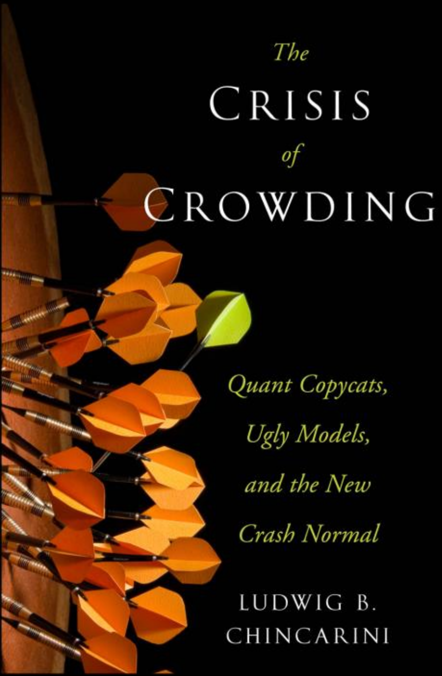
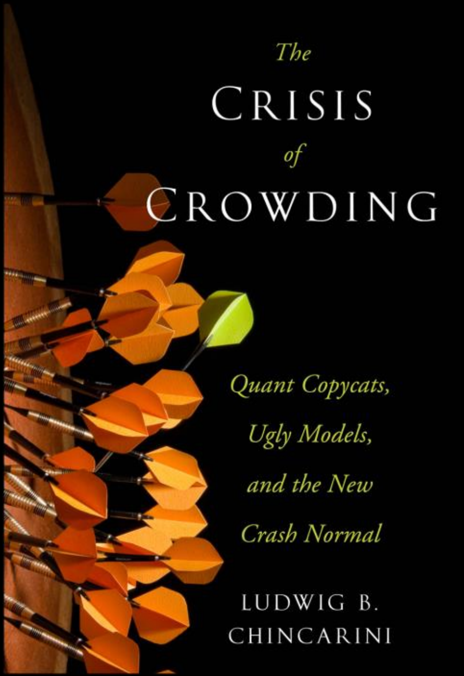


Crowded Spaces & Anomalies



November 30, 2022

Presentation as Finalist
For the Cromwell Prize 2022

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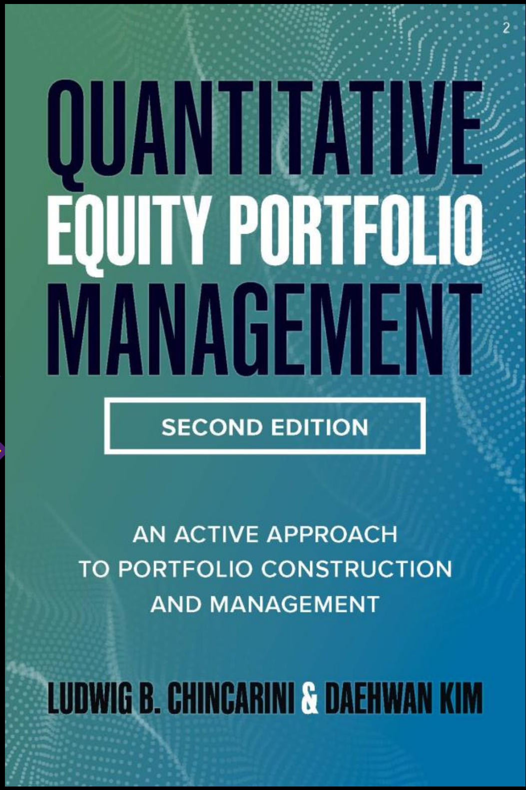
University of San Francisco

UNIVERSITY OF SAN FRANCISCO | School of Management

- Thank you PanAgora Asset Management.

The new edition of QEPM just released – you will love it.



1. Crowding Idea is Spreading

- *The Crisis of Crowding* by Ludwig Chincarini.
- A new academic literature on crowding has been burgeoning in the last eight years.
- Practitioner research has also exploded and been very dedicated to crowding research.
- For more info, go to: http://ludwigbc.com/presentations/slides/

(Lots of stuff, including latest research, definitions, etc)

2. Research on Crowding

Most of the new observations are contained in Appendix A to this presentation which has summaries of the latest articles on crowding. For a complete list of articles, check other presentations on my website: https://ludwigbc.com/presentations/slides/

You can get a copy of this presentation from me directly (chincarinil@hotmail.com) or from PanAgora Asset Management.

3. Anomalies & Crowding

A. Background

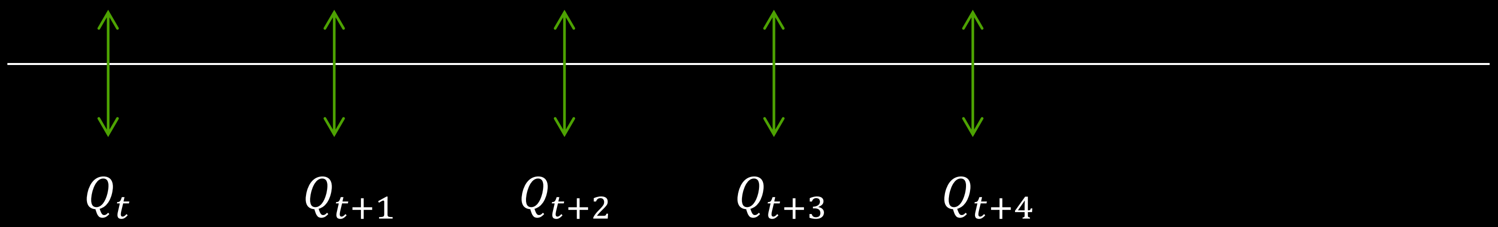
- Many quantitative investors might seek "alpha generating" strategies which are sometimes called "anomalies" in the investment space.

- Suppose every anomaly has some level of saturation at which point ALPHA=0.

- Because "crowding" might be unobservable or observable with an error, could it lead to crash risk and/or fragile exits and even other risks that are not anticipated?

3. Anomalies & Crowding

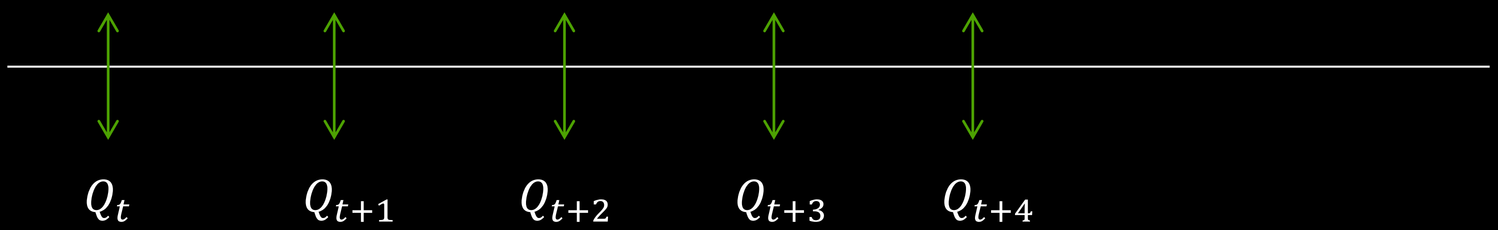
B. Theoretical Reasoning



Let's assume some demand impact on prices for now. Thus, if a relatively larger group of investors purchases an anomaly stock they put positive price pressure (longs) and negative price pressure (shorts) on these stocks, provided $\emptyset^{A}$ (the fraction dollar of anomaly investors) is larger than $\emptyset^{NA}$ (the fraction of dollar non-anomaly investors).

3. Anomalies & Crowding

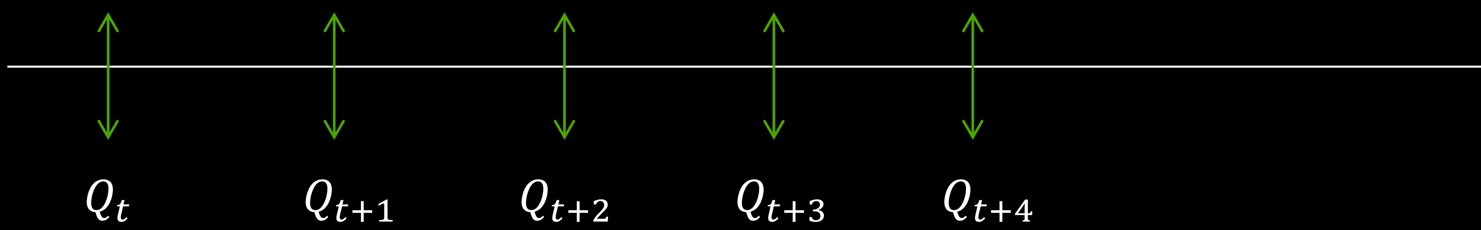
B. Theoretical Reasoning



- Thus, if we measure crowding at time t, an increase in crowding at time t can cause returns to move at time t.
- If we want to see how crowding impacts future returns, we should look at crowding at time t-1 on returns at t and beyond.
- Crowding may also build slowly and be a slow moving variable.

3. Anomalies & Crowding

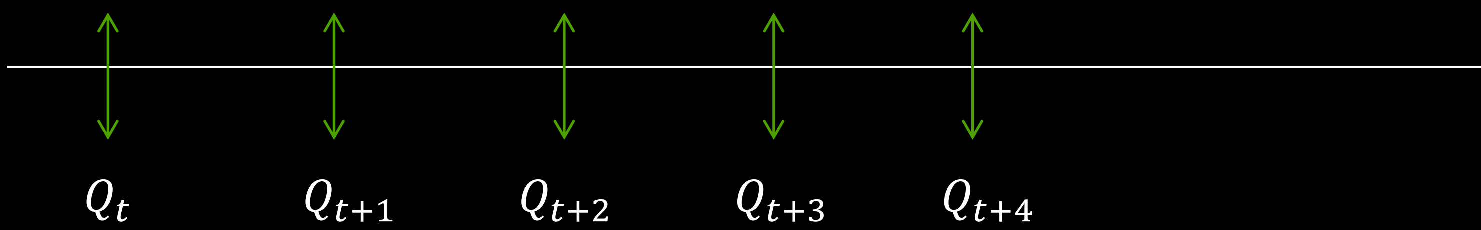
B. Theoretical Reasoning



- In addition, crowding effects may be dynamic, in the sense, that if crowding is building, returns may be strong, until they are not.
- Thus as crowding grows (t), we would expect returns at t to be correlated.
- Returns at t+1, may be positive or negatively correlated depending on revelation of earnings/growth data (in case of value).
- As crowding builds, we would might expect crash risk to build.

3. Anomalies & Crowding

B. Theoretical Reasoning



Question: So why do anomalies have alpha? Think value or P/B.
(*Not covered by our paper, but worth chatting about*)

1. Institutional constraints (e.g. passive investing) exacerbate other investors' overreactions and as new data comes in, mispricing get corrected.
2. Crowding can temporarily speedup convergence.

3. Anomalies & Crowding

C. Summary of Our Work

1. We attempt to measure aggregate crowding from a dataset of institutional investors and determine some of the mechanics of crowding.
2. We find that crowding by institutional investors (even in aggregated sense) causes returns to be higher of crowded stocks.
3. We expand the literature by documenting that the effect of crowding on returns is stronger for anomaly stocks.
4. We find that crowding is related to crash risk – which is stronger when considering anomaly stocks.

3. Anomalies & Crowding

D. Descriptive Statistics and Data

Definition 1: Crowding

$$\textbf{Days ADV}_{i,j,t} = \frac{\sum_{j=1}^{N} \mathrm{InstHold}_{i,j,t}}{\mathrm{ADV}_{i,t}}$$

- Would be expected to be positive with returns at t → it's the buildup phase.
- We later lag this variable so that its also publicly available.
- We do not lag ADV from Holding, which would not worry about endogeneity of ADV and holding buildup.
- Measure considers two important aspects of crowding: the ownership in a particular stock (InstHold) and the size of the exit door (ADV).
- Use measure with varying LAGS.

3. Anomalies & Crowding

D. Descriptive Statistics and Data

Definition 2: Crowding

$$\mathrm{ActRatio}_{i,t} = \frac{\mathrm{Shares}_{i,t-2}}{\mathrm{AvgTurn}_{i,t-1}}$$

- Various lags selected by previous authors (Brown et al. and Zhang et al.)

3. Anomalies & Crowding

D. Descriptive Statistics and Data

Definition 3: Crowding

$$C = \frac{\sum_{i=1}^{M}\sum_{j=1}^{M} S_{i,j} - M}{M^2 - M}$$

- Where this is the crowding of the entire set of portfolio managers at a given point in time
- Where S comes from the similarity between all pairwise sets of portfolio managers

$$s_{ij} = \frac{\mathbf{w}_i'\mathbf{w}_j}{|\mathbf{w}_i||\mathbf{w}_j|}$$

- Measure does not focus on specific stocks, but rather the aggregate “crowding” in the fund manager world

3. Anomalies & Crowding

D. Descriptive Statistics and Data

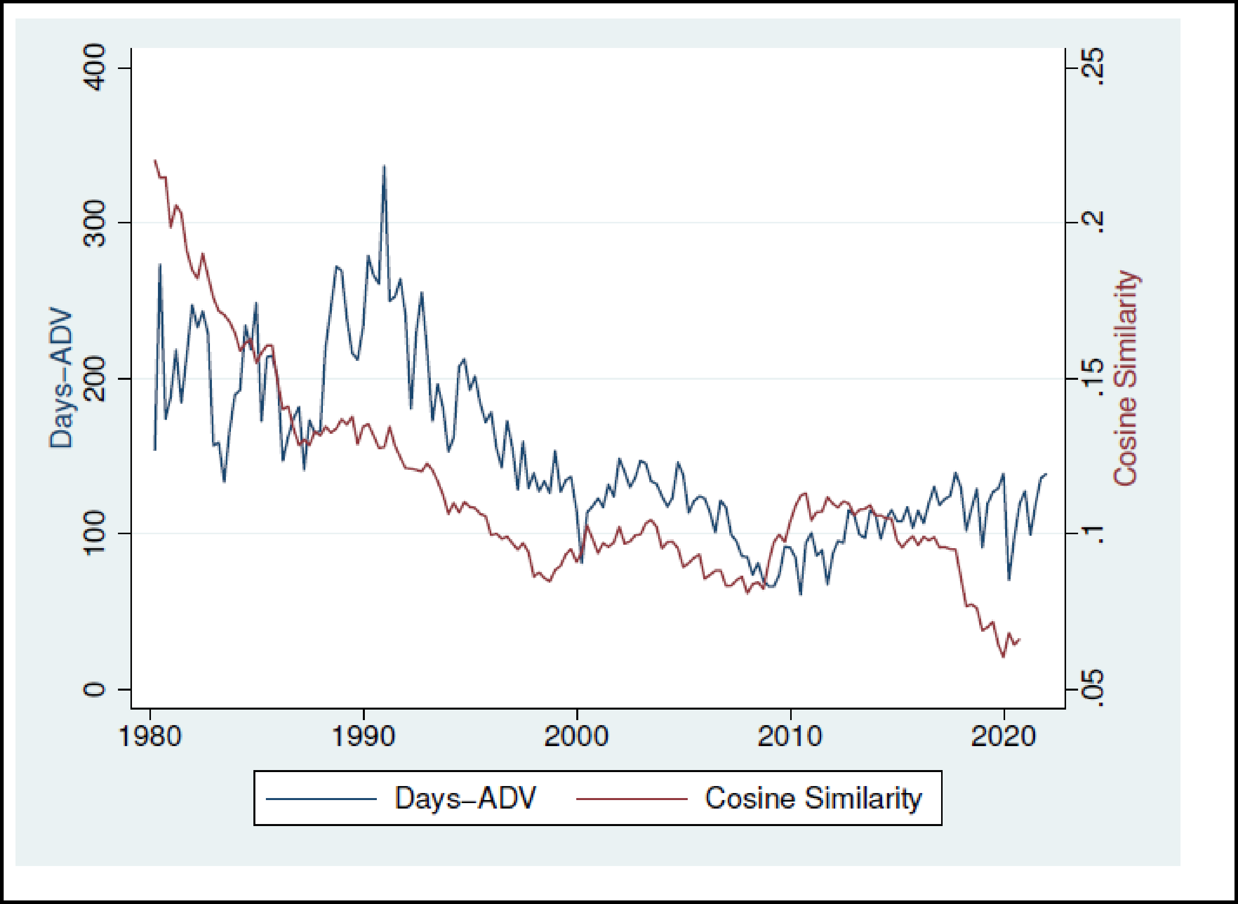
Definition 4/5: Crowding

- NI = number of institutional investors (although not related to money or anchored, thus a crude measure of crowding)
- PSO = percentage of share ownership by a group of investors (another crude measure)

3. Anomalies & Crowding

D. Descriptive Statistics and Data

- Different crowding measures are related



3. Anomalies & Crowding

D. Descriptive Statistics and Data

- Use CRSP, Compustat Data and 13-F filings

Table 2: Summary Statistics

	Full Sample			1980-1992			1993-2021		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
NI	2,209	1,815	1512	764	775	181	2857	2717	1391
NStocks	232	100	411	244	120	265	206	91	477
AUM	6,489.1	933.2	33,640.1	6,298.0	1,708.3	13,335.5	6,574.7	585.8	42,742.1
NIpermno	93	47	139	40	15	67	117	62	171
USDpermno	1,599.73	130.43	7,229.95	221.36	16.42	925.52	2,217.62	181.53	10,056.08
Days-ADV	378	151	700	660	214	1167	251.038	122.203	490.686
PSO	40.25%	38.77%	27.11%	24.16%	19.49%	19.88%	47.47%	47.41%	30.34%
Turnover	0.74%	0.28%	1.97%	0.26%	0.09%	1.07%	0.96%	0.37%	2.38%

Note: This table reports descriptive statistics of the following variables: Number of Institutional Investors (NI); Number of stocks held in the institutional investor's portfolio (NStocks); Total Assets under management (AUM) in millions of USD dollars; Number of institutional investors holding the same stock (NIpermno); Total amount of money invested by all 13f institutional investors in a given stock(USDpermno), in millions of US dollars; Days-ADV, defined as the money value held in a security by all institutional investors relative to the security's average daily money volume; stock percentage of shares outstanding owned by the 13F investors (PSO); And, stock average daily volume relative to total market capitalization. The data on institutional holdings is obtained from Thomson Reuters (TR) 13F database. Stock price, trading volume, and total shares outstanding data is from CRSP. Number of institutional investors is a counter of the number of distinct institutional investors holding the same stock. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The variables Days-ADV, PSO, and turnover are winsorized at the 1% and the 99% levels. The sample period is from 1980:Q1 to 2021:Q4.

3. Anomalies & Crowding

D. Descriptive Statistics and Data

- Use CRSP, Compustat Data and 13-F filings

Table A1: Summary of 13F database

Period	NIpermno Median	NIpermno P90	USDpermno Median	USDpermno P90	NStocks Median	NStocks P90
1980-1990	13	101	13.9	392.3	121	472
1991-2000	25	143	42.8	1,094.3	111	622
2001-2010	62	250	169.9	3,326.6	85	540
2011-2021	88	404	279.3	7,044.7	82	565

Period	Days-ADV Mean	Days-ADV Median	Days-ADV P90	PSO (%) Mean	PSO (%) Median	PSO (%) P90	Illiquidity Mean	Illiquidity Median	Illiquidity P90
1980-1990	1,129.5	205.2	1,722.8	23.7	18.4	52.4	7,733.5	1197.8	9,522.2
1991-2000	627.1	156.6	925.8	43.8	29.1	70.2	3,286.8	611.7	4,027.8
2001-2010	269.6	105.4	441.6	52.0	48.7	91.5	1,018.3	270.8	1,821.3
2011-2021	309.3	111.2	383.4	60.3	59.5	95.8	1,456.6	210.3	915.3

3. Anomalies & Crowding

D. Descriptive Statistics and Data

- Use CRSP, Compustat Data and 13-F filings

Table A2: Summary of 13F institution by type

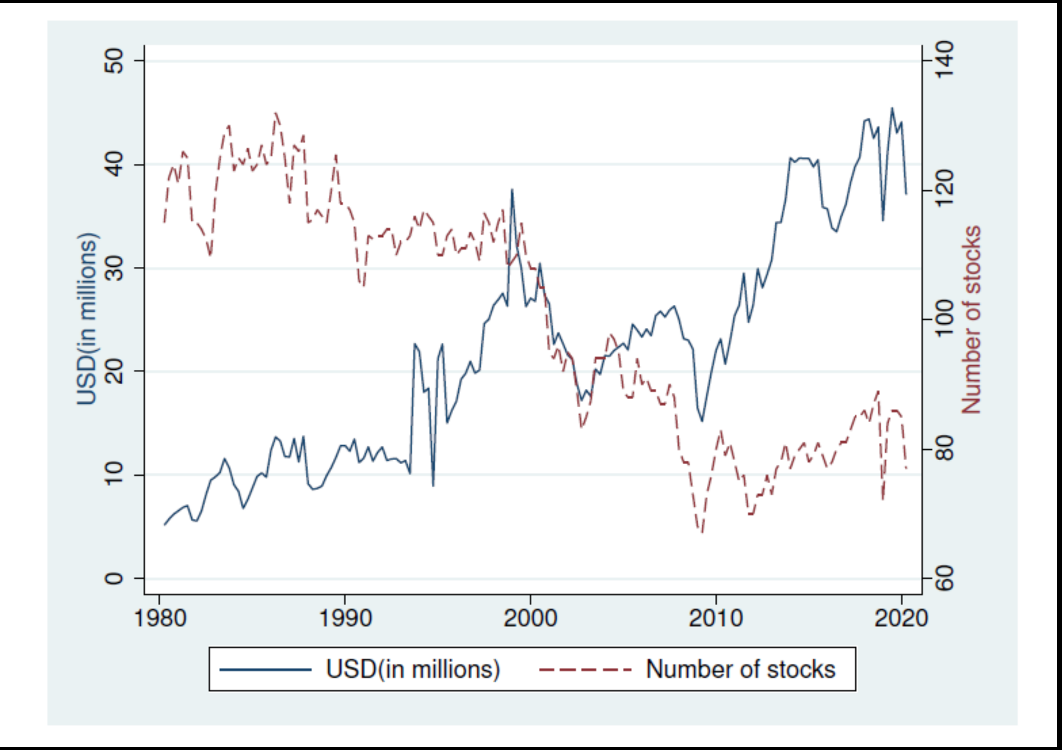
	NInst	NIpermno		USDpermno		NStocks	
		Median	P90	Median	P90	Median	P90
A. Dedicated							
1980-1990	58	2	11	3.6	68.5	96	451
1991-2000	60	2	7	3.9	134.9	49	499
2001-2010	70	1	4	4.2	236.9	15	145
2011-2021	82	1	3	9.4	309.4	16	103
B. Quase-indexer							
1980-1990	511	11	76	10.3	286.8	127	492
1991-2000	884	18	102	29.5	752.9	117	646
2001-2010	1,462	41	170	114.1	2,396.9	99	584
2011-2021	2,536	59	289	171.5	5,051.6	112	676
C. Transient							
1980-1990	126	4	22	4.8	107.3	135	464
1991-2000	291	7	39	10.9	287.3	127	645
2001-2010	726	20	77	42.1	776.1	76	554
2011-2021	995	23	97	72.5	1,472.3	71	584

Note: This table reports descriptive statistics of the following variables: Number of 13F institutional investors (NInst); the number of 13F institutional investors holding the same stock (NIpermno); total amount of money invested by all 13F institutional investors in a given stock (USDpermno), in millions of US dollars; Number of stocks held in 13F institutional investor's portfolio (NStocks). We identify institutional investors following Brian Bushee's classification (Bushee, 2001). *Dedicated* and *quase-indexers* provide long-term, stable ownership to firms because they are geared toward longer-term dividend income or capital appreciation. *Dedicated* institutions are characterized by large average investments in portfolio firms and very low turnover. *Quase-indexers* are also characterized by low turnover, but they tend to have diversified holdings, consistent with passive buy-and-hold strategies. *Transient* institutions are characterized by having short investment horizons and high portfolio turnover. We include only stocks whose CRSP share code is 10 and 11 (ordinary common shares). Also, we exclude firms with stock prices less than USD $5 to reduce the effects of microcaps. The sample period is from 1980:Q1 to 2021:Q4.

3. Anomalies & Crowding

D. Descriptive Statistics and Data

- Portfolio managers are holding fewer stocks in their portfolios and more dollars are chasing each stock.



3. Anomalies & Crowding

E. Empirical Observations

What anomalies do we consider in this paper?

Table 1: Sample Anomalies

	Anomaly	Label	Paper	Description
1	Composite equity issuance	CEI	Daniel and Titman (2006)	CEI measures the amount of equity a firm issue or retires in exchange for cash or services. Firms with higher CEI earn lower risk-adjusted returns
2	Net stock issuance	NSI	Loughran and Ritter (1995)	Issuing firms underperform compared to the overall market and such performance lasts for up to three years.
3	Total accruals	ACC	Sloan (1996)	Stock prices may not reflect the accrual component of earnings. Firms with higher total accounting accruals underperform those with lower accounting accruals
4	Net operating assets	NOA	Hirshleifer et al. (2004)	NOA is negatively related to firm's future long-run risk-adjusted return.
5	Gross profitability	GP	Novy-Marx (2013)	Profitable firms earn significantly higher risk-adjusted returns than unprofitable ones
6	Asset growth	AG	Cooper et al. (2004)	Firms with higher asset growth rates subsequently underperform those with lower growth rates.
7	Capital investments	CI	Titman et al. (2004)	Increases in firms capital investments strongly predicts future lower risk adjusted returns.
8	Investment-to-assets	IVA	Xing (2008)	Firms with low investment-to-assets ratios show higher risk-adjusted returns compared to those with higher ratios
9	Momentum	MOM	Jegadeesh and Titman (1993)	A profitable strategy is to buy shares of firms with positive performance in the past six months, skip one month, and hold it for the following six months.
10	Ohlson O-score	OSC	Dichev (1998)	Higher bankruptcy risk, measured by the O-score Ohlson (1980), is not rewarded with higher returns. Firms facing increased bankruptcy risk earn subsequently lower returns.
11	Failure probability	FP	Campbell et al. (2008)	Financial distress, estimated based on a dynamic logit model, negatively predicts firm's future return.

3. Anomalies & Crowding

E. Empirical Observations

Does "Crowding" influence returns? YES

Table 3: Crowding-sorted Portfolio returns

Panel A: FF3 alphas - *Value-weighted*	High (Q5)	Q4	Q3	Q2	Low(Q1)	Q5-Q1
NI	-0.03	-0.07	-0.16	-0.01	-0.02	-0.01
	(-0.65)	(-1.63)	(-3.28)	(-0.20)	(-0.29)	(-0.10)
PSO	-0.11	-0.04	-0.06	-0.01	-0.11	0.00
	(-1.94)	(-0.89)	(-1.20)	(-0.13)	(-1.45)	(0.05)
Actratio	0.54	0.25	-0.01	-0.29	-0.70	1.26
	(8.20)	(1.85)	(-3.15)	(-6.51)	(-7.42)	(8.44)
Days-ADV	0.54	0.04	-0.16	-0.55	-0.90	1.44
	(8.87)	(0.87)	(-4.11)	(-6.69)	(-7.86)	(9.67)

Panel B: FF3 alphas - *Equal-weighted*	High (Q5)	Q4	Q3	Q2	Low(Q1)	Q5 - Q1
NI	-0.02	-0.11	-0.15	-0.10	-0.10	0.09
	(-1.40)	(-2.11)	(-2.54)	(-1.21)	(-0.94)	(0.80)
PSO	-0.06	-0.01	0.00	-0.04	-0.29	0.23
	(-1.21)	(-0.27)	(-0.04)	(-0.60)	(-2.94)	(2.08)
Actratio	0.55	0.07	-0.12	-0.49	-0.80	1.38
	(10.20)	(5.14)	(-0.21)	(-4.51)	(-8.19)	(11.92)
Days-ADV	0.63	0.29	0.02	-0.69	-0.94	1.57
	(10.64)	(4.96)	(0.21)	(-3.08)	(-9.40)	(12.23)

3. Anomalies & Crowding

E. Empirical Observations

Does "Crowding" influence returns? By Institutional Type

(Now shown here, but in paper we do 5 factor alphas for all)

Panel B: Quintile portfolios returns and alphas sorted on Days-ADV by Inst type

	Excess return and alpha					
	Exc ret	FF3	Carhart	FF5	FF5 + Stamb	FF5 + Amihud
Short Horizon	1.285	1.375	1.149	0.970	0.982	0.914
	(7.97)	(9.03)	(7.93)	(7.02)	(7.06)	(6.49)
Long Horizon	1.164	1.288	1.141	0.721	0.737	0.703
	(5.67)	(8.24)	(7.36)	(5.83)	(5.92)	(5.56)
Transient	1.254	1.336	1.111	0.954	0.960	0.907
	(8.40)	(9.12)	(8.01)	(7.20)	(7.16)	(6.75)
Dedicated	0.762	0.820	0.731	0.417	0.414	0.443
	(5.07)	(6.48)	(5.75)	(3.77)	(3.67)	(3.89)
Quase-indexer	1.268	1.387	1.226	0.864	0.872	0.803
	(6.46)	(8.78)	(7.86)	(6.56)	(6.58)	(6.00)
Mutual funds	1.271	1.367	1.200	0.900	0.908	0.865
	(7.80)	(9.21)	(8.24)	(7.05)	(7.06)	(6.57)
Invs Advisor	1.111	1.251	1.041	0.763	0.764	0.709
	(7.11)	(8.61)	(7.49)	(6.19)	(6.14)	(5.62)
Pension Funds	0.911	1.098	0.945	0.543	0.540	0.482
	(4.84)	(7.92)	(6.93)	(5.12)	(5.04)	(4.44)
Others	0.694	0.905	0.806	0.463	0.468	0.453
	(4.47)	(7.16)	(6.37)	(4.36)	(4.37)	(4.13)

3. Anomalies & Crowding

E. Empirical Observations

Does “Crowding” influence anomaly returns in particular? YES

1. Sort stocks by the anomaly factor into quintiles. Look at returns of high minus low (e.g. Low Accruals – High Accruals).

2. Double-Sort by the anomaly factor in thirds and then the crowd-measure in quintiles and look at returns in comparison with 1.

3. Anomalies & Crowding

E. Empirical Observations

	Low Crowd		Mid Crowd		High Crowd
High Accrual (30%)	1				2
Middle Accrual (40%)					
Low Accrual (30%)	3				4

Look at Portfolio (4) – Portfolio (1). That is, (Low Accrual– High Accrual), but with the “most and least crowded” elements.

3. Anomalies & Crowding

E. Empirical Observations

Table 5: Double-sorted portfolio on days-ADV and stock market anomalies

	Single sort	Double sort -Anomaly and Days -ADV		
	FF3	FF3	FF5 + Pastor	FF5 + Amihud
ACC	0.171	1.333	0.979	0.820
	(1.32)	(5.34)	(3.82)	(3.18)
In-sample	0.135	2.353	1.740	1.515
	(0.55)	(6.76)	(4.80)	(3.98)
Post pub	0.083	0.915	0.490	0.328
	(0.50)	(2.46)	(1.30)	(0.86)

3. Anomalies & Crowding

E. Empirical Observations (Average 11 Anomalies)

EWPort	0.390	1.78	1.33	1.179
	(6.42)	(10.94)	(8.92)	(7.99)
In sample	0.536	1.885	1.355	1.274
	(5.24)	(8.36)	(6.48)	(6.07)
Post pub	0.301	1.679	1.167	0.994
	(3.89)	(7.08)	(5.20)	(4.51)

The effect of crowding is STRONGER when looking at anomalies.

3. Anomalies & Crowding

E. Empirical Observations

Do we observe the effect of crowding on returns when we control for factors? Factors like:

- market capitalization (size),
- the number of months since stock's first appears in CRSP (age),
- the standard deviation of monthly returns over the previous two years,
- book-to-market ratio,
- dividend yield,
- average monthly turnover over the past three months,
- cummulative return over the past three months,
- cummulative return over the past nine months preceding the beginning of quarter

Is the effect stronger for anomaly stocks and controls?

3. Anomalies & Crowding

E. Empirical Observations

Most recently stronger

YES!

Table 7: Fama-MacBeth r ys-ADV and next quarter cumulative returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LADV	0.546	0.717	0.485	0.538	0.536	0.526	0.471	0.465	0.445
	(4.31)	(2.01)	(4.75)	(4.23)	(4.23)	(4.14)	(3.71)	(3.68)	(3.50)
Long - only				-0.556		-0.921			
				-(0.95)		-(1.53)			
Long only*l_ADV				0.135		0.180			
				(1.32)		(1.82)			
Short - only					-2.722	-2.853			
					-(2.91)	-(2.94)			
Short only*l_ADV					0.350	0.374			
					(2.14)	(2.20)			
long - at							-2.153		-0.950
							-(4.02)		-(1.80)
Long at*l_ADV							0.387		0.189
							(4.37)		(2.14)
Short - at								-3.323	-2.840
								-(6.38)	-(5.71)
Short at*l_ADV								0.511	0.418
								(5.96)	(5.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	299,694	79,352	213,299	294,301	294,301	294,301	294,301	294,301	294,301
Adj. R^2 (%)	8.86	10.71	8.04	8.24	8.21	9.23	8.50	9.15	9.44

3. Anomalies & Crowding

E. Empirical Observations

Do lags matter in terms of results? Not really, although one published paper shows reverse results, we cannot replicate their work. Crowding is persistent drag.

Table A5: Returns on Days-ADV and ACTratio sorted portfolios

	Days-ADV				Actratio			
	Ex_ret	t-stat	FF3	t-stat	Ex_ret	t-stat	FF3	t-stat
H_t/V_t	1.230	(6.36)	1.385	(8.50)	1.243	(6.75)	1.411	(9.03)
H_t/V_{t-1}	1.316	(7.27)	1.483	(9.21)	1.317	(7.84)	1.497	(10.18)
H_t/V_{t-2}	1.421	(8.80)	1.250	(7.14)	1.245	(7.62)	1.401	(9.68)
H_{t-1}/V_{t-1}	1.296	(7.46)	1.435	(9.67)	1.285	(7.37)	1.466	(9.80)
H_{t-1}/V_{t-2}	1.204	(7.28)	1.357	(9.24)	1.253	(7.42)	1.414	(9.64)
H_{t-2}/V_{t-2}	1.251	(7.30)	1.388	(9.41)	1.233	(7.06)	1.396	(9.29)
H_{t-1}/V_t	1.136	(5.96)	1.242	(7.84)	1.225	(6.63)	1.386	(8.77)
H_{t-2}/V_{t-1}	1.192	(6.42)	1.297	(8.37)	1.233	(7.06)	1.396	(9.29)
H_{t-2}/V_t	1.106	(5.73)	1.199	(7.55)	1.179	(6.69)	1.334	(8.90)

3. Anomalies & Crowding

E. Empirical Observations

So if crowding seems to create positive returns, what's so bad? 1. Identifying the precise crowding group is difficult, especially in broad data sets. 2. However, even in broad data sets do we see a FRAGILITY of the trading space?

One way to measure FRAGILITY is to ask does crowding create or is it associated with CRASH RISK?

3. Anomalies & Crowding

E. Empirical Observations: Measuring Crash Risk

Step 1: Take residual returns, rather than actual returns.

Following (Hutton et al., 2009) and (Callen and Fang, 2015) we define crash risk using *weekly* firm-specific return using the residuals from the following equation 5.[13]

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \epsilon_{j,t} \tag{5}$$

where $r_{j,t}$ is the return on stock j in week t, $r_{m,t}$ is the return on the CRSP value-weighted market index in day t, and $r_{i,t}$ is the return on the value-weighted industry index based on the two-digit

3. Anomalies & Crowding

E. Empirical Observations: Measuring Crash Risk

Step 2: Take residual returns, rather than actual returns and compute MEASURE 1: NCSKEW..

$$\text{NCSKEW}_{j,t} = -\frac{n(n-1)^{3/2}\sum R_{j,t}^3}{((n-1)(n-2)(\sum R_{j,t}^2)^{3/2})} \tag{6}$$

where n is the number of observations per firm j during the fiscal year, t. Since an increase in NCSKEW points out to a stock's return having more left-skewed distribution, we follow the convention that higher NCSEW value implies a higher *crash risk*.

3. Anomalies & Crowding

E. Empirical Observations: Measuring Crash Risk

Step 3: Take residual returns, rather than actual returns and compute MEASURE 2: DUVOL.

The second measure of crash risk that we use *down-to-up volatility* (DUVOL) and is estimated as shown in equation 9. This measure captures the asymmetric volatility of positive and negative firm-specific weekly returns.

$$\text{DUVOL}_{j,t} = log\left(\frac{(n_u - 1)\sum_{DOWN} R^2_{j,t}}{(n_d - 1)\sum_{UP} R^2_{j,t}}\right) \tag{7}$$

For a given firm j we count the number of weeks with returns above (n_u) and below (n_d) the daily mean. Then, we proceed to estimate the log ratio of the standard deviation of the sample of *up weeks* and the sample of *down weeks*. Similar to the NCSKEW measure, an increase in DUVOL indicates that a firm is prone to crash risk.

3. Anomalies & Crowding

E. Empirical Observations: Measuring Crash Risk

Table 8: Crash risk(NCSkew), anomalies and crowding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LADV	0.011	0.003	0.008	0.011	0.010	0.010	0.007	0.006	0.005
	(3.29)	(0.85)	(2.28)	(3.16)	(2.98)	(3.23)	(2.31)	(1.82)	(1.63)
Log - only				-0.109		-0.111			
				(-1.96)		(-1.99)			
Long only*l_ADV				-0.041		-0.030			
				(-1.57)		(-1.13)			
Short - only					0.044	0.026			
					(2.66)	(1.95)			
Short only*l_ADV					0.100	0.090			
					(3.67)	(3.34)			
long - at							-0.125		-0.092
							(-1.99)		(-2.02)
Long at*l_ADV							0.083		0.025
							(4.26)		(1.97)
Short - at								0.035	0.043
								(2.79)	(3.23)
Short at*l_ADV								0.149	0.134
								(7.56)	(6.23)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	102,940	23,996	78,652	102,940	102,940	102,940	102,940	102,940	102,940
Adj. R^2 (%)	8.60	13.20	7.71	8.71	8.96	9.01	8.73	8.96	9.06

3. Anomalies & Crowding

E. Empirical Observations: Measuring Crash Risk

Table 9: Crash risk(Duvol), anomalies and crowding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LADV	0.018	0.004	0.010	0.011	0.010	0.011	0.009	0.008	0.008
	(5.13)	(0.69)	(3.93)	(5.29)	(4.93)	(5.08)	(4.19)	(3.91)	(3.66)
Log - only				-0.064		-0.060			
				(-2.96)		(-2.36)			
Long only*l_ADV				-0.013		-0.008			
				(-0.78)		(-0.48)			
Short - only					0.035	0.025			
					(3.28)	(2.29)			
Short only*l_ADV					0.041	0.036			
					(2.33)	(2.08)			
long - at							-0.075		-0.059
							(-2.99)		(-2.62)
Long at*l_ADV							0.051		0.024
							(4.13)		(1.80)
Short - at								0.021	0.028
								(2.63)	(3.31)
Short at*l_ADV								0.075	0.063
								(6.09)	(4.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	102,940	23,996	78,652	102,940	102,940	102,940	102,940	102,940	102,940
Adj. R^2 (%)	11.10	16.51	9.15	11.32	11.22	11.39	11.20	11.34	11.43

3. Anomalies & Crowding

E. Empirical Observations: Measuring Liquidity Risk

Measure 1: Amihud Illiquidity

We start by estimating Amihud's (2002) illiquidity measure, which is defined as:

$$\text{Illiquid}_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{j,t}} \frac{|R_{j,t,d}|}{V_{j,t,d}} \tag{8}$$

where $D_{i,t}$ is the number of observations with volume data in a given month t, $|R_{j,t,d}|$ is the absolute daily return of stock j over month d, and $V_{j,t,d}$ is the daily dollar volume for stock j over month d. We obtain the monthly aggregate value of the illiquidity measure by averaging the values all days with trading data in each month.

3. Anomalies & Crowding

E. Empirical Observations: Measuring Liquidity Risk

Measure 2: Pastor-Stambaugh Liquidity Beta

For the liquidity risk measure, we estimate the *liquidity beta* as the parameter loading on the (Pastor and Stambaugh, 2003) traded liquidity factor added to the (Fama and French, 1993) three-factor model.

$$R_{j,d} = \alpha_{j,d} + \beta_{j,d}^{mkt} MKT_d + \beta_{j,d}^{size} SMB_d + \beta_{j,d}^{value} HML_d + \beta_{j,d}^{size} LIQ_d + \epsilon_{j,d} \tag{9}$$

where LIQ_d is the measure of liquidity created by Pastor and Stambaugh (2003), $R_{j,d}$ denotes the monthly excess return for each stock in our sample. We estimate the *liquidity beta* ($\beta_{j,d}^{liq}$) for each month on a rolling 60-month window.

3. Anomalies & Crowding

E. Empirical Observations: Liquidity

Crowding affects liquidity

Table 10: liquidity risk, anomalies and crowding

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LADV	0.009	0.006	0.004	0.008	0.010	0.009	0.011	0.015	0.016
	(2.98)	(1.26)	(1.91)	(2.60)	(3.16)	(2.79)	(3.21)	(4.43)	(4.02)
Log - only				-0.032		-0.028			
				(-3.00)		(-2.67)			
Long only*l_ADV				0.005		0.004			
				(3.45)		(3.19)			
Short - only					0.031	0.027			
					(2.20)	(1.78)			
Short only*l_ADV					-0.006	-0.005			
					(-1.90)	(-1.32)			
long - at							0.017		-0.011
							(0.87)		(-0.46)
Long at*l_ADV							0.000		0.002
							(-0.07)		(0.44)
Short - at								0.057	0.077
								(3.02)	(2.32)
Short at*l_ADV								-0.010	-0.013
								(-2.88)	(-2.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	408,860	107,803	301,865	408,860	408,860	408,860	408,860	408,860	408,860
Adj. R2 (%)	29.85	48.35	32.08	29.83	29.83	29.83	29.83	29.84	29.84

4. Summary of Findings

1. We find that crowded institutional holdings lead to higher returns in the immediate and short-term regardless of specific lag structure.

2. We find that crowded institutional holdings have a larger impact on the returns of anomaly stocks in the 11 particular anomalies that we considered.

3. We find that the cost of this crowding is in the potential for tail events or crash risk. That is, crowding causes predicts higher crash risk for all stocks and for anomaly stocks.

4. Crowding also has an impact on future liquidity of stocks.

5. FURTHER RESEARCH

- Understanding the specific dynamic mechanism of crowding would be important for empirical work and for aiding practitioners.

- Fine tuning the data sets to specifically identify the exact players in the anomaly space and/or in smart beta space would make the work more impactful.

- Understanding how the interactions between different types of investors and crowding work (e.g. passive might fuel the anomaly cheapness depending on relative amount in group).

REFERENCES

1. Chincarini, Ludwig, Lazo-Paz, Renato, and Fabio Moneta. "Crowded Spaces and Anomalies." Working Paper, 2022. Available upon request.

3. Chincarini, Ludwig B. and Daehwan Kim. *Quantitative Equity Portfolio Management*. New York, McGraw-Hill, 2022. *Note*: New Edition with lots of new stuff.

4. Chincarini, Ludwig B. *The Crisis of Crowding. Quant Copycats, Ugly Models, and the New Crash Normal*, Wiley, 2012.

Thank you

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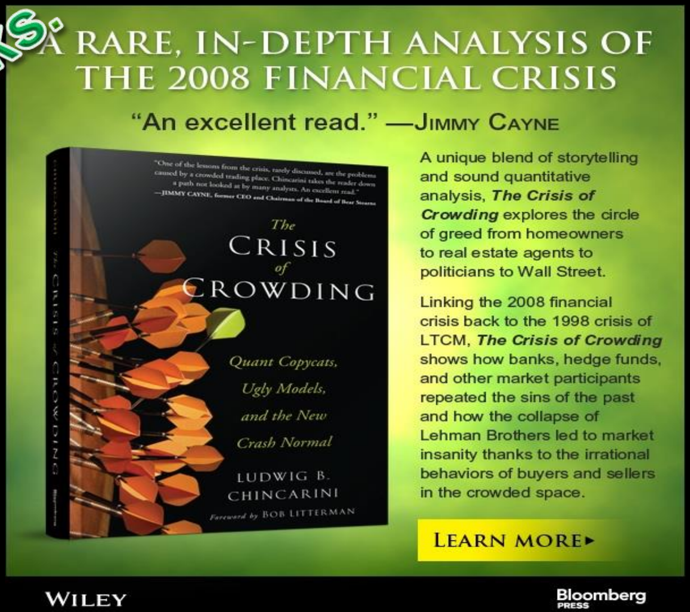
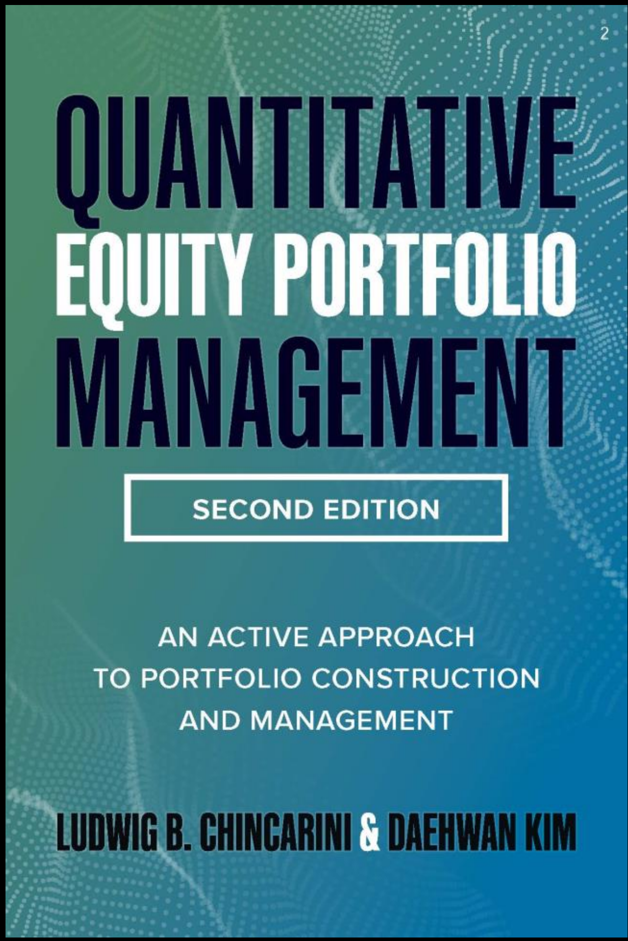
For more information on quantitative investing and crowding – buy the books:





Open Discussion for all Participants

Appendix A: Recent Research on Crowding

1. "Is there too much benchmarking in asset management?", Anil K Kashyap, Natalia Kovrijnykh†, Jian Li‡, and Anna Pavlova, Working Paper, June 2022.

Creates a model that shows that too many assets following passive investing might create crowding problems.

2. "Hedge Funds and the Financial Crisis", Klofas, Jeffrey, Undergraduate Thesis, Boston College, May 2016.

Discusses the crowding of real estate market and its relation to hedge funds.

Appendix A: Recent Research on Crowding

3. "Systemic Risk in Financial Networks: A Survey", Matthew Jackson and Agathe Pernoud, Working Paper, December 2020.

Discusses the systemic effects from networks that may also be influenced by copycat investing.

4. "Crowded Trades, Market Clustering, and Price Instability", Kralingen, Marc, Diego Garlaschelli, Karolina Scholtus, and Iman van Lelyveld, *Entropy*, March 2021.

Paper shows how market clustering or crowding leads to price instability.

Appendix A: Recent Research on Crowding

5. "The Challenges of Oil Investing: Contango and the
- Financialization of Commodities", Chincarini, Ludwig B. and Fabio Moneta, *Energy Economics*, March 2021.

Papers shows how the crowding and changing nature of the crowding in oil futures markets has effected the returns from oil futures negatively.

6. "Crowding and Factor Returns", Kang, Rouwenhourst, and Tang, Working Paper, March 13, 2021.

The authors find that anomaly returns (momentum, value, and basis) in the commodity markets are LOWER in the presence of crowding.

Appendix A: Recent Research on Crowding

7. "Factor Crowding and Liquidity Exhaustion", Marks, Joseph and Chenguang Shang, *The Journal of Financial Research*, Spring 2019.

In this article, we demonstrate that correlated trading due to the use of similar multifactor models affects the trading activity, volatilities, and liquidities of individual stocks.

Appendix B: "Older" Research on Crowding

1. "Are Crowded Crowds Still Wise? Evidence from Financial Analysts' Geographic Diversity," Gerken and Painter Working Paper, June 2020.

Examines when crowds can be damaging. Specifically, studies the behavior of analysts concentrated in one geographical region. They tend to infer too much from the local environment and behave similarly.

Appendix B: "Older" Research on Crowding

2. "Trade Less and Exit Overcrowded Markets. Lessons from International Mutual Funds," Dyakov, Jiang, Verbeek. Review of Finance, 2020.

Examines the capacity constraints (crowding) in active equity markets which have exploded (global AUM has grown from $29T in 2002 to $71 trillion in 2015). They define limits to aggregate active management. They find that a 1% increase in active funds versus the entire US equity market leads to a decline in 14 bps per month performance.

My discussion of their paper before published:
https://onh.ccd.myftpupload.com/pres/Discussion_Crowding_MFs_2019.pdf

Appendix B: “Older” Research on Crowding

5. “Currency Crowdedness Generated by Global Bond Funds,” Konstantinov, Geuorgui, Journal of Portfolio Management, Winter 2017. *Note*: Older paper, but I only recently learned about it.

Examines the potential crowding of global fund managers due to their currency-related strategies. The author finds that global funds are crowded using style analysis exposure to various currency factors, such as the global carry, value, FX vol, and trend factors.

6. “The Mismatch Between Mutual Fund Scale and Skill,” Song, Yang. Journal of Finance, October 2020.

Examines mutual fund exposures to common factors and asset flows. Finds that funds with prior factor related returns receive large uninformed flows and these “crowded” styles have subsequent poor returns.

Appendix B: "Older" Research on Crowding

3. "What alleviates Crowding in Factor Investing," DiMiguel, Martin-Utrera, and Uppal, Working Paper, January, 2020.

Examines the issue of crowding amongst smart beta funds. The authors find (quite intuitive) that if managers have several unrelated smart beta strategies and trade them at the same time, they can reduce market impact costs that damage any specific smart beta strategy. Also, mentions the tradeoff between competition in smart beta and crowding. *Note (LBC)*: Does not reduce the danger of exogenous shock in a particular crowded strategy causing dislocation.

Appendix B: "Older" Research on Crowding

4. "Crowding: Evidence from Fund Managerial Structure," Harvey, Liu, Tan, and Zhu. Working Paper, March 2020.

Examines the trend in fund management from 30% teams to 70% teams in last 30 years. They argue that it's a direct result of crowding. That, as AUM grew, teams needed to form so that there was a diversification of ideas and investments. That is, to eliminate the crowding of ideas. The authors attempt to show that this is true with several statistical tests.

Appendix B: “Older” Research on Crowding

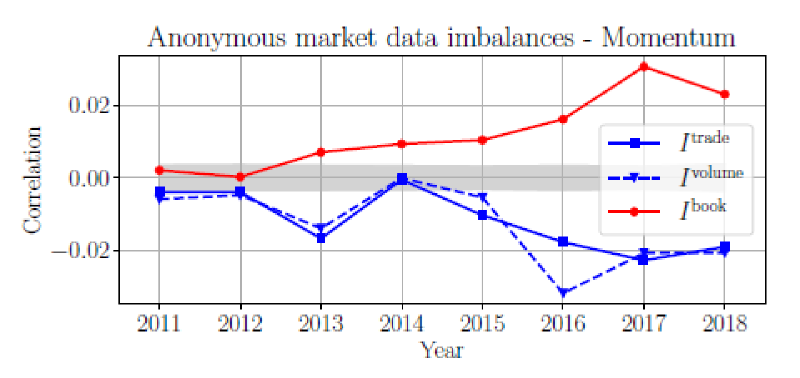
7. “Optimal Disclosure in Crowded Markets,” Kim, Taejin and Vishal Mangla, Working Paper, November 2018. *Note*: Also an older paper, but just recently became aware of it.

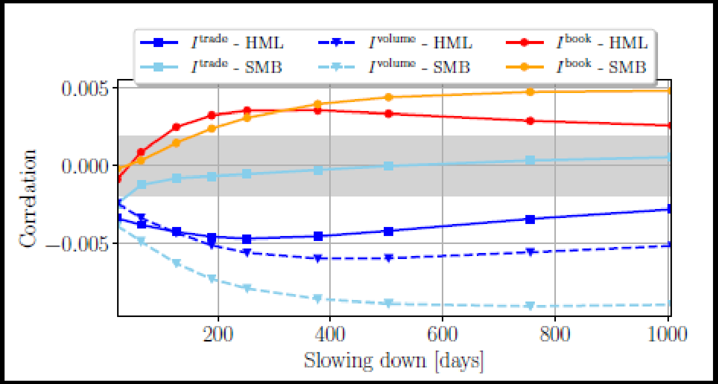
Examines whether a regulator that observes the crowding can alleviate the problems from a liquidity shock to a crowded space. They find that announcements done randomly (not all the time) about crowding can reduce the harmful effects of crowding.

Appendix B: “Older” Research on Crowding

8. “Zooming in on Equity Factor Crowding,” Volpati, Benzaquen, Eisler, Mastromatteo, Toth, and Bouchaud, Working Paper, January 20, 2020.

Examines the trading imbalance or pressure as a results of common factor strategies. They find that momentum and value strategies are crowded and have positive correlation with trade imbalance measures and this correlation has increased over time.





Appendix C: Even "Older" Academic References on Crowding

A. "The Failure of LTCM," Chincarini (1998)
B. "Sophisticated Investors and Market Strategy," Stein (2009)
C. *The Crisis of Crowding*, Chincarini (2012)
D. "The Externalities of Crowded Trades," Blocher (2013)
E. "Standing out from the Crowd. Measuring Crowding in Quantitative Strategies," Cahan and Luo (2013)
F. "Stock portfolio structure of individual investors infers future trading behavior," Bohlin and Rosvall (2014)

Appendix C: Even "Older" Academic References on Crowding

G. "Dimensions of Popularity," Ibbotson and Idsorek (2014)).

H. "Crowded Trades: An Overlooked Systemic Risk for Central Clearing Counterparties," Menkveld (2014)

I. "The Effects of Short Sales and Leverage Constraints on Market Efficiency," Yan (2014).

J. "Omitted Risks or Crowded Strategies: Why Mutual Fund Comovement Predicts Future Performance," Chue (2015).

K. "Fire, Fire. Is Low Volatility a Crowded Trade," Marmar (2015)

L. "Days to Cover and Short Interest," Hong et al. (2015)

Appendix C: Even "Older" Academic References on Crowding

M. "Portfolio Construction and Crowding" Bruno, Chincarini, Davis, and Ohara (2018).

N. "Transaction Costs and Crowding" Chincarini (2017)

O. "Mutual Fund Crowding and Stock Returns," Zhong et al. (2016)

P. "Hedge fund crowds and mispricing," Sias et al. (2016)

R. "Individual stock Crowded Trades, Individual Stock Investor Sentiment, and Excess Returns," Yang and Zhou (2016)

Appendix C: Even "Older" Academic References on Crowding

S. "The Impact of Pensions and Insurance on Global Yield Curves", Greenwood and Vissing-Jorgenson (2018)

T. "Institutional Selling of Stocks with Illiquidity Shock", Krystaniak (2016)

U. "Arbitrage Crowdedness and Portfolio Momentum," Chen (2018)

V. "Copycatting and Public Disclosure: Direct Evidence from Peer Companies' Digital Footprints," Cao et al. (2018).

W. "Crowded Trades and Tail Risk," Brown et al (2019)

Appendix C: Even "Older" Academic References on Crowding

X. "Granularity and Downside Risk in Equity Markets," Ghysels et al (2018)

Y. "The Impact of Crowding in Alternative Risk Premia Investing," Baltas (2019)

Z. "Mutual Fund Herding after 13-D Filings," (Agapova and Rodriguez (2019))

AA. "Optimal Timing and Tilting of Equity Factors," Dicthl et al. (2019)

BB. Systematic Investment Strategies (Giamourdis (2017))

CC. Trading in Crowded Markets (Gorban et al. (2018))

Appendix C: Even "Older" Academic References on Crowding

DD. "Institutional Consensus: Information or Crowding?" Klein et al. (2019)

EE. "Stochastic investor sentiment, crowdedness and deviation of asset prices from fundamentals," Zhou and Yang (2019)

FF. "Modelling Transaction Costs when Trades May Be Crowded: A Bayesian Network Using Partially Observable Orders Imbalance," Briere et al. (2019)

GG. "Everybody's Doing It: Short Volatility Strategies and Shadow Financial Insurers," Bhansali and Harris (2018)