How Smart Is Institutional Trading?

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Motivation

- Hedge funds are different from the other institutional investors in regulation and incentive structure, which can lead to superior performance as a result of information acquisition (Agarwal et al, 2013; James, 2015), persistent performance among top hedge funds (Jagannathan et al, 2010), and better liquidity timing ability (Cao, et al, 2013). There is also evidence that hedge fund flow mitigates market mispricing (Akbas, et al, 2015).
- Most empirical studies rely on 13F filings to identify institutional holdings and use the position changes to represent institutional trades.
- What about their trading skills? To answer the question, measures of institutional trading at a finer granularity are needed.

"High frequency" institutional order flow

- It is possible to obtain institutional order flow in horizons shorter than a quarter:
    1. NYSE's Consolidated Equity Audit Trail Data (CAUD) give account type information (Kaniel, et al, 2012). However, this data set has a short history and is not publicly available.
    2. NYSE used to sell program traders' and retail traders' data until April 2016.
    3. Lee and Radhakrishna (2000) develop a size-based algorithm to classify institutional trades in public tick data.
- Without account names, it is impossible to disentangle hedge fund order flow from the rest using the methods above.

"High frequency" institutional order flow (cont'd)

- Two alternatives are available for the purpose:
    1. Campbell, Ramadorai, and Schwartz (2009) estimate the relation between change in aggregate institutional holdings in 13F and quarterly order flow of different trade size bins in TAQ. They calculate daily institutional order flow by extrapolating the relation from quarterly to daily observations.
    2. Abel Noser provides detailed institutional trades for a certain period. Puckett and Yan (2011) find institutions profit from intra-quarter trading.
- Compare CRS and AN:
    - CRS covers all institutions that file 13F while AN is estimated to cover about 10% of total institutional trades. Trades reported to AN can be self-selected.
    - CRS can be a noisy estimate while AN cleanly identifies institutional trades.

What we do in this study

- We calculate daily aggregate hedge fund (smart) order flow and non-hedge fund (dumb) order flow using both CRS and AN.
- We examine how they perform in terms of:
    - Contemporaneous price impact;
    - Information content about future returns;
    - Capturing well documented asset pricing anomalies.

Data and variables

- The sample period is 1999 to 2012.
- Procedure to apply CRS:
  - Use Lipper Tass to classify hedge funds and non-hedge funds among 13F filers. Calculate quarterly hedge fund and non-hedge fund position changes for every stock.
  - Calculate market order flow based on Lee and Ready (1991) in 19 trade size bins in TAQ for every stock and aggregate to quarterly order flow.
  - Estimate a nonlinear function of 13F position changes on quarterly TAQ order flow.
  - Fit daily TAQ order flow into the estimated nonlinear function to obtain daily institutional order flow for hedge funds (CRSSM) and non-hedge funds (CRSDU).
- We follow the procedure in Agarwal, Jiang, Tang, and Yang (2013) to map 13F filers to manager codes in Abel Noser data, and calculate hedge fund order flow (ANSM) and non-hedge fund order flow (ANDU) respectively.

Correlations of order flow estimates

	CRS	*CRSSM*	*CRSDU*	*AN*	*ANSM*	*ANDU*
CRS	1.000					
CRSSM	0.689	1.000				
CRSDU	0.925	0.763	1.000			
AN	0.032	0.004	0.024	1.000		
ANSM	0.013	0.002	0.008	0.437	1.000	
ANDU	0.030	0.003	0.023	0.897	0.029	1.000
TAQOI	0.552	0.524	0.538	0.007	0.007	0.003
RET	0.188	0.151	0.180	0.068	0.041	0.057

Contemporaneous price impact

Fama-MacBeth (1973) regressions of risk-adjusted mid quote return on day t

	CRS		AN	
$SMART_t$	5.096***	9.005***	3.394***	5.058***
	(12.37)	(14.22)	(26.81)	(22.84)
$DUMB_t$	5.371***	7.019***	1.941***	3.003***
	(50.27)	(29.41)	(40.47)	(44.52)
$D(SPRD)_t \times SMART_t$		16.374***		0.281**
		(26.78)		(2.12)
$D(SPRD)_t \times DUMB_t$		1.012***		0.192***
		(8.02)		(4.29)
$D(TURN)_t \times SMART_t$		-13.774***		-1.854***
		(-25.18)		(-11.32)
$D(TURN)_t \times DUMB_t$		-2.411***		-1.206***
		(-8.10)		(-24.29)
	CRSSM	*CRSDU*	*ANSM*	*ANDU*
Std. dev.	0.042	0.137	0.102	0.249

Information regarding future returns

Fama-MacBeth (1973) regressions of risk-adjusted mid quote return on day $t+1$

	CRS	AN
$SMART_{t-1}$	0.791***	0.318***
	(7.67)	(5.78)
$SMART_{t-2}$	0.099	-0.057
	(1.11)	(-1.14)
$SMART_{t-3}$	-0.051	-0.091*
	(-0.60)	(-1.85)
$SMART_{t-4}$	-0.132	-0.084*
	(-1.58)	(-1.71)
$SMART_{t-5}$	0.081	-0.089**
	(0.89)	(-2.12)
$DUMB_{t-1}$	-0.044	0.127***
	(-1.17)	(7.68)
$DUMB_{t-2}$	-0.277***	-0.006
	(-9.37)	(-0.41)
$DUMB_{t-3}$	-0.121***	-0.007
	(-4.00)	(-0.47)
$DUMB_{t-4}$	-0.125***	-0.047***
	(-4.10)	(-3.34)
$DUMB_{t-5}$	-0.142***	-0.027*
	(-4.86)	(-1.92)

Additional analysis

- CRS SMART is more informative for small and illiquid stocks, and before 2005.
- CRS DUMB, AN SMART and DUMB do not have permanent price impact even in subsamples of stocks.
- CRS SMART predicts CAR around permanent price jumps while the other types of institutional order flow do not.

Do institutions trade on anomalies?

Fixed effect panel regressions with daily observations:

	CRSSM	*CRSDU*	*ANSM*	*ANDU*
MISP	0.002	-0.265***	0.054***	0.053***
	(0.81)	(-31.92)	(8.58)	(3.65)
FirstWeek	-0.000*	-0.001	-0.001	0.000
	(-1.87)	(-1.39)	(-1.08)	(0.07)
LastWeek	-0.001***	0.001	0.001**	0.003*
	(-3.27)	(1.09)	(2.21)	(1.91)
FirstWeek $\times$*MISP*	-0.006	-0.018	0.015	0.017
	(-1.34)	(-1.18)	(1.24)	(0.62)
LastWeek $\times$*MISP*	0.000	-0.032**	-0.030***	-0.034
	(0.12)	(-2.20)	(-2.63)	(-1.29)

MISP is the mispricing index as in Stambaught, Yu, and Yuan (2012, 2015)

Are institutions good at trading anomalies?

Monthly double-sorted portfolio returns:

Panel A. CRS Smart

		MISPRICING						
		Under	4	3	2	Over	UMO	T-stat
Abnormal $\lvert CRSSM \rvert$	Low	0.0265	0.0201	0.0200	0.0215	0.0230	0.0035	(0.55)
	2	0.0238	0.0146	0.0212	0.0164	0.0160	0.0078	(1.20)
	3	0.0180	0.0171	0.0107	0.0201	0.0128	0.0053	(0.68)
	4	0.0129	0.0080	0.0095	0.0116	0.0107	0.0022	(0.31)
	High	0.0182	0.0180	0.0158	0.0068	0.0025	0.0157	(1.72)
	HML	-0.0083	-0.0021	-0.0042	-0.0147	-0.0205	0.0122	
	T-stat	(-1.60)	(-0.41)	(-0.76)	(-2.70)	(-3.27)	(1.56)	

Are institutions good at trading anomalies? (cont'd)

Monthly double-sorted portfolio returns:

Panel B. CRS Dumb

		MISPRICING						
		Under	4	3	2	Over	UMO	T-stat
Abnormal $\|CRSDU\|$	Low	0.0343	0.0228	0.0176	0.0211	0.0226	0.0116	(1.68)
	2	0.0239	0.0206	0.0211	0.0137	0.0192	0.0047	(0.59)
	3	0.0229	0.0114	0.0151	0.0126	0.0052	0.0177	(2.47)
	4	0.0093	0.0075	0.0037	0.0040	-0.0083	0.0176	(2.65)
	High	0.0089	0.0163	0.0195	0.0249	0.0273	-0.0184	(-1.78)
	HML	-0.0254	-0.0065	0.0019	0.0038	0.0047	-0.0300	
	T-stat	(-4.53)	(-1.30)	(0.43)	(0.60)	(0.61)	(-3.53)	

Are institutions good at trading anomalies? (cont'd)

Monthly double-sorted portfolio returns:

Panel C. AN Smart								
		MISPRICING						
		Under	4	3	2	Over	UMO	T-stat
Abnormal $\vert ANSM\vert$	Low	0.0132	0.0130	0.0183	0.0147	0.0175	-0.0043	(-0.69)
	2	0.0240	0.0203	0.0199	0.0184	0.0175	0.0065	(1.15)
	3	0.0164	0.0171	0.0174	0.0127	0.0124	0.0040	(0.68)
	4	0.0132	0.0167	0.0137	0.0152	0.0200	-0.0068	(-0.94)
	High	0.0236	0.0184	0.0166	0.0173	0.0123	0.0113	(1.52)
	HML	0.0104	0.0055	-0.0017	0.0026	-0.0052	0.0155	
	T-stat	(2.62)	(1.42)	(-0.43)	(0.66)	(-1.00)	(2.59)	

Are institutions good at trading anomalies? (cont'd)

Monthly double-sorted portfolio returns:

Panel D. AN Dumb								
		MISPRICING						
		Under	4	3	2	Over	UMO	T-stat
	Low	0.0121	0.0192	0.0143	0.0197	0.0146	-0.0025	(-0.43)
Abnormal	2	0.0219	0.0161	0.0127	0.0167	0.0166	0.0052	(0.74)
$\|ANDU\|$	3	0.0175	0.0146	0.0193	0.0171	0.0106	0.0069	(0.97)
	4	0.0228	0.0170	0.0177	0.0166	0.0167	0.0060	(0.78)
	High	0.0286	0.0188	0.0229	0.0203	0.0275	0.0011	(0.13)
	HML	0.0165	-0.0004	0.0086	0.0006	0.0129	0.0036	
	T-stat	(2.82)	(-0.11)	(1.50)	(0.12)	(1.77)	(0.50)	

Conclusion

- Hedge funds are smarter than the other institutional investors in three ways:
  1. Hedge funds generate smaller contemporaneous price impact;
  2. CRS hedge fund trades contain price information;
  3. AN hedge fund trades capture asset pricing anomalies.
- The difference in trading skills between hedge funds and the other institutional investors seems smaller for the measures based on Abel Noser data than those calculated following Campbell et al. (2009).