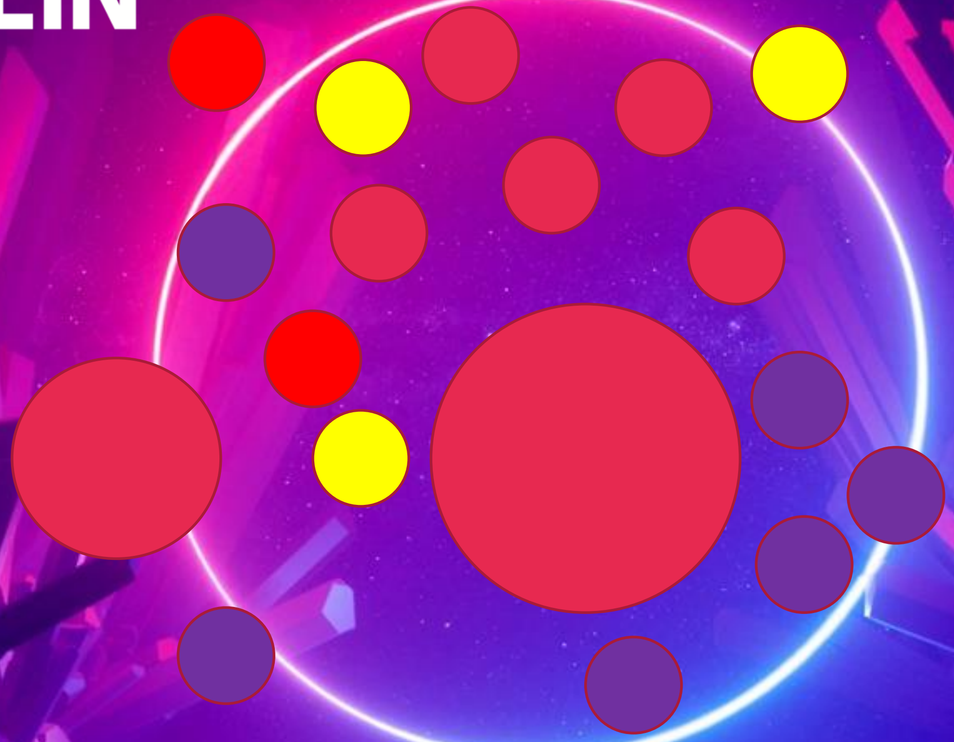


BERNSTEIN

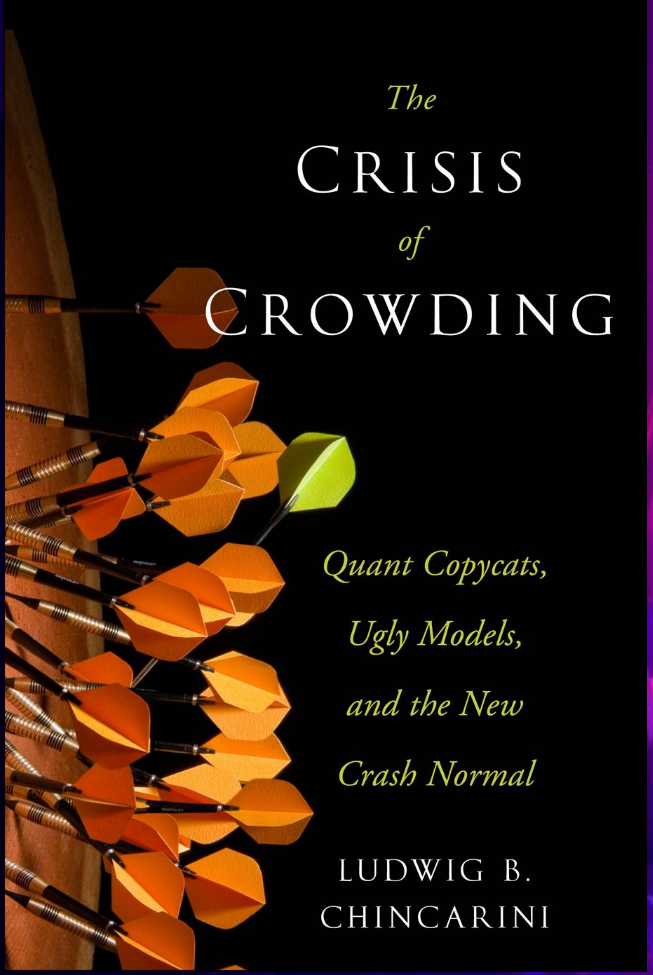
LUDWIG CHINCARINI

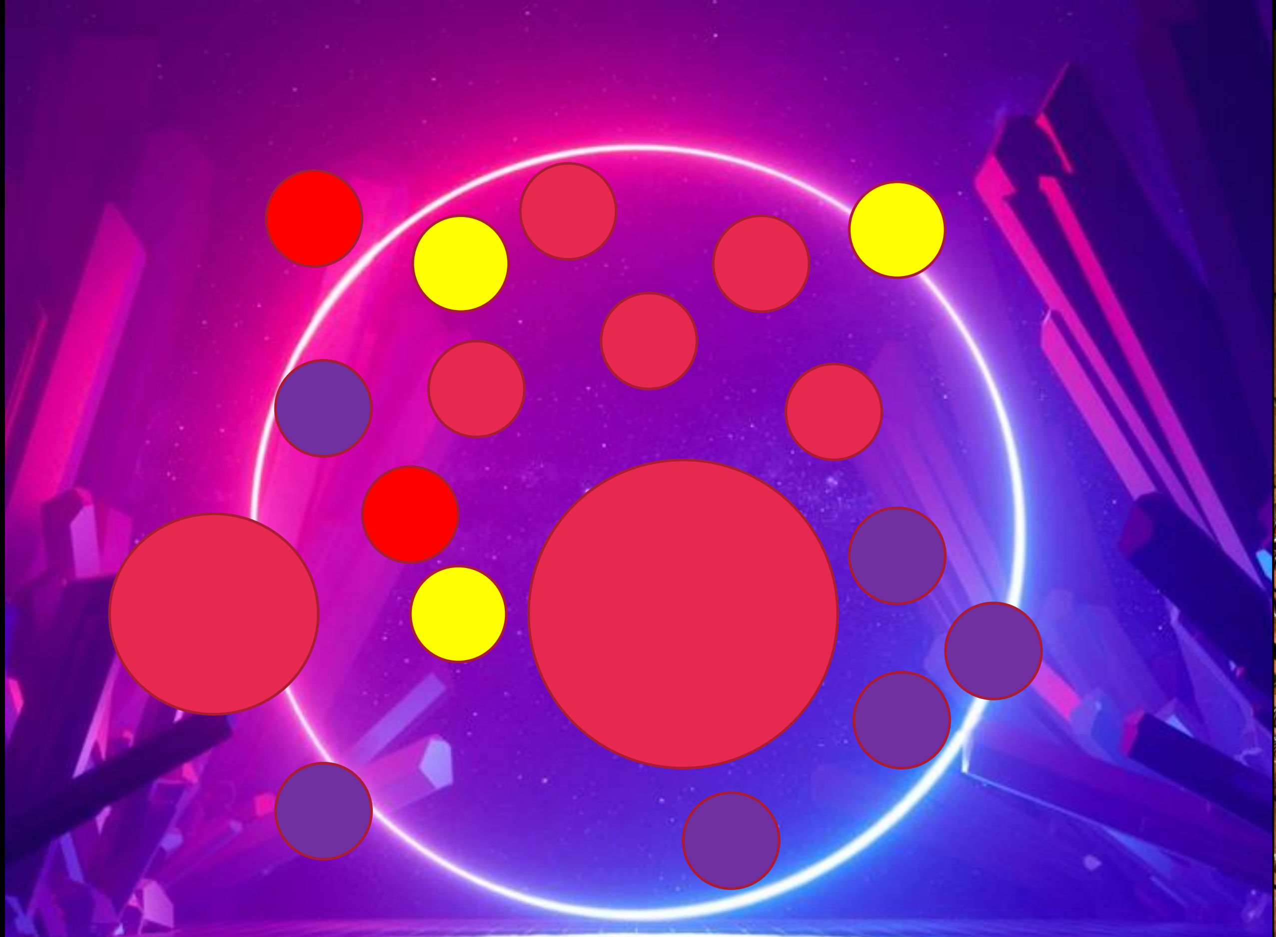
Crowded Spaces and Anomalies

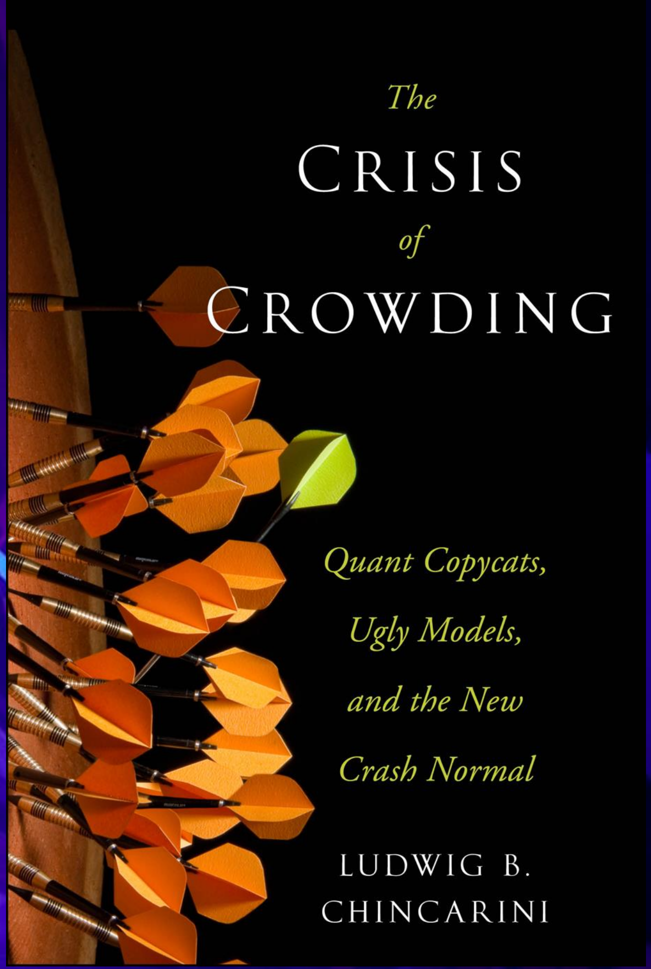
21st Annual New York Quant Conference

New York, NY

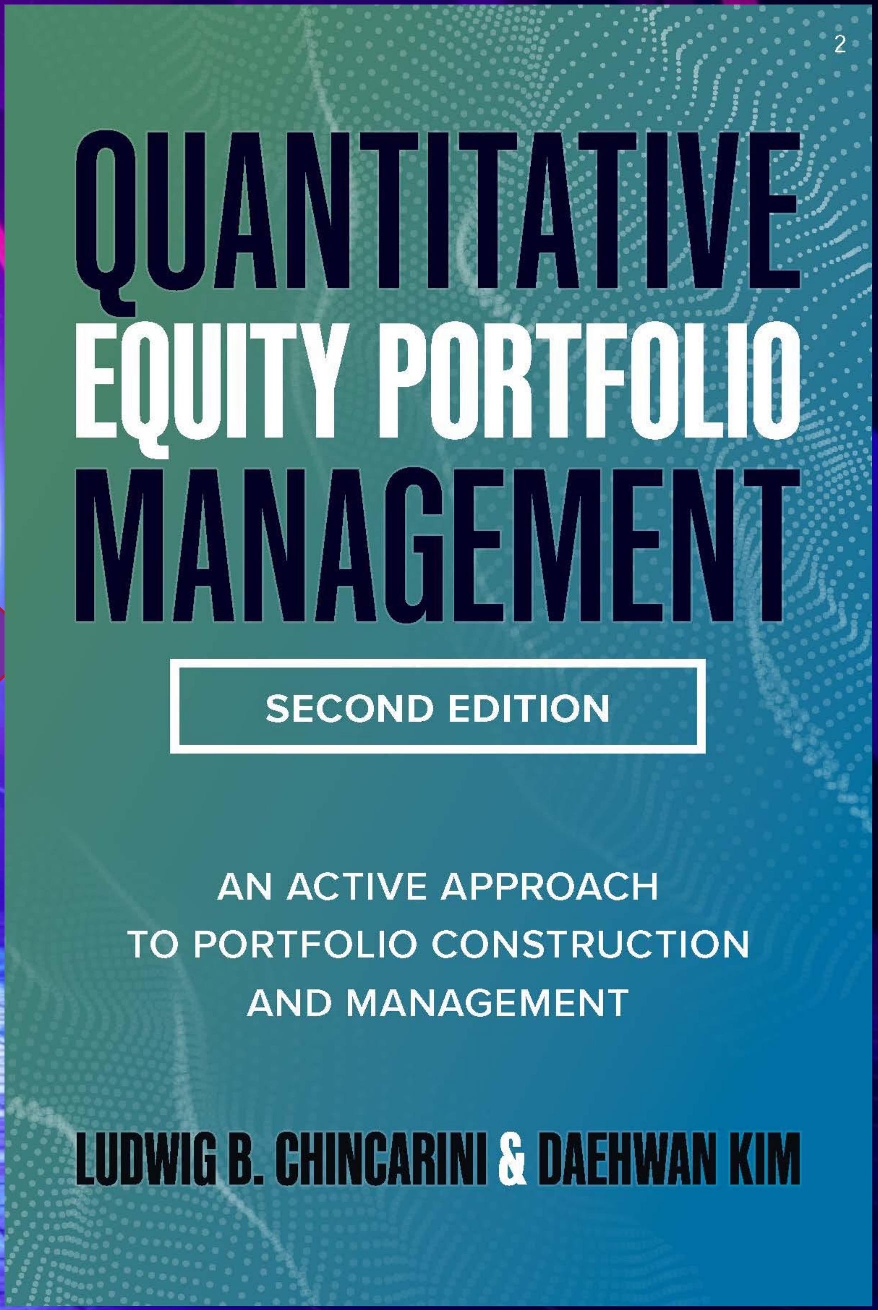
October 17, 2024







Thank you to Ann Larson and all the wonderful people at Sanford Bernstein.



The new edition of QEPM just released – please check it out.

Introduction

An increasingly crowded investment space might lead to additional risk concerns for arbitrageurs.

- This paper investigates the relation between crowded trades (crowding), those in which many investors hold the same stocks, possibly exhausting their liquidity provision, and the cross-section of stock returns focusing on institutional investors and anomalies.
- Investment strategies based on stock market anomalies are good candidates to become crowded as investors are aware of their existence once they are published (McLean and Ponti, 2016), and institutional investors trade to exploit them (Calluzzo, Moneta, Topaloglu, 2019).
- Focus on 11 well-known stock anomalies used by Stambaugh, Yu, and Yuan (2012)

The Specific Anomalies

	Anomaly	Label	Paper
1	Composite equity issuance	CEI	Daniel and Titman (2006)
2	Net stock issuance	NSI	Loughran and Ritter (1995)
3	Total accruals	ACC	Sloan (1996)
4	Net operating assets	NOA	Hirshleifer et al. (2004)
5	Gross profitability	GP	Novy-Marx (2013)
6	Asset growth	AG	Cooper et al. (2004)
7	Capital investments	CI	Titman et al. (2004)
8	Investment-to-assets	IVA	Xing (2008)
9	Momentum	MOM	Jegadeesh and Titman (1993)
10	Ohlson O-score	OSC	Dichev (1998)
11	Failure probability	FP	Campbell et al. (2008)

*Many versions of these anomalies are described in detail in *Quantitative Equity Portfolio Management*, 2nd Edition, 2022. https://ludwigbc.com/books/qepm-2/

Motivation

There is an increases sensitivity to crowding. In the Crisis of Crowding, Chincarini describes early evidence with LTCM, to the Quant Crisis of 2007, to various flash crashes.

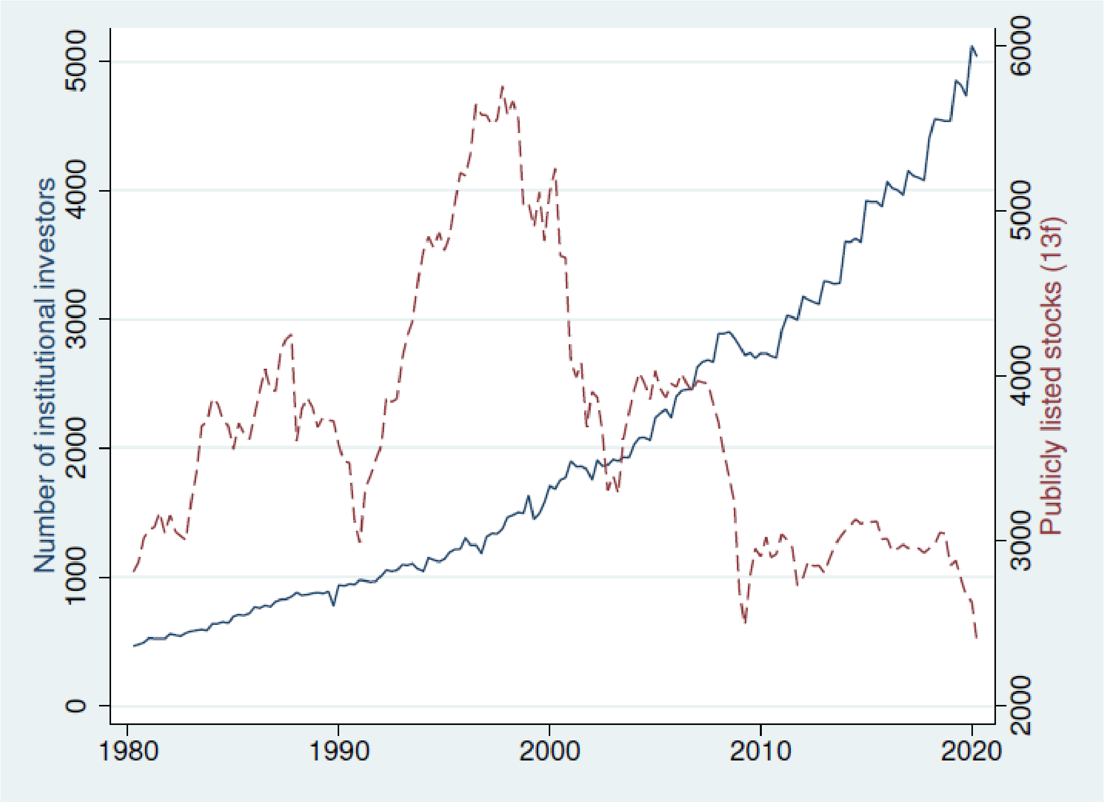
- The **key observation was that the behavior of participants causes dislocation of prices**. That is, it appeared as if investors entered a space without taking into account the externalities of others in the space and/or could not measure it well.
- With the rise of more sophisticated management and a broader knowledge of investing, one might believe that crowding could become more important and perhaps be more important in popular or crowded spaces, like anomaly trading.
- **One of the problems with being aware of crowding** and with measuring the effects of crowding is that oftentimes you need to know the players that would be likely to crowd a space (e.g. fixed income arb funds in the LTCM era).

Motivation

The aggregate data probably isn’t right for measuring crowding effects, but it’s what we have…

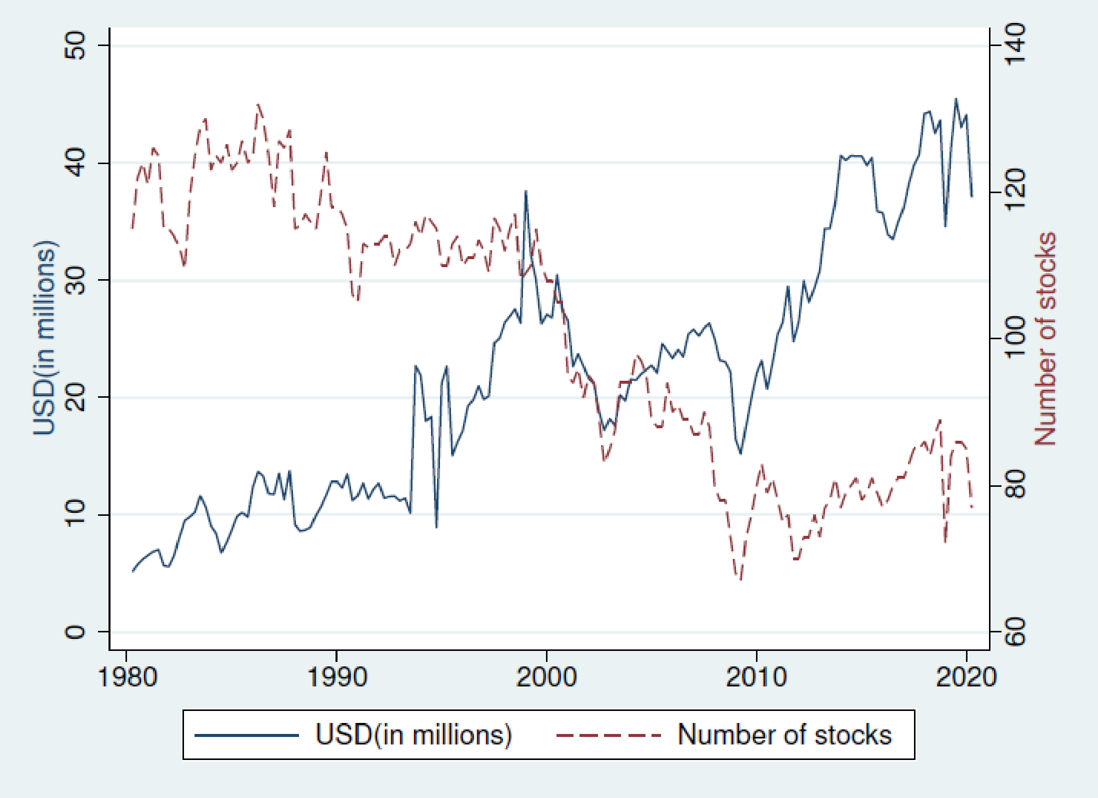
- There have been aggregate effects in the stock market that may lead to a very diverse and large group to have effects of crowding. That is, institutional crowding despite the large differences between institutions.
- **There has been an enormous growth in investment institutions and a decrease in available securities to trade**.

Motivation



- 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



- 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 an average security (blue line)

Crowding and Investing

- Chincarini (1998) discussed the idea of copycat traders in an investment space and the difficulty or lack of transparency in accounting for this crowding. These concepts were formalized in a small toy model by Stein (2009). More is explained in the Crisis of Crowding.
- Since 2012, much research has come out on the topic that is related to our work.
- According to Stein (2009) **crowding may exacerbate mispricing when arbitrageurs are unaware of the identity and the number of other investors** actively implementing the same investment strategy.
- Moreover, **crowding might persist over time**, especially in strategies for which investors do not base their demand on an independent measure of fundamental value (e.g., momentum).
- Additional risks in specific market conditions, such as during exogenous demand shocks, leading to crash risks and fire sales (e.g., Coval and Stafford, 2007; Hau and Lai, 2017).
- Crowding may become an additional risk for arbitrageurs for which they want be compensated for.

Empirical Work – Hypotheses

H_1: **Crowding and expected returns**:

Crowding is associated with higher expected returns

H_2: **Crowding and anomaly returns:**

The relation between crowding and returns should be stronger among anomaly stocks.

H_3: **Crowding and crash/liquidity risks:**

Crowding may be related to crash and liquidity risks and stronger among anomaly stocks.

Empirical Work – Main Results

- Based on a portfolio sorting approach, we find that the most crowded stocks outperform the least crowded ones in our institutional investors' holdings database.
  - Results hold across different models and for different type of institutions (e.g., mutual funds, hedge funds, transient, etc.)

- Across **11** well-known stock anomalies, abnormal returns are significantly higher (lower) among the most (least) crowded anomaly stocks - 3-Factor monthly alpha of 1.68-1.78% for the long-short portfolio.
  - Results remain significant after publication and concentrated in the crowding portfolio.

- We also find that crowding is positively and significantly related to *crash* and *liquidity* risk.
  - Results stronger for anomaly stocks

Empirical Work – Literature and Our Contribution

- Mixed evidence on the effects of crowding (see literature summary at end of slides).

Our Contribution

1. Expands the work of Brown et al. (2021) to **all institutions** (not just hedge funds) and to **anomalies**.
2. We extend the anomaly literature by looking at anomalies and their relation to crowding (too many arbitrageurs chasing same anomalies).
3. Crash Risk literature – we extend this with crowding and anomalies.
4. Limits to arbitrage (crowding becomes additional concern).

Empirical Work – Definition of Stock-Level Crowding

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

$$\text{Days-ADV}_{i,t} = \frac{\sum_{j=1}^{N} \text{InstHold}_{i,j,t}}{\text{Dollar ADV}_{i,t}} \tag{1}$$

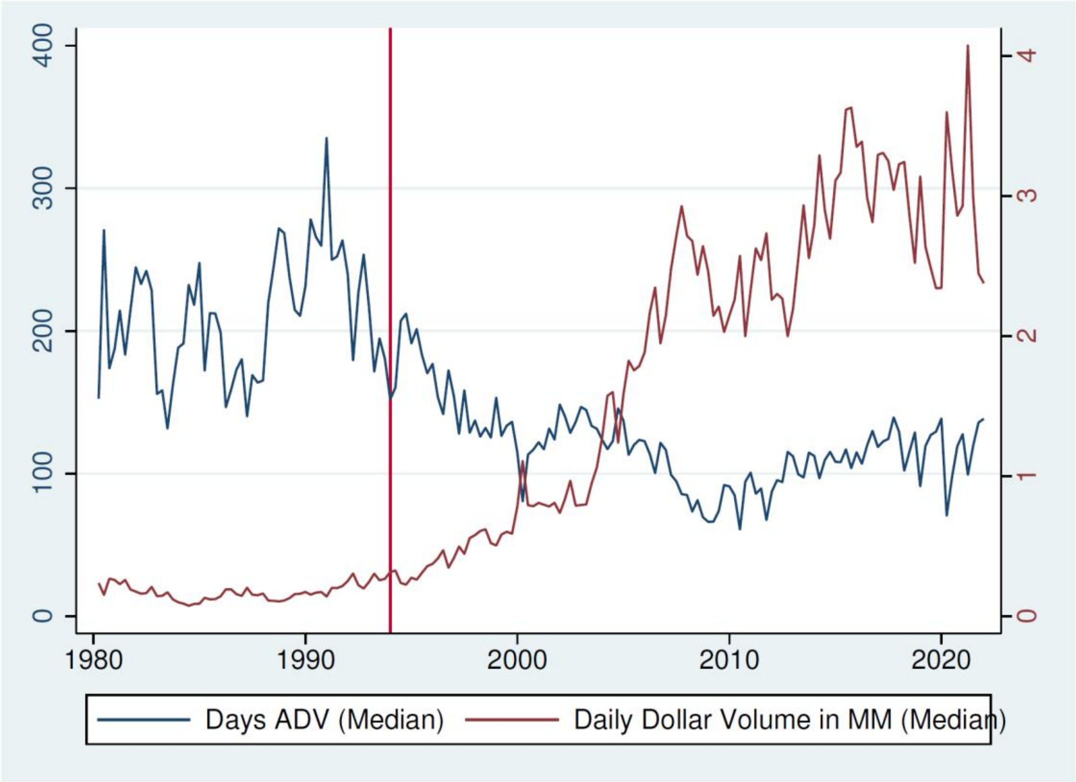
where:

- $InstHold_{i,j,t}$ is the total *value* invested in a security i by institutional investor j in quarter t;
- Dollar $\text{ADV}_{i,t}$ is the average daily *dollar* volume of security i estimated over the previous 90 trading days.

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.

Empirical Work – Definition of Stock-Level Crowding

Time series plot of median Days-ADV and median Daily Dollar Volume (in MM)



Note: We perform a test for structural breaks on the time-series of *days-ADV* based on Bai and Perron (1998) . Our results point out an estimated break date occurring at 1993:Q1. Daily money volume is calculated as the average for each security using the daily dollar volume over the previous 90 trading days.

Empirical Work – Other Measures of Stock-Level Crowding

Also, we estimate three additional measures of crowdedness employed in previous studies:

1. $NI_{i,t}$ is the total number of institutional investors (NI) invested in an individual security i in each quarter t.

2. $PSO_{i,t}$ is the security i percentage of shares outstanding owned by the set of institutional investors.

3. $Actratio_{i,t}$ is estimated as the percentage of shares of security i held by all institutional investors at the end of quarter *(t-2)* divided by the security's average turnover during quarter *(t-1)*.

$$\text{Actratio}_{i,t} = \frac{\sum_{j=1}^{N} \text{Shares}_{i,j,t-2}}{\text{AvgTurn}_{i,t-1}} \tag{2}$$

Empirical Work – Data

- Thomson/Refinitv **13F** Institutional holdings - s34
  - The Securities and Exchanges Commission (SEC) requires that 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.
  - Sample period 1980Q1 - 2021Q4
- Stock price, volume, and shares outstanding data from **CRSP**.
  - All common stocks (10,11) trading on the NYSE, AMEX, and NASDAQ and we exclude utilities, financial firms, and stocks priced under $5 (microcaps).
- Stock characteristics from **COMPUSTAT**.
  - To ensure that the accounting variables were known to investors, we use data for the last fiscal year end in calendar year t-1.
  - On June 30th of each year, we rank stocks into quintiles according to each anomaly variable and form long and short portfolios.

Empirical Work – Data

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Empirical Work – Data

- SUMMARY STATISTICS

Table 1: Summary statistics

	Full Sample			1980-1992			1993-2021		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
NStocks	232	100	411	244	120	265	206	91	477
AUM	6,489.10	933.2	33,640.10	6,298.00	1,708.30	13,335.50	6,574.70	585.8	42,742.10
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
Turnover	0.74%	0.28%	1.97%	0.26%	0.09%	1.07%	0.96%	0.37%	2.38%
Dollar ADV	13.35	1.32	34.05	1.48	0.32	5.24	18.68	1.84	46.96
NI	2,209	1,815	1512	764	775	181	2857	2717	1391
PSO	40.25%	38.77%	27.11%	24.16%	19.49%	19.88%	47.47%	47.41%	30.34%
Actratio	29.18	7.59	290.71	54.45	10.17	437.43	17.85	6.44	224.93
Days-ADV	378	151	700	660	214	1,167	251	122	491

Empirical Work – Data

- CORRELATION AMONGST CROWDING MEASURES

	1980-1992					1993-2021			
	NI	Days-adv	PSO	Actratio		NI	Days-adv	PSO	Actratio
NI		0.15	0.53	0.15	NI		-0.03	0.45	-0.06
Days-adv			0.30	0.99	Days-adv			0.12	0.99
PSO				0.29	PSO				0.07

Empirical Work – Data

- SUMMARY WHEN WE SORT ON DAYS-ADTV

		Mkt cap (in MM)		NIpermno		ADV (in MM)		PSO (%)		Turnover (%)		Bid-ask (%)		Nanalyst
	Period	Mean	Med	Mean	Med	Mean	Med	Mean	Med	Mean	Med	Mean	Med	Mean
5 (High)	1980-2000	1,738.1	230.6	72	30	1.19	0.06	40.9	39.1	0.04	0.03	1.20	0.74	6
	2001-2021	3,635.9	295.2	103	56	5.65	0.35	57.6	59.1	0.15	0.12	0.83	0.65	3
4	1980-2000	1,566.8	215.2	71	33	2.83	0.19	38.3	36.1	0.12	0.09	1.19	0.78	7
	2001-2021	7,148.6	761.0	196	112	24.78	2.85	64.5	69.6	0.38	0.36	0.76	0.62	6
3	1980-2000	995.2	169.5	58	28	3.18	0.28	34.4	30.7	0.22	0.17	1.27	0.90	6
	2001-2021	5,673.5	1,003.9	200	129	32.03	6.13	63.7	68.3	0.62	0.59	0.74	0.60	7
2	1980-2000	608.2	106.0	37	18	3.57	0.27	25.3	19.5	0.38	0.26	1.46	1.14	4
	2001-2021	3,092.6	551.0	142	83	30.03	4.07	51.7	50.2	0.96	0.82	0.76	0.60	5
1 (Low)	1980-2000	271.9	75.0	17	7	8.38	0.24	10.2	3.8	1.36	0.29	1.55	1.22	2
	2001-2021	1,880.5	218.3	70	21	46.88	2.15	27.3	14.6	3.41	1.28	0.81	0.55	2

Empirical Work – Data

- SUMMARY WHEN WE SORT ON CROWDING

Table 2: 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 A: FF3 alphas - *equally-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)

Empirical Work – Data

- SUMMARY WHEN WE SORT ON CROWDING WITH DIFFERENT FACTOR MODELS FOR ALPHA

Table 4: Quintile portfolios(*value-weighted*) formed on Days-ADV

	FF3	FF3M	FF5	FF5S	FF5A	FF5AM
5 (high)	0.536	0.454	0.371	0.358	0.362	0.312
	(8.87)	(7.78)	(6.73)	(6.46)	(6.37)	(5.71)
4	0.037	0.002	-0.069	-0.078	-0.094	-0.152
	(0.87)	(-0.01)	(-1.77)	(-1.74)	(-2.31)	(-3.65)
3	-0.159	-0.147	-0.147	-0.149	-0.160	-0.148
	(-4.11)	(-3.74)	(-3.64)	(-3.67)	(-3.86)	(-3.81)
2	-0.554	-0.445	-0.273	-0.287	-0.244	-0.186
	(-6.69)	(-5.55)	(-3.77)	(-3.93)	(-3.29)	(-2.59)
1 (low)	-0.898	-0.806	-0.583	-0.600	-0.530	-0.484
	(-7.86)	(-7.06)	(-5.61)	(-5.74)	(-4.96)	(-4.54)
5 - 1	1.435	1.264	0.954	0.958	0.892	0.796
	(9.67)	(8.68)	(7.55)	(7.52)	(6.89)	(6.29)

We adjust risk exposures using the three factor model of Fama and French (1993) - *FF3*, the Fama-French three factors augmented with the Carhart (1997) momentum (MOM) factor- FF3M, the five factor model of Fama and French (2015) - FF5, the Fama-French five factor model augmented with the traded liquidity measure proposed by Pastor and Stambaugh (2003) - *FF5S*, the Fama-French five factor augmented with the *illiquid-minus-liquid* (IML) factor of Amihud (2019) - *FF5A*, the Fama-French five factor that includes both the IML and the momentum (MOM) factors - *FF5AM*.
The reported alphas are in percent per month.
The t-values are in parentheses.

Empirical Work – Data

- SUMMARY WHEN WE SORT ON CROWDING WITH DIFFERENT FACTOR MODELS FOR ALPHA FOR DIFFERENT INSTITUTIONS

	Alpha			
	FF3	FF5	FF5A	FF5AM
Short Horizon	1.375	0.970	0.914	0.767
	(9.03)	(7.02)	(6.49)	(5.77)
Long Horizon	1.288	0.721	0.703	0.627
	(8.24)	(5.83)	(5.56)	(5.02)
Transient	1.336	0.954	0.913	0.766
	(9.12)	(7.20)	(6.75)	(6.04)
Dedicated	0.820	0.417	0.438	0.396
	(6.48)	(3.77)	(3.87)	(3.49)
Quasi-indexer	1.387	0.864	0.805	0.716
	(8.78)	(6.56)	(6.00)	(5.43)
Mutual funds	1.367	0.900	0.865	0.771
	(9.21)	(7.05)	(6.57)	(5.99)
Invs Advisor	1.251	0.763	0.709	0.592
	(8.61)	(6.19)	(5.62)	(4.90)
Pension Funds	1.098	0.543	0.482	0.411
	(7.92)	(5.12)	(4.44)	(3.85)
Others	0.905	0.463	0.453	0.411
	(7.16)	(4.36)	(4.13)	(3.74)

- Note: Categories come from

Brain Bushee and Yan and Zhang, and

Kojien and Yogo

Empirical Work – Data

- SUMMARY WHEN WE SORT ON CROWDING WITH DIFFERENT FACTOR MODELS FOR ALPHA FOR DIFFERENT INSTITUTIONS (most held)

	Alpha			
	FF3	FF5	FF5A	FF5AM
Short horizon	0.946	0.862	0.841	0.464
	(5.48)	(4.92)	(4.73)	(3.48)
Long horizon	0.236	0.205	0.201	0.007
	(1.79)	(1.49)	(1.46)	(0.06)
Transient	1.284	1.243	1.151	0.845
	(5.13)	(4.42)	(4.66)	(3.64)
Quase-indexer	0.431	0.369	0.360	0.063
	(2.86)	(2.35)	(2.24)	(0.50)
Transient	0.863	0.815	0.802	0.546
	(3.67)	(3.32)	(3.19)	(2.73)
Dedicated	0.301	0.182	0.204	0.027
	(1.99)	(1.16)	(1.27)	(0.18)
Invs Advisor	0.759	0.822	0.801	0.610
	(4.20)	(4.29)	(4.27)	(3.39)
Mutual funds (MF)	0.440	0.374	0.375	-0.036
	(2.11)	(1.72)	(1.68)	-(0.20)
Invs Advisor + MF	0.709	0.696	0.684	0.345
	(3.39)	(3.74)	(3.01)	(2.43)
The rest	0.362	0.334	0.301	0.146
	(3.01)	(2.70)	(2.41)	(2.03)

Mostly held is by paired groups and indicates that a Particular group has more ownership (first minus Second group). Thus, when we look at FF3 Of "Short Horizon" ,these are the stocks that they have An excess (Own/ADTV) than the other group.

The crowding-effect (i.e. crowding→returns) is more pronounced amongst the most active and those with shorter horizons.

Empirical Work – Results

- Anomalies and Crowding – Understanding Results

MOM	Low Crowd	Mid Crowd	High Crowd
High return (Q5)	1		**2**
Low return (Q1)	**3**		4

A first sorting approach looks at Portfolio (2) - Portfolio (3) (High past return - Low past return), but with the ”*most and least crowded*” elements.

Empirical Work – Results

- Anomalies and Crowding – Momentum (Single – on Anomaly; Double – first factor, then Crowding (opposite doesn't change))

	Single sort	Double sort: Anomalies and Days -ADV		
	FF3	FF3	FF5 + Pastor	FF5 + Amihud
MOM	0.309	1.172	1.298	1.001
	(1.98)	(4.16)	(4.43)	(3.38)
In-sample	0.711	1.340	0.702	0.518
	(2.31)	(2.17)	(0.94)	(0.68)
Post-publication	0.180	1.009	1.207	0.993
	(0.88)	(2.81)	(3.25)	(2.77)

MOM = Following Stambaugh et al (2007) and Jegadeesh and Titman (1993) we employ portfolios ranked on cumulative returns from month-7 to month-2.
The first rows show the results for the complete sample period (1980:Q1 to 2021:Q4)
The reported alphas are in percent per month.
The t-values are in parentheses.

Empirical Work – Results

- Anomalies and Crowding – Aggregate Results with Double Sorting (Each anomaly is double-sorted, then equal weights for all 11)

Panel A: Conditional-sort on anomaly variables and then on days-ADV

	FF3(Single)	FF3	FF5 + Pastor	FF5 + Amihud
Equal Weighted Portfolio	0.390	1.693	1.267	1.149
	(6.42)	(11.09)	(9.05)	(8.20)
In-sample	0.536	1.957	1.415	1.352
	(5.24)	(9.32)	(7.38)	(7.04)
Post-publication	0.301	1.609	1.154	1.037
	(3.89)	(7.67)	(5.76)	(5.18)

Panel B: Conditional-sort on Days-ADV and then on anomaly variables

	FF3 (Single)	FF3	FF5 + Pastor	FF5 + Amihud
Equal Weighted Portfolio	0.39	1.780	1.330	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-publication	0.301	1.679	1.167	0.994
	(3.89)	(7.08)	(5.20)	(4.51)

Panel C: Independent-sort Days-ADV and Anomaly portfolio

	FF3 (Single)	FF3	FF5 + Pastor	FF5 + Amihud
Equal Weighted Portfolio	0.390	1.682	1.246	1.137
	(6.42)	(11.18)	(9.08)	(8.26)
In-sample	0.536	1.792	1.266	1.225
	(5.24)	(9.04)	(6.92)	(6.71)
Post-publication	0.301	1.455	1.048	1.056
	(3.89)	(8.46)	(6.43)	(5.93)

Empirical Work – Results

- Anomalies and Crowding – Questions.
- We already showed that crowding leads to higher returns.
- We showed that crowding in anomalies leads to higher returns.
- Question #1: Do anomaly portfolios still exhibit relationship to crowding after controlling for various variables?
  - 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,
  - cumulative return over the past three months,
  - cumulative return over the past nine months preceding the beginning of quarter.

Empirical Work – Results

- Anomalies and Crowding – Fama-MacBeth Regressions (Log Days-ADV and Next Quarter Returns (at least in one anomaly – maybe more)

We have value of ADTV of each stock.

We know whether a stock is in long or

Short side of any anomaly.

R(t+1) = a + b (LADV) + c (CONTROLS)

[*Note*: long-at – dummy, a long at*LADV

Is interaction term with LADV)

	(1)	(2)	(3)	(4)	(5)
LADV	0.546	0.717	0.485	0.460	0.460
	(4.31)	(2.01)	(4.75)	(3.66)	(3.61)
long - at				-1.690	-1.691
				(-3.13)	(-3.24)
Long at*LADV				0.287	0.206
				(3.12)	(3.01)
Short - at				-3.038	-3.038
				(-5.25)	(-5.30)
Short at*LADV				0.485	0.308
				(4.86)	(3.83)
Pos-Pub					1.042
					(1.12)
Pos-Pub x Long-at x LADV					0.810
					(1.62)
Pos-Pub x Short-at x LADV					0.178
					(2.92)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	294,301	79,352	213,299	294,301	294,301
Adj. R^2	8.86	10.71	8.04	9.28	9.12

Empirical Work – Results

How do we explain the alpha associated with crowding?

- We are capturing short-term price movements due to buying pressure (test to see if there is a reversal in alpha?)
- Maybe it's compensation for acquiring or taking on crowded positions that could lead to crash risk?
- Maybe it's a new anomaly?

Empirical Work – Results

Crowding returns seem to persist, so not obviously short-term.

Although, with a simple model (see end of presentation), if flows persist in one way, in a certain type of institutions, then we could get persistent as we see here.

	Q_{t+2}	Q_{t+3}	Q_{t+4}	Q_{t+5}	Q_{t+6}
FF3	1.398	1.395	1.207	1.224	1.049
	(9.19)	(9.70)	(8.70)	(9.52)	(9.08)
FF5P	0.891	0.977	0.814	0.872	0.853
	(6.82)	(7.58)	(6.58)	(7.58)	(7.43)
FF5A	0.831	0.961	0.792	0.823	0.809
	(6.24)	(7.31)	(6.28)	(7.06)	(6.91)
FF5AM	0.725	0.831	0.671	0.695	0.629
	(5.60)	(6.66)	(5.57)	(6.36)	(6.23)

Empirical Work – Results

Why do we care? So what?

Crowding may cause spaces to become vulnerable to crash risk, and investors are thus mispricing the value of their trades, for example, overestimating the value of the anomaly.

If this is true, we should at least document that crowded spaces are more related to potential crash risk. *Of course, measuring crash risk is very difficult*.

Empirical Work – Results

Measuring Crash Risk

1. NCSKEW - is the negative of the third moment of firm-specific weekly residual returns (*negative coefficient of skewness*)

$$NCSKEW_{i,t} = -\frac{n(n-1)^{3/2}\sum R^3_{i,t}}{((n-1)(n-2)(\sum R^2_{i,t})^{3/2})}$$

2. DUVOL - down-to-up volatility (asymmetric volatility of positive and negative returns) of weekly residual returns.

$$DUVOL_{i,t} = log\left(\frac{(n_u-1)\sum_{DOWN} R^2_{i,t}}{(n_d-1)\sum_{UP} R^2_{i,t}}\right)$$

Empirical Work – Results

Crash Risk (NCSKEW) against Variables of Crowding

Note: These regressions use Year 0 crowding with Year 1 Crash Risk.

Results are weak and maybe not bad for Anomaly investor, but still linked to crash Risk.

	(1)	(2)	(3)	(4)	(5)
LADV	0.011	0.003	0.008	0.008	0.009
	(3.29)	(0.85)	(2.28)	(2.16)	(2.30)
Long - at				-0.066	-0.075
				(-3.05)	(-3.34)
Long at*LADV				0.003	0.003
				(1.06)	(1.67)
Short - at				0.007	0.102
				(3.12)	(4.21)
Short at*LADV				0.008	0.002
				(2.16)	(1.58)
Pos-Pub					-0.031
					(-2.87)
Pos-Pub x Long-at x LADV					-0.005
					(-1.69)
Pos-Pub x Short-at x LADV					0.004
					(1.74)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	102,940	23,996	78,652	102,940	102,940
Adj. R^2	8.60	13.20	7.71	8.73	9.06

Empirical Work – Results

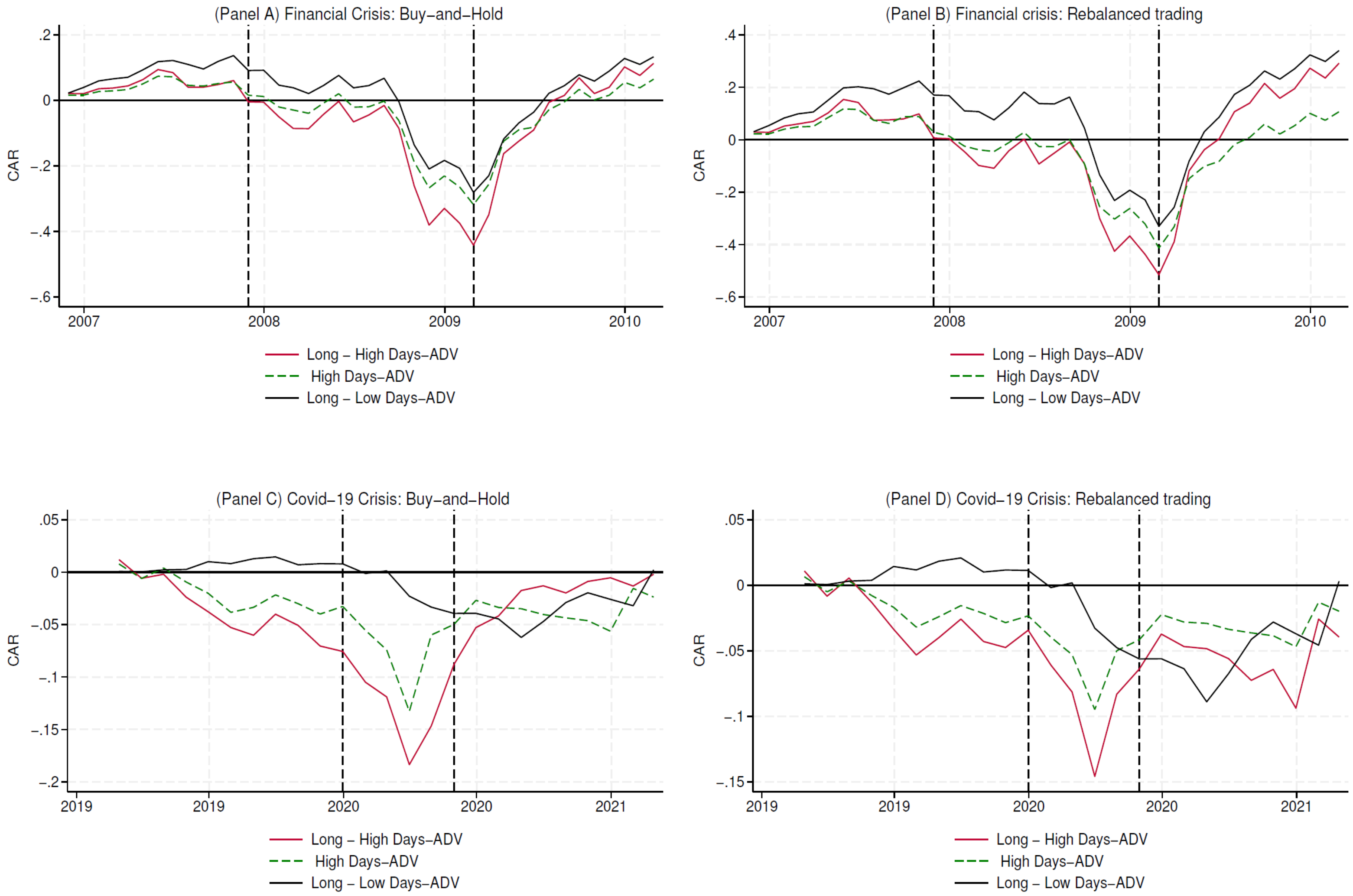
Crash Risk (DUVOL) against Variables of Crowding

Note: These regressions use Year 0 crowding with Year 1 Crash Risk (crash is measured using weekly returns over 1 year).

Results are weak but shows related, Although parts may be good for anomaly Investor.

	(1)	(2)	(3)	(4)	(5)
LADV	0.018	0.004	0.001	0.009	0.012
	(5.13)	(0.69)	(3.93)	(3.36)	(4.64)
Long - at				-0.046	-0.066
				(-3.34)	(-4.74)
Long at*LADV				0.015	0.005
				(1.68)	(1.81)
Short - at				0.034	0.051
				(2.29)	(3.48)
Short at*LADV				0.005	0.002
				(1.89)	(1.47)
Pos-Pub					-0.017
					(-2.86)
Pos-Pub x Long-at x LADV					-0.005
					(-1.89)
Pos-Pub x Short-at x LADV					0.006
					(2.30)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	102,940	23,996	78,644	102,940	102,940
Adj. R^2	11.10	16.51	9.15	11.38	8.69

Empirical Work – Results



Empirical Work – Results

SUMMARY OF RESULTS:

1. Crowded stocks lead to higher returns in Q(t+1), not only for hedge funds. Maybe not an informational story.
2. Crowded – Anomaly stocks have even higher effects of crowding on returns.
3. Crowded portfolio are mildly related to crash risk.

Empirical Work – Results

Robustness Exercises

1. Use a larger set of anomalies a la McLean and Potiff (2016). A total of 97 anomalies and results do not change.
2. We look at anomalies that are NOT in crowded portfolios and results are insignificant or even negative.
3. Different periods, different lags, and excluding financial crises, still find results.
4. Factor model for alpha doesn't matter.

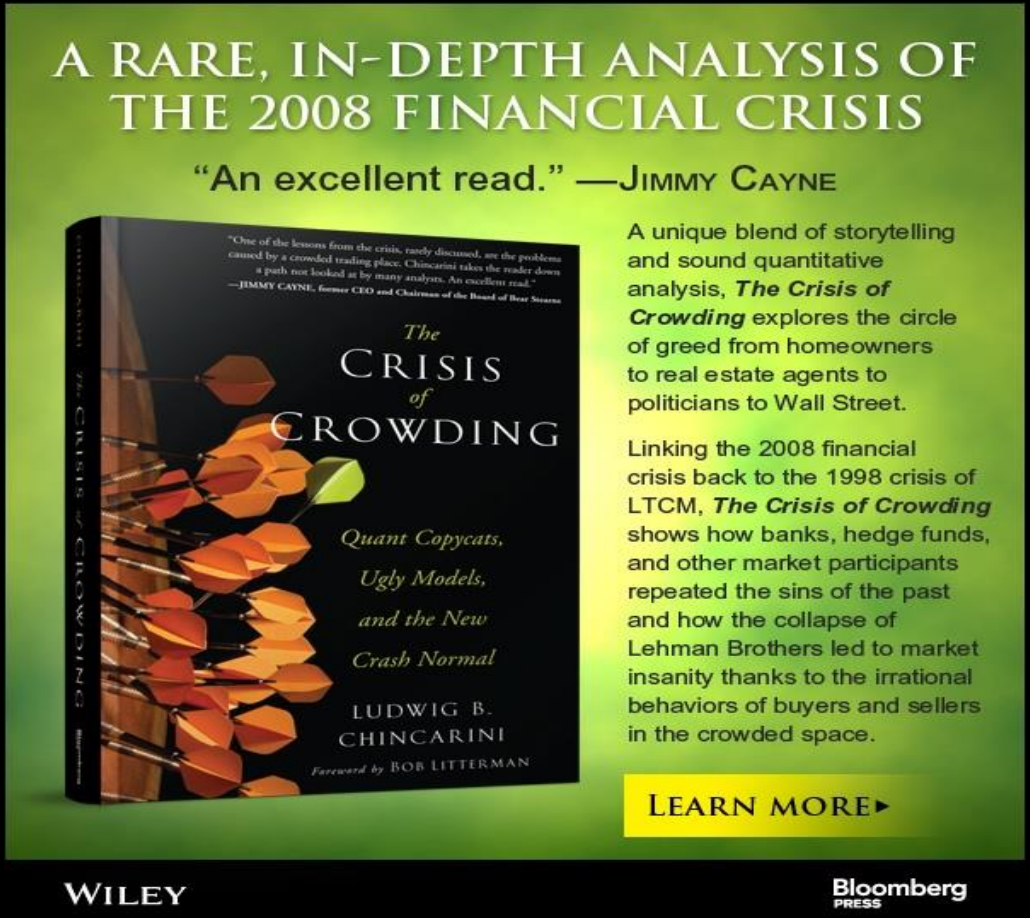
UNIVERSITY OF SAN FRANCISCO | School of Management

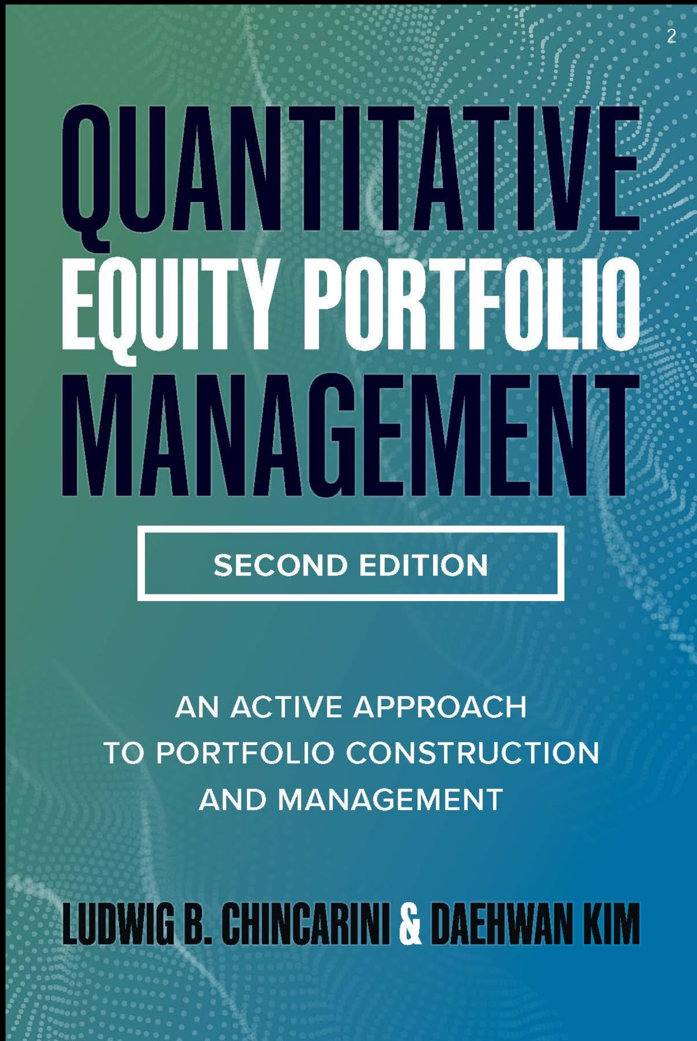
Thank you

WEDGE Capital Management®

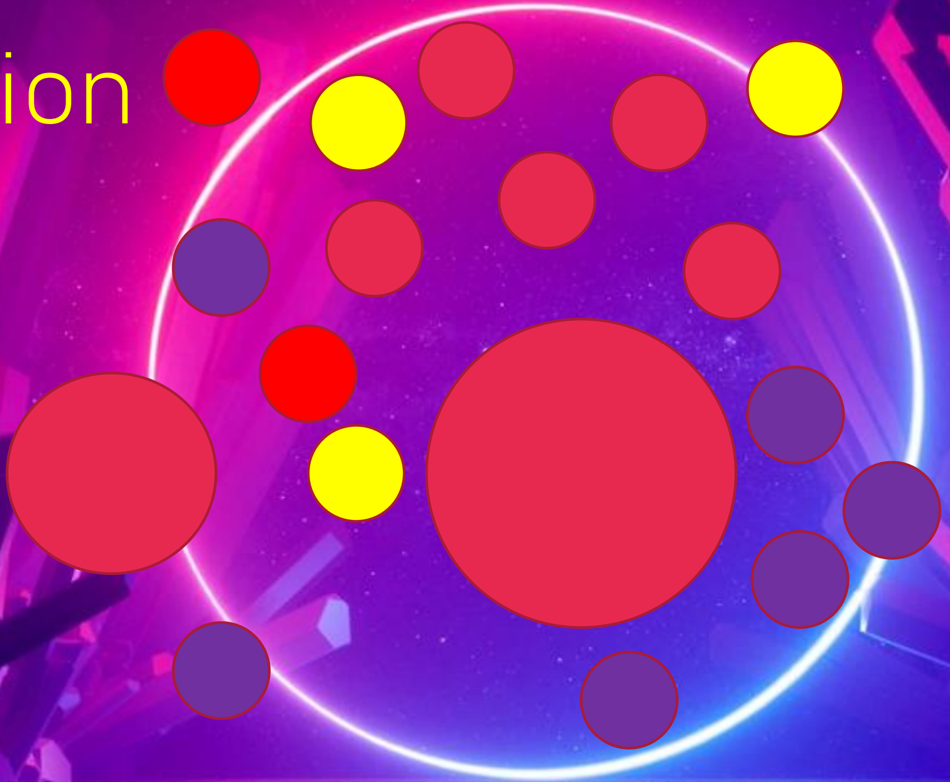
- Dr. Ludwig Chincarini , CFA — www.ludwigbc.com
- University of San Francisco — chincarinil@hotmail.com

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





Appendix:
Extra Information



Empirical Work – Results

97 Anomalies

	Single Sort	Double sort				
	FF3	FF3	FF5P	FFF5A	FF5AM	FF5C
Panel A: Event						
Full sample	0.170	1.250	0.892	0.822	0.680	0.805
	(6.54)	(10.57)	(8.06)	(6.90)	(6.72)	(8.38)
In-sample	0.186	1.299	0.900	0.873	0.667	0.849
	(2.84)	(7.79)	(5.99)	(5.41)	(4.46)	(5.90)
Post-publication	0.127	1.083	0.777	0.689	0.508	0.727
	(2.54)	(8.88)	(6.70)	(5.59)	(5.46)	(6.51)
Panel B: Market						
Full sample	0.393	1.550	1.115	0.999	0.755	0.930
	(5.43)	(10.66)	(7.98)	(6.61)	(6.72)	(8.93)
In-sample	0.466	1.913	1.281	1.222	0.905	1.027
	(3.99)	(8.70)	(5.84)	(5.01)	(4.69)	(6.32)
Post-publication	0.369	1.530	1.082	0.971	0.775	0.833
	(4.95)	(10.84)	(8.07)	(6.97)	(6.71)	(7.32)
Panel C: Valuation						
Full sample	0.121	1.306	0.974	0.927	0.853	0.983
	(2.48)	(10.18)	(8.14)	(7.47)	(7.02)	(8.44)
In-sample	0.276	1.429	1.087	1.106	1.030	1.040
	(4.74)	(9.81)	(7.23)	(7.13)	(6.66)	(7.41)
Post-publication	0.109	1.190	0.890	0.723	0.638	0.993
	(1.39)	(8.58)	(6.46)	(5.78)	(5.29)	(6.66)
Panel D: Fundamental						
Full sample	0.289	1.408	1.061	0.930	0.796	0.974
	(7.45)	(10.79)	(9.09)	(7.30)	(7.22)	(9.32)
In-sample	0.367	1.492	1.055	1.024	0.895	0.935
	(5.54)	(9.44)	(7.67)	(7.42)	(6.85)	(7.05)
Post-publication	0.152	0.982	0.603	0.480	0.365	0.475
	(2.02)	(6.47)	(4.64)	(3.64)	(2.90)	(3.68)

Empirical Work – Results

Non-Crowded Portfolios (We remove most and least crowded and then double sort and what do we see?)

	Single sort	Double sort			
	FF3	FF3	FF5P	FF5A	FF5AM
Full-sample	0.390	0.009	-0.076	-0.101	-0.105
	(6.42)	(0.18)	(-1.63)	(-2.14)	(-2.21)
In-sample	0.536	0.071	-0.022	-0.080	-0.082
	(5.24)	(0.85)	(-0.27)	(-0.95)	(-0.97)
Post-publication	0.301	0.004	-0.004	-0.031	-0.039
	(3.89)	(0.05)	(-0.04)	(-0.34)	(-0.41)

Empirical Work – Results

Lags Do Not Seem to Matter

Not really, although one published paper shows reverse results, we cannot replicate their work. Crowding is persistent drag.

Table 8: 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)

Empirical Work – Results (Short Side – Different?)

For the short legs of anomalies low crowding stocks may be associated with more limits to arbitrage.

- Hong et al. (2016) propose the Days-to-Cover (DTC) ratio: short ratio divided by the average daily turnover.
  - Interpreted as number of days required for all short sellers to cover their positions based on the average daily trading volume.
  - Stocks with higher DTC values have higher marginal costs due to lower liquidity, which indicates that short-sellers are taking larger risks.

- Days-ADV had a -0.53 rank correlation with DTC

- Examine a strategy that buys long-leg anomaly stocks with high Days-ADV and sell short-leg anomaly stocks with high DTC

Empirical Work – Results (Using DTC on Short ~~Side)~~

Panel A: Double sorted: High Days-ADV, High DTC	FF3			FF5P			FF5A			FF5AM		
	L	S	L-S	L	S	L-S	L	S	L-S	L	S	L-S
EWPort	0.582	-0.529	1.116	0.525	-0.419	0.936	0.443	-0.297	0.723	0.444	-0.296	0.723
	(6.02)	(-3.44)	(5.67)	(5.38)	(-2.73)	(4.79)	(4.47)	(-2.32)	(3.69)	(4.64)	(-2.19)	(4.01)
VWPort	0.495	-0.450	0.944	0.383	-0.306	0.689	0.315	-0.211	0.526	0.306	-0.205	0.511
	(5.12)	(-2.92)	(4.82)	(4.58)	(-2.32)	(4.07)	(3.80)	(-1.97)	(3.14)	(3.94)	(-1.86)	(3.41)

Panel B: Double sorted: Low Days-ADV, Low DTC	FF3			FF5P			FF5A			FF5AM		
	L	S	L-S	L	S	L-S	L	S	L-S	L	S	L-S
EWPort	-0.393	-0.038	-0.357	-0.356	-0.014	-0.327	-0.260	0.030	-0.273	-0.182	0.079	-0.261
	(-3.18)	(-0.44)	(-2.62)	(-3.07)	(-0.16)	(-2.37)	(-2.34)	(0.33)	(-1.90)	(-2.33)	(0.33)	(-1.93)
VWPort	-0.321	-0.031	-0.290	-0.254	-0.010	-0.243	-0.175	0.020	-0.195	-0.124	0.054	-0.177
	(-2.59)	(-0.36)	(-2.13)	(-2.50)	(-0.13)	(-1.93)	(-1.90)	(0.27)	(-1.55)	(-1.90)	(0.27)	(-1.57)

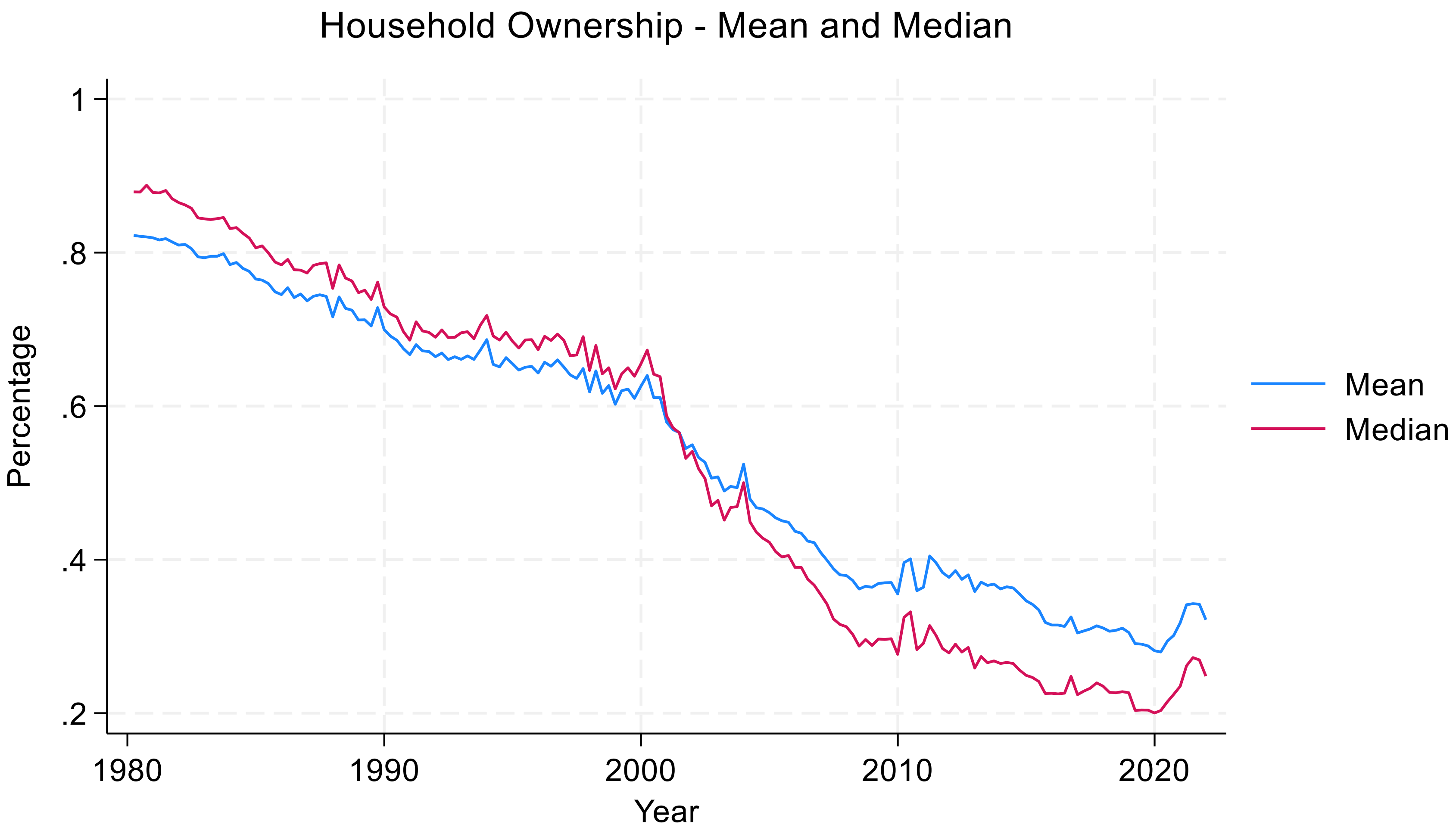
Empirical Work – Results

Empirical Work & Theory (Understanding)

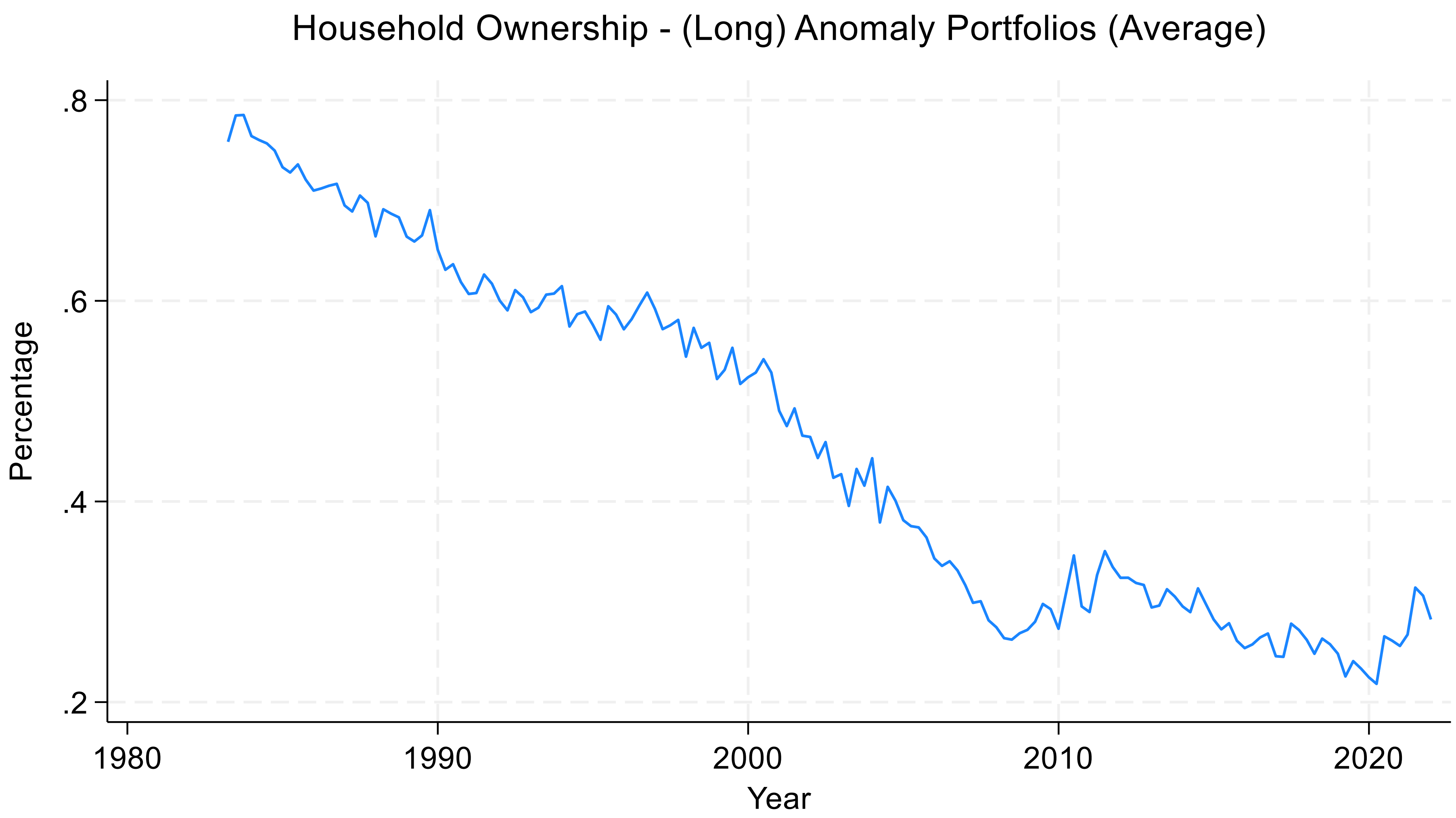
Li, Sokolinski, and Tamoni (2022) use the work of Koijen and Yogo (2019) to find that **most of anomaly returns are driven by household demand** (i.e. Market Capitalization minus 13F (Institutional)). That is changes in preferences. Maybe a theory must be derived from that.

Our data shows some of the time series properties of this "household demand".

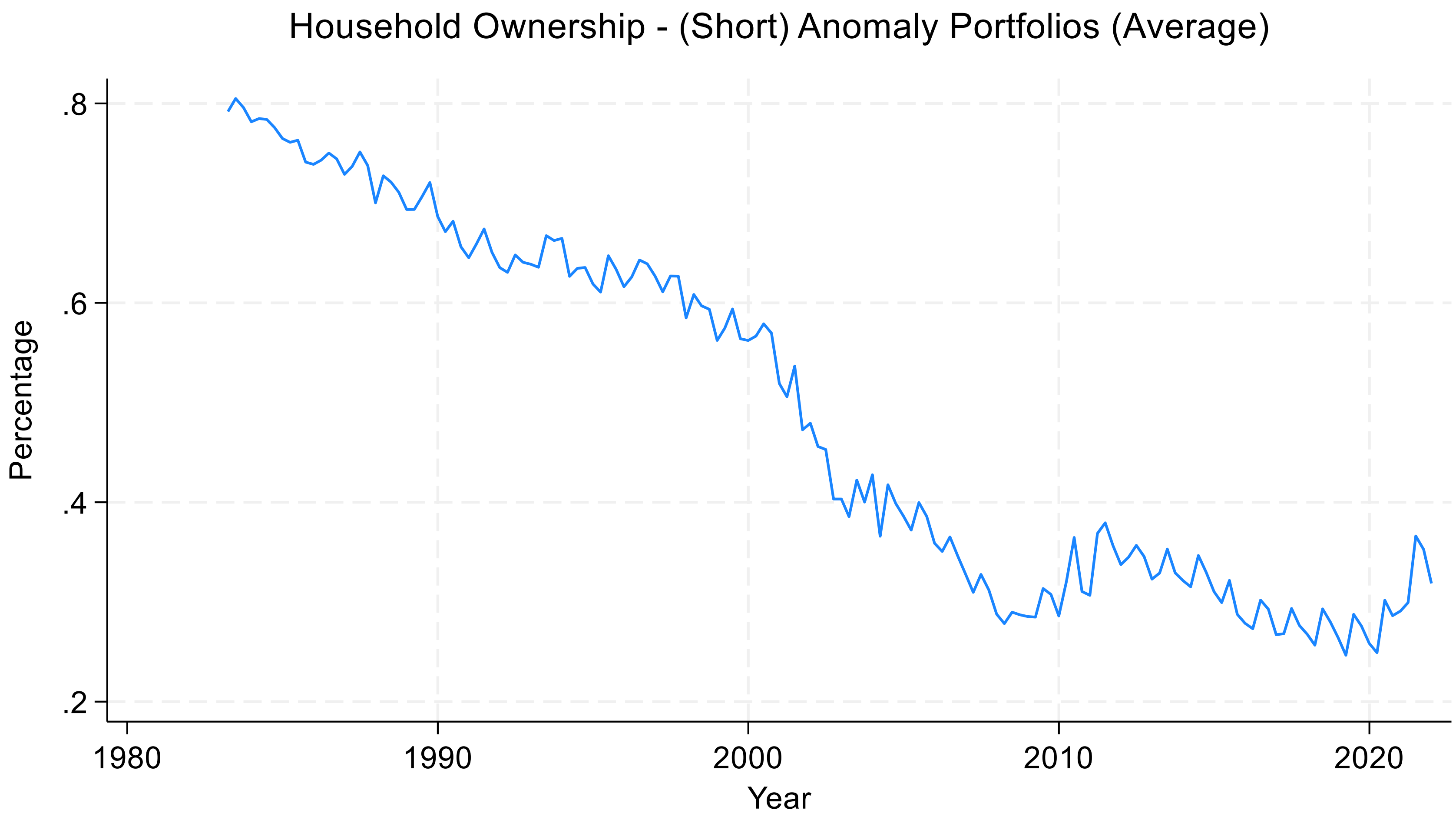
Empirical Work – Results (Household Demand)



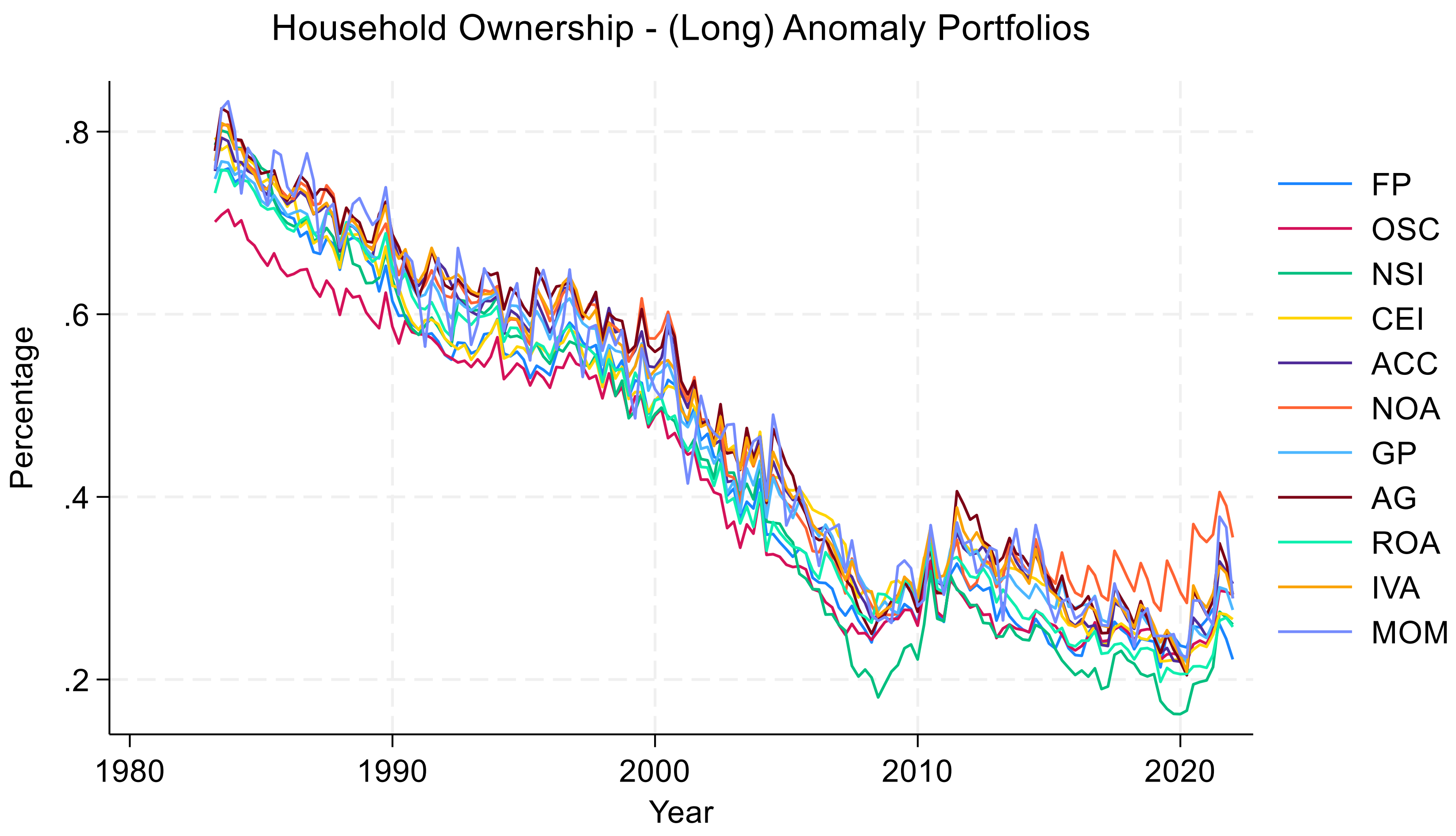
Empirical Work – Results (Household Demand)



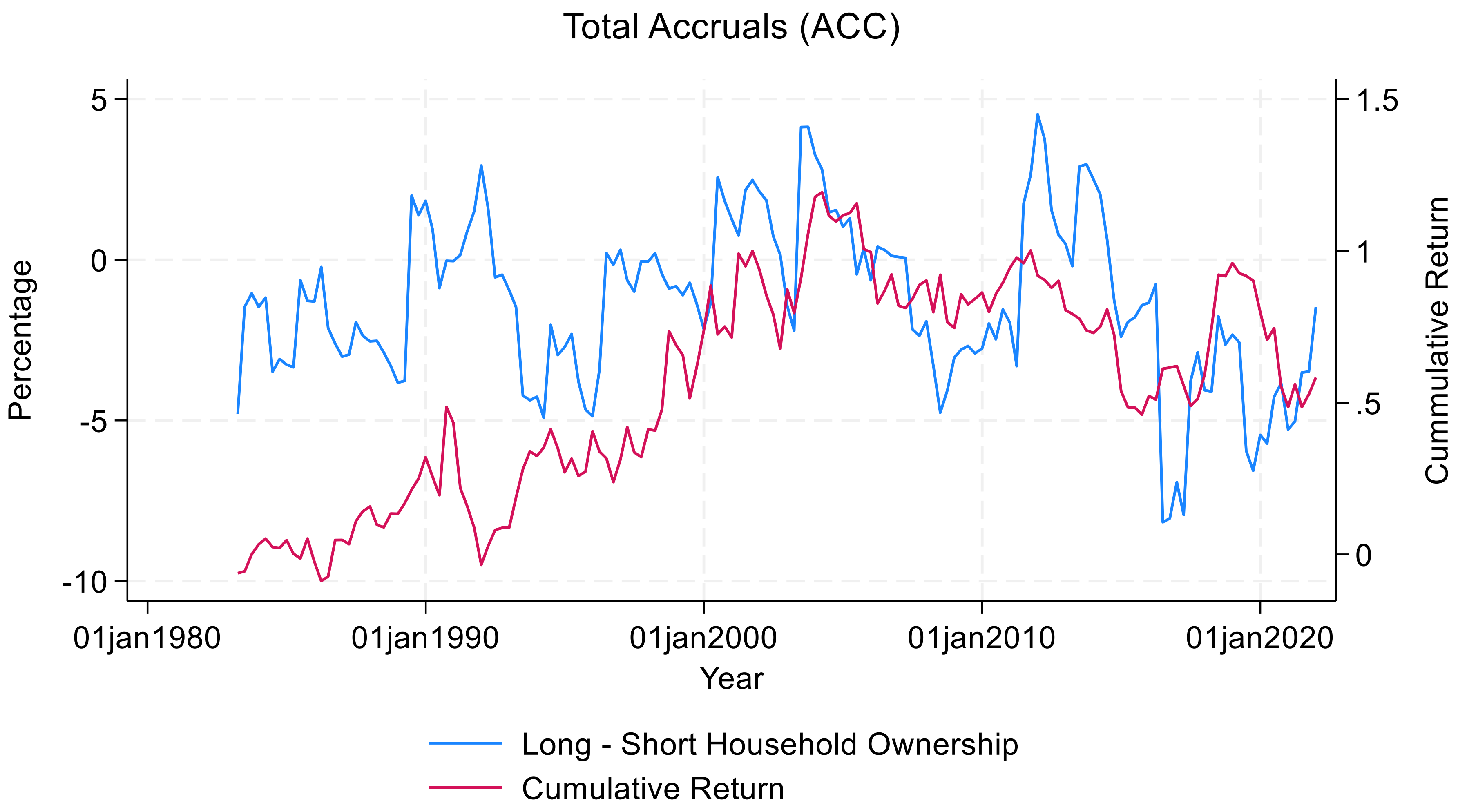
Empirical Work – Results



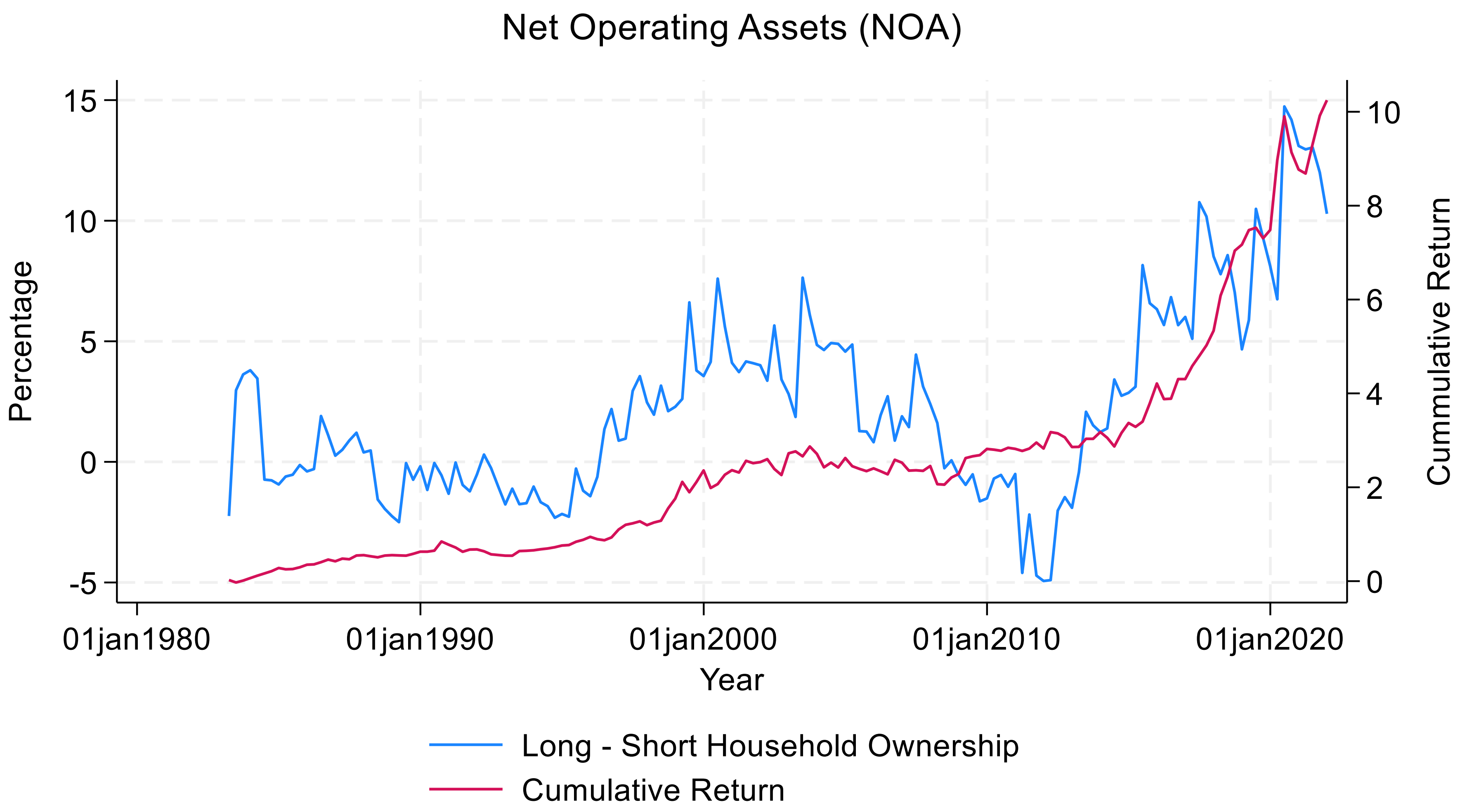
Empirical Work – Results (HD Anomalies)



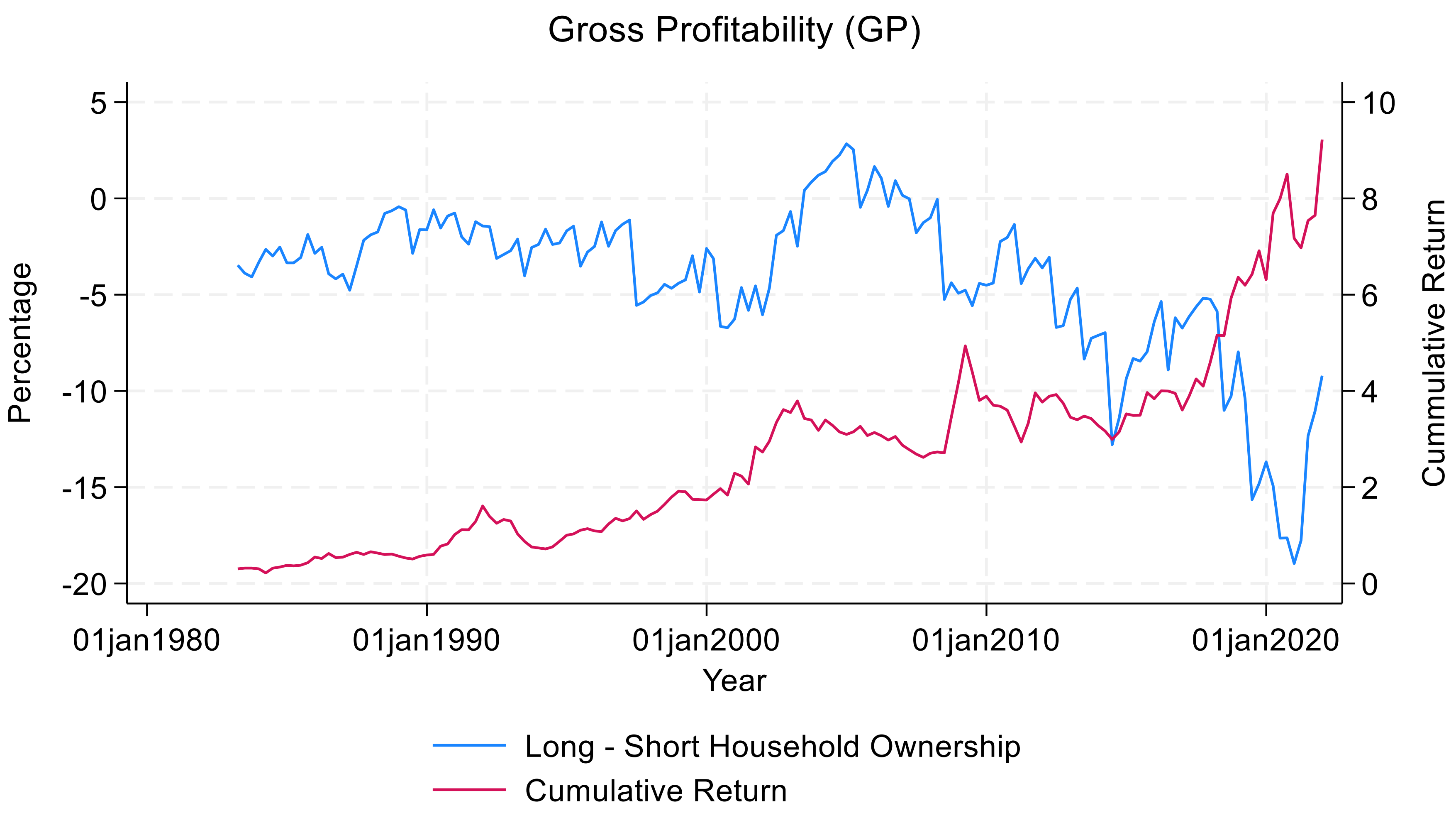
Empirical Work – Results (Specific Anomalies)



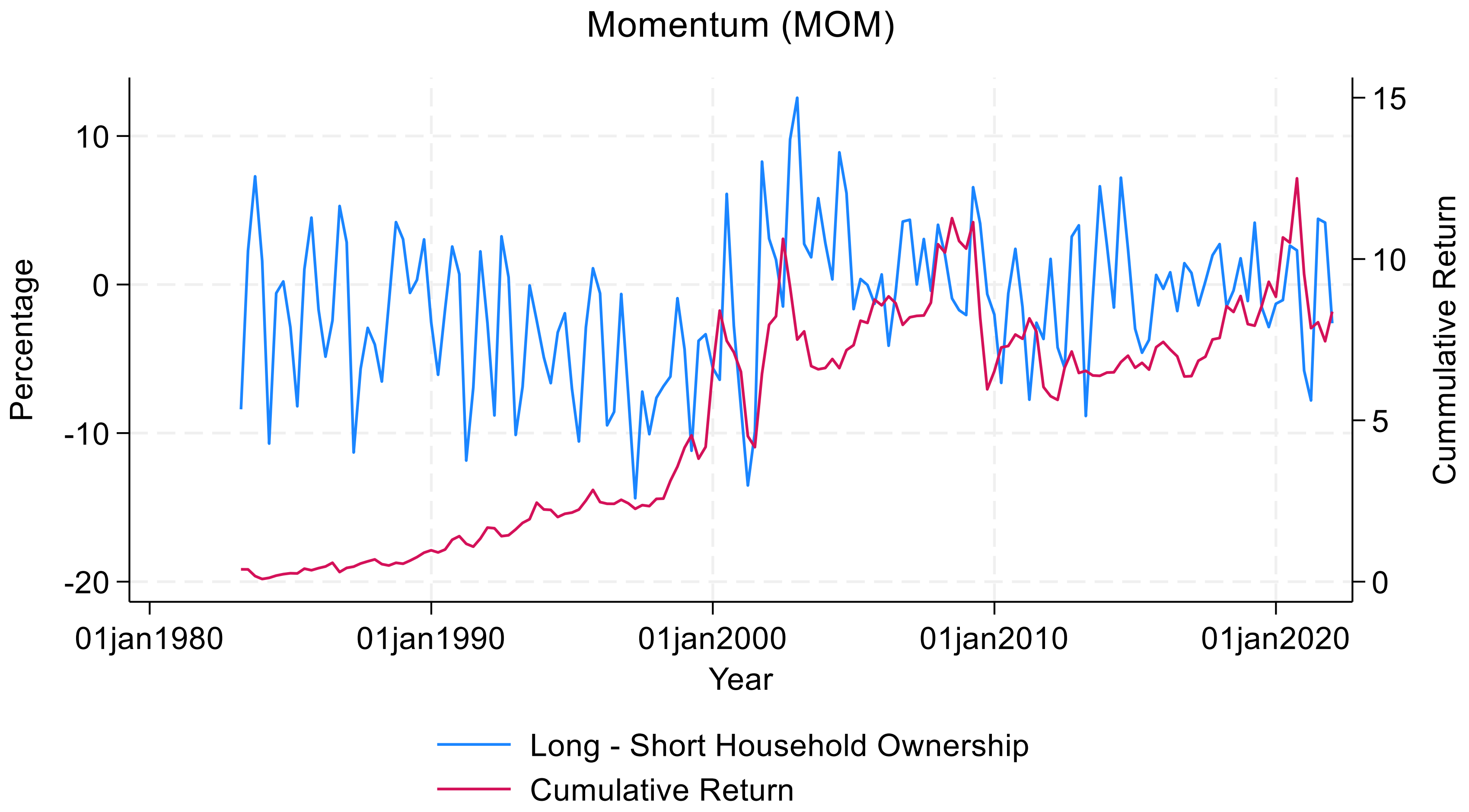
Empirical Work – Results (Specific Anomalies)



Empirical Work – Results (Specific Anomalies)



Empirical Work – Results (Specific Anomalies)



Models of Crowding

- There is really no encompassing model for crowding. In economic sciences, we rarely have the beauty that might exist from something like a Theory of Relativity.
- Several authors have built pieces that might be related (CITE).
- Here we walk through a semi-model and/or a theoretical though experiment. We borrow from some of the work of Gabaix and Kojien (2020). Their model is really about how **investor demand can affect the price of assets**.
- First we review their simplest model
- Then we modify for a world inhabitated by anomaly investors.

Review of Simple Market Impact Model

- A fund that invests in equities and bonds in some constant proportion adjusted for a risk premium.
- As new money flows in, because supply is fixed, equilibrium quantity cannot move, so prices must move. They do a Taylor Series expansion to show how a change in asset flows could move prices.
- Investment in Equities: $$\frac{PQ^d}{W} = \theta e^{\kappa \pi}$$
- Flow of Funds and Wealth: $$W = P'Q + B + \Delta F$$
- Small Changes from Baseline: $$\begin{aligned} \frac{\Delta W}{\bar{W}} &= \frac{\Delta P}{P}\frac{\bar{P}Q}{\bar{W}} + \frac{\Delta F}{\bar{W}} \\ &= \theta p + f \end{aligned}$$
- Take Logs and Taylor Series Expansion: $$q^d = w - p + \kappa \hat{\pi}$$

Review of Simple Market Impact Model

- We can rearrange to find:

$$\begin{aligned} q^d &\approx (\theta p + f) - p + \kappa\hat{\pi} \\ &\approx -(1-\theta)p + f + \kappa\hat{\pi} \end{aligned}$$

- For q(D)=0 (quantity cannot change) and pihat=0, they get that the percentage price change of equities is given by:

$$p \approx \frac{f}{\zeta}$$

- The basic idea is that change in prices of equities will be larger the bigger the flow of funds and the lower the elasticity of demand (\ci).
- In their work, they argue that aggregate flows can alter equity prices by as much as 5% for every 1% of new flow.

A Simple Model of Market Impact and Institutional Investors

- We assume a world with three types of investors. **Institutional Index investors** represents ALPHA of the world's wealth, **Anomaly investors** represent BETA of the world's wealth (but they are actually index investors with a tilt), and 1-ALPHA-BETA are **random investors** (i.e. Investor's whose collective investments looks like random in aggregate).
- In all cases, what's important is NET DEMAND, not actual demand. That is, for any group receiving a flow, there will always be some latent supply or groups selling, either measured by random investors or a proxy like ADTV.
- If there is a FLOW of funds of F, then the governing equations will be: (Note: We assume in the Gabaix/Kojien model that THETA(1) = THETA(2)=THETA(3) and mu(i)=0.

$$
\begin{aligned}
q_1^d &= w_1 - p_1 + \kappa\hat{\pi}_1 \\
q_2^d &= w_2 - p_2 + \kappa\hat{\pi}_2 \\
q_3^d &= w_3 - p_3 + \kappa\hat{\pi}_3
\end{aligned}
$$

A Simple Model of Market Impact and Institutional Investors

- We can make this model more realistic by having relative attractiveness of various positions with the \hat \pi(i), but in the simplest case we have something like:

$$\frac{p_1}{p_2} = \frac{\alpha}{\beta} \frac{\bar{W}_2}{\bar{W}_1}$$

- Which impies that if the flow distribution is different than the wealth distribution, we get effects. For example, if the world is 50% index investors and 50% anomaly investors, then a flow to index funds (e.g. alpha=0.90 beta=0.10), would result in a movement of index stock prices by 9x that of anomaly stocks.
- Also depending on the percentage of random investors, we can have other situations.
- **Obviously much more work to be done to make this a viable model.**

A Simple Model of Market Impact and Institutional Investors

- **What is the take away?** Even in the simplest scenario, we can have flows alter asset prices in relative categories in such a way that we might observe the following:

1. Crowded institutional stocks tend to perform well (flows are pushing prices).
2. Crowded institutional and anomaly stocks tend to perform even better (flows pushing prices relatively more).
3. The crowding and the returns are persistent. More flows, more going to relative categories, thus pushing relative prices.
4. Unless model is modified, it doesn't yet explain crash risk. However, with a more robust model that changes the relative attractiveness of stocks (via \hat\pi(i)), we might get a unexpected shock that realigns the relative prices so quickly that we have correlation between crowding and crashes.

Conclusion

1. We investigate the consequences of crowding on a the cross-sectional returns of equities.
2. We also examine how crowding affects 11 well-known anomaly portfolios.
3. We present evidence that crowding is related to anomaly returns, weakly related to various crash risk measures, and adds to the limits of arbitrage.
4. We also find that anomaly returns remain alive after publication dates and are concentrated in crowded portfolios.

Appendix A: Recent New Research on Crowding

Note: There are lots of publications from Sanford Bernstein, Bank of America, JP Morgan, MSCI, Credit Suisse, Wells Fargo, and other banks on crowding, but I do not quote this extensive and important research.

1. "The Cross-Predictive Ability of Crowding: Does Beta Arbitrage Predict Momentum Profits?" Ralitsa Petkova, Working Paper, December, 2023

2. "Mutual Fund Stock Holdings and the Cross-Section of Option Returns." Li Shuaiqi, Working Paper, January 11, 2022.

3. "What happens with more funds than stocks? Analysis of Crowding in Style Factors and Individual Equities." Madhaven, Ananth, Sobczyk, and Andrew Ang. Journal of Investment Management, 2021.

Appendix A: Recent New Research on Crowding

Note: There are lots of publications from Sanford Bernstein, Bank of America, JP Morgan, MSCI, Credit Suisse, Wells Fargo, and other banks on crowding, but I do not quote this extensive and important research.

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

5. "Crowding and Factor Returns," Kang, Wenjin, Rouwhenhorst, K. Geert, and Ke Tang. Working Paper, September 2020.

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