Following the crowd: Anomalies and crowding by Institutional Investors

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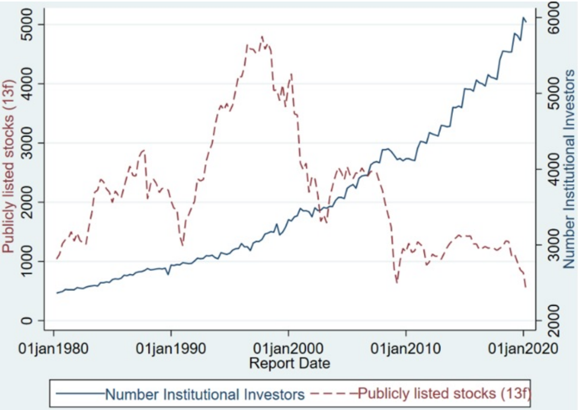
Motivation

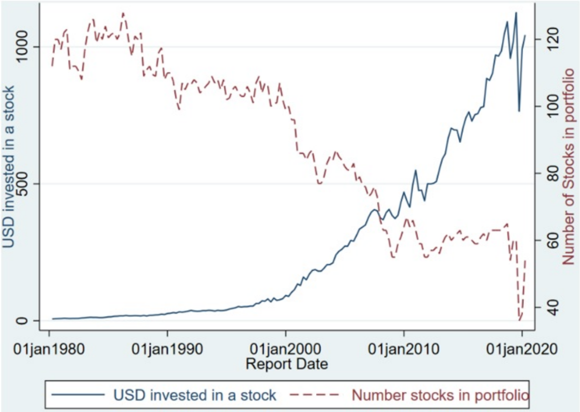
13F Thomson/Refinitv Institutional holdings



- The **number of institutional investors grew more than ten times** (blue line) from around 400 in 1980 to more than 4,000 in the first quarter of 2020.
- The **number of publicly listed companies steadily decreased** (red line) after reaching its peak of 5,756 in the late 1990s **to a total of 2,386 in 2020**.

Motivation

13F Thomson/Refinitv Institutional holdings



- The **decline in the median number of stocks held** in a typical institutional investor's portfolio (red line) contrasted to the **increase in the amount of money, in millions of USD, allocated** in average security (blue line)

Crowding

Crowded holdings = those in which many investors hold the same stocks possibly exhausting their liquidity provision.

Mechanisms

- Trading spaces may become crowded if investors follow *similar trading models*, either by coincidence or intentionally.
- Even if they have different models for generating their expected returns, investors' use of *similar techniques for portfolio construction* can cause their portfolios to converge.

Hypothesis development

H_1**:** Crowding and the return dynamics in institutional investors' holdings:

$\uparrow$ crowding leads to $\uparrow$ excess return

H_2**:** Crowding in anomaly stocks:

Anomaly stocks should exhibit $\uparrow$ crowding specially those selected from non-fundamentally anchored trading strategies (e.g. momentum).

H_3**:** The determinants of crowding, liquidity, and crash risk:

$\uparrow$ crowding related to $\uparrow$ liquidity and $\uparrow$ crash risk and stronger among short-term investors.

Main Results/Contributions

- Based on a portfolio sorting approach, we find that **the most crowded stocks outperform the least crowded ones** in our database of institutional investors' holdings.

- Across **12** well-known stock anomalies, **abnormal returns are significantly higher among most(least) crowded**.

- We also find that crowding is **positively and significantly related to liquidity and crash risk**.

We contribute to the literature on the **limits to arbitrage** by showing that **crowded holdings pose additional liquidity/crash risk concerns** to arbitrage trading.

Measuring crowding at the stock level

We extend Brown et al.(2021) **Days-ADV** ($ADV_{i,j,t}$) measure and estimate it for our sample of institutional investors (13F)

$$Days - ADV_{i,j,t} = \frac{\text{InstHold}_{i,j,t}}{\text{ADV}_{i,t}} \tag{1}$$

where:

- $InstHold_{i,j,t}$ is the total value invested in a security i by institutional investor j at quarter t;
- $ADV_{i,t}$ is the average daily turnover of security i during quarter t.

This measure provides an estimate of **how long (in days) it would take** the institutional investors universe **to collectively divest itself of a position** in an individual security.

Anomalies

	Anomaly	Label	Paper	SSRN year
1	Composite equity issuance	CEI	Daniel and Titman (2006)	2001
2	Net stock issuance	NSI	Loughran and Ritter (1995)	
3	Total accruals	ACC	Sloan (1996)	
4	Net operating assets	NOA	Hirshleifer et al. (2004)	2003
5	Gross profitability	GP	Novy-Marx (2013)	2010
6	Asset growth	AG	Cooper et al. (2004)	2005
7	Capital investments	CI	Titman et al. (2004)	2001
8	Investment-to-assets	IVA	Xing (2008)	2008
9	Momentum	MOM	Jegadeesh and Titman (1993)	2001
10	Ohlson O-score	OSC	Dichev (1998)	2001
11	Return to assets	ROA	Fama and French (2006)	2001
12	Book-to-market	BM	Fama and French (1992)	

Data

1. Stock data from **CRSP** and **Compustat**
   - All common stocks (10,11) trading on the NYSE, AMEX, and NASDAQ.
   - Filters: we exclude utilities, financial firms, and stocks priced under $5 (microcaps).
   - Sample period: 1980Q1 until 2020Q1

2. Thomson/Refinitv **13F** Institutional holdings - s34
   - All investment managers with discretion over securities worth $100 Million or more to report all equity positions greater than 10,000 shares or $200,000.
   - Following convention we correct errors on missing holdings and cap IO (Institutional Ownership) to 100%.

Univariate Portfolio sorts

Table 1: Quintile portfolios(*value-weighted*) formed on days-ADV

	Excess return and Alpha					
	Exc Ret	FF3	FF4	FF5	FF3+liq	MISP
Quintile 5 -High	1.18	0.62	0.55	0.49	0.65	0.34
	(6.31)	(8.86)	(8.63)	(7.91)	(9.73)	(4.81)
Quintile 4	0.70	0.12	0.03	-0.02	0.09	-0.10
	(3.82)	(2.13)	(0.83)	(-0.51)	(2.17)	(-1.76)
Quintile 3	0.55	-0.08	-0.11	-0.15	-0.10	-0.15
	(2.77)	(-1.77)	(-2.61)	(-3.61)	(-2.57)	(2.74)
Quintile 2	0.37	-0.31	-0.29	-0.14	-0.38	-0.07
	(1.55)	(-4.07)	(-4.30)	(-2.41)	(-5.41)	(-0.07)
Quintile 1 -Low	-0.14	-0.96	-0.76	-0.61	-0.94	-0.37
	(-0.46)	(-8.06)	(-7.62)	(-6.34)	(-8.99)	(-2.91)
High-minus-Low(HML)	**1.32**	**1.58**	**1.31**	**1.09**	**1.59**	**0.71**
	(6.24)	(9.52)	(9.38)	(8.25)	(9.63)	(4.19)

MISP = is the model proposed by Stambaugh et al (2007) that combines two mispricing factors with the market and size factors
The reported alphas are in percent per month. The t-values are in parentheses.

Anomaly stocks and Crowding: Double-sorted Portfolios

Table 2: Anomaly stocks and crowding

Panel A: Sorted on days-ADV and then on anomaly variables

	High/Long	Low/Short	Diff
Full Sample	0.64	-1.23	**1.87**
	(9.81)	(-10.84)	(12.19)
Pre-publication	0.50	-0.75	**1.25**
	(5.97)	(6.20)	(10.69)
Post-publication	0.36	-0.54	**0.90**
	(4.31)	(-4.88)	(8.78)

Panel B: Sorted on anomaly variables and then based on days-ADV

	High/Long	Low/Short	Diff
Full Sample	0.40	-1.24	**1.64**
	(6.54)	(-9.58)	(10.30)
Pre-publication	0.37	-0.78	**1.16**
	(3.92)	(-6.29)	(9.84)
Post-publication	0.25	-0.53	**0.77**
	(2.89)	(-4.54)	(7.54)

The aggregate anomaly portfolio is estimated by taking the equally-weighted average each quarter across all available anomaly returns.
We run our estimations for three sample periods (i) the complete period spanning 1980Q1 to 2020Q1 – the first row, (ii) the period after 1980Q1 until just the publication year (pre-pub) – the second row, and (iii) after the publication (post-pub) to the first quarter of 2020.
The reported alphas are in percent per month. The t-values are in parentheses.

Fama-Macbeth regressions

Crowding and future returns

Table 3: Crowding and next quarter returns

Panel A: Return in the next quarter $(t+3)$

	$CumRet_{t,t+3}$		$ExcessRet_{t,t+3}$	
	1980-1996	1997-2020	1980-1996	1997-2020
$log(ADV_{t-1})$	**0.0056**	**0.0060**	**0.0016**	**0.0018**
	(3.373)	(4.164)	(2.925)	(3.626)
Obs.	24,198	28,624	24,206	28,624
R-squared	0.099	0.111	0.101	0.114
Controls	Yes	Yes	Yes	Yes

Panel B: Return in the next year $(t+12)$

	$CumRet_{t,t+3}$		$ExcessRet_{t,t+3}$	
	1980-1996	1997-2020	1980-1996	1997-2020
$log(ADV_{t-1})$	**0.0312**	**0.0303**	**0.0016**	**0.0019**
	(5.565)	(6.293)	(4.751)	(6.067)
Obs.	21,977	27,336	21,975	27,336
R-squared	0.099	0.111	0.101	0.114
Controls	Yes	Yes	Yes	Yes

Crash risk and crowding

Table 4: Crash risk and crowding

	$NCSkew_{t,t+3}$		$Duvol_{t,t+3}$		$CrashCount_{t,t+3}$	
	1980-1996	1997-2020	1980-1996	1997-2020	1980-1996	1997-2020
$log(ADV_{t-1})$	**0.0482**	**0.0508**	**0.0199**	**0.0158**	**0.0624**	**0.0662**
	(2.387)	(2.581)	(2.901)	(2.980)	(2.190)	(3.491)
Obs.	36,015	56,882	36,015	56,882	36,015	56,882
R-squared	0.316	0.209	0.345	0.246	0.269	0.197
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

NCSKEW = Negative coefficient of firm-specific daily returns. It is the negative of the third moment divided by the cubed standard deviation;
DUVOL = "Down-to-Up volatility"we separate all days with firm-specific daily returns above(below) the mean of the period and call them up(down) sample;
CrahCount = based on the number of firm-specific daily returns exceeding 3.09 std above and below the mean firm-specific daily return over the year (3.09 to generate frequencies of 0.1% of the normal distribution)

Liquidity, Liquidity risk, and crowding

Table 5: Liquidity, Liquidity risk, and crowding

	$\beta_{liq,t+1}$	$Illiquid_{t+1}$
$log(ADV_{t-1})$	**0.0021**	**0.0969**
	(2.23)	**(6.35)**
Anomaly dummy$_{t-1}$	-0.0004	**0.0333**
	(-0.23)	**(2.81)**
$Size_{t-1}$	-0.006	-0.179
	(-3.75)	(-11.82)
BM_{t-1}	0.013	0.056
	(4.48)	(2.45)
$Volatility_{t-1}$	0.011	-0.965
	(0.59)	(-3.95)
Ret_{t-1}	0.015	-0.512
	(5.20)	(-4.43)
NASDAQ dummy$_{t-1}$	0.201	0.261
	(4.04)	(4.66)
Obs.	178,837	258,444
R-squared	0.378	0.111

$\beta_{liq,t+1}$ = is the parameter loading on the Pastor (2003) traded liquidity factor added to the Fama and French (1993) three-factor model.
$Illiquid_{t+1}$ = is the Amihud (2002) illiquidity measure calculated using daily data, aggregated at the month level, and estimated as the average over the past 3 months sample;

Conclusion

- We investigate the effects of the *concentration of stock ownership (i.e. crowding) by institutional investors* on the cross-section of stock returns.
- Our analysis is focused on a set of 12 well-known asset pricing anomalies.
- We find that **anomaly risk-adjusted returns appear to be concentrated among the most (least) crowded stocks** for the long-leg (short-leg) portfolio.
- Moreover, crowding shows **significantly positive relationship with crash and liquidity risk** after controlling for a broad set of variables.

Our results are consistent with crowded holdings being an **additional consideration to the limits of arbitrage**.