mean
CENTRAL BANK	-0.133	-0.21	0.0326	1.16	*
EMPTY	0.224	3.39	0.0106	3.23	1.68
FUND	0.189	4.99	0.0110	5.91	0.75
GOVERNMENT	-0.070	-0.24	0.0564	3.57	1.24
INSURANCE & PENSION	-0.763	-4.71	0.0216	2.88	0.09
NON-FINANCIAL	1.174	19.03	0.0133	4.38	3.28

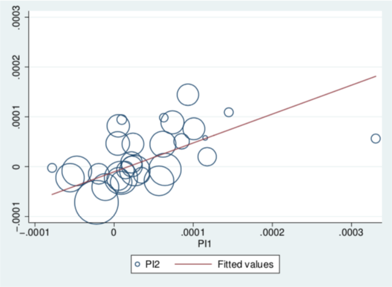
- Average markups line up with average price impact.
- 1-day PI highest for non-financials who pay highest markup.
- Evidence for 'price-discrimination' of non-financials mostly driven by 1-mn horizon.

$\rightarrow$ Dealer horizon?

Persistence of price impact



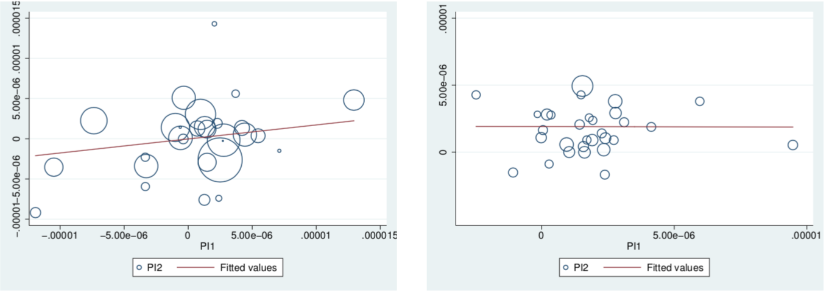
Panel A (1 minute).



Panel B (1 day).

- 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

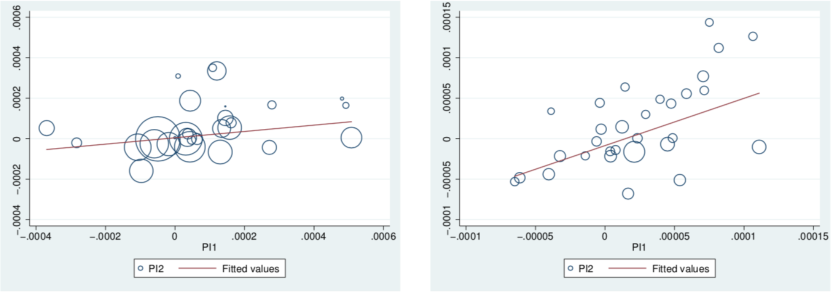
Persistence of 1-minute price impact



Panel A (HFT). Panel B (non-HFT).

- 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



Panel A (HFT). Panel B (non-HFT).

- 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

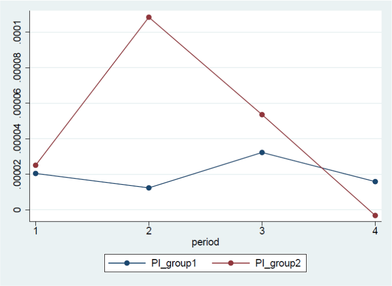
Persistence: regression results

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

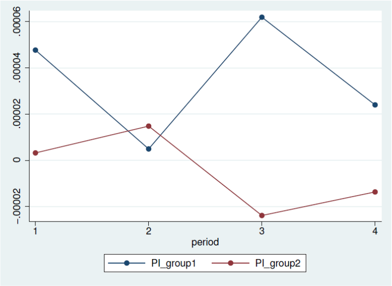
	(1)	(2)	(3)	(4)	(5)	(6)
	all	all	non-HFT	non-HFT	HFT	HFT
	1 min	1 day	1 min	1 day	1 min	1 day
PI1	0.33**	0.34**	-0.01	0.72***	0.37***	0.20**
	(0.14)	(0.14)	(0.16)	(0.21)	(0.13)	(0.09)
Constant	0.00	0.00	0.00***	-0.00	-0.00	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	30	30	30	30	29	29
r2	0.17	0.24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

$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Persistence: performance over time



Panel A (all traders).



Panel B (non-HFT).

- 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

	non-HFT		HFT	
	neg-PI	high-PI	neg-PI	high-PI
notional/trade (EUR)	21.4mn	9.6mn	11.9mn	1.4mn
counterparties	4.1	1.2	6.1	3.8
avg. monthly trades	102.9	3.0	706.0	1221.0
average maturity (days)	34	61	62	69

- 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.

Predicting (1-day high-PI) informed traders: regressions

	(1)	(2)	(3)	(4)	(5)
avg. monthly counterparties (CPs)	-84.70***				-12.07***
	(12.17)				(3.22)
avg. monthly trades		-0.19**			-7.87***
		(0.09)			(0.23)
avg. monthly trades × HFT dummy					7.91***
					(0.23)
avg. notional in EUR			-23.31***		4.82
			(7.95)		(5.99)
HFT dummy				-0.52***	-0.57***
				(0.08)	(0.08)
Constant	1.07***	0.96***	0.96***	0.96***	1.03***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
N	9628	9628	9628	9628	9628
r2	0.26	0.03	0.00	0.03	0.80

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- 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 ($buys - sells$):

$$\frac{rate_{t+1} - rate_t}{rate_t} = \beta_{0,i} + \beta_{1,i} sum\_OI_i + \varepsilon_{it},$$

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

Variable	Mean	Min	Max
R^2	0.022383	.000002	0.27981
Sharpe ratio	1.72584	0.020974	9.855478

Characterizing informed dealers

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

	2.5% > volume > 0.5%		volume > 2.5%	
	uninformed	informed	uninformed	informed
% G16	66.6%	16.7%	100%	100%
dealer's avg. notional/trade	12.1mn	9.2mn	17.5mn	16mn
D2C counterparties	1399	1288	5106	3947
D2D counterparties	123	102	266	220
% of total notional D2C volume (in EUR)	5.2%	8.7%	50%	30.3%

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

→ Distinct from classic centrality/connectedness?

Markups and dealer informedness?

	(2)	(3)
realized 1-day impact × informedness dummy	0.0099**	
	(0.0043)	
realized 1-day impact × connectedness dummy		-0.0068
		(0.0042)
realized 1-day impact	0.0091***	0.0171***
	(0.0015)	(0.0031)
realized 1-minute impact	0.0949***	0.0892***
	(0.0330)	(0.0337)
market conditions:		
volatility	0.7146*	0.7286*
	(0.3640)	(0.3804)
Smart average 1-day impact group	0.0013	0.0019
	(0.0061)	(0.0064)
time-varying trader characteristics:		
log(traders' monthly counterparties)	-0.0139	-0.0145
	(0.0212)	(0.0213)
log(traders' monthly trades)	0.0269***	0.0276***
	(0.0086)	(0.0086)

- 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).

Information and network structure

	excluding HFT		
	(1)	(2)	(3)
avg. 1-day impact	10.83***	10.81***	8.98**
	(3.77)	(3.77)	(3.75)
avg. 1-min impact		148.05*	153.02*
		(81.34)	(81.03)
realized 1-day impact		0.02	0.03
		(0.05)	(0.05)
realized 1-min impact		3.82***	3.88***
		(0.98)	(0.98)
log(monthly counterparties)			-21.45**
			(9.58)
log(monthly trades)			-6.75
			(6.63)
volatility			428.48***
			(131.95)
Constant	0.54***	0.54***	0.56***
	(0.01)	(0.01)	(0.01)

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.

Model

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.

$\rightarrow$ 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).