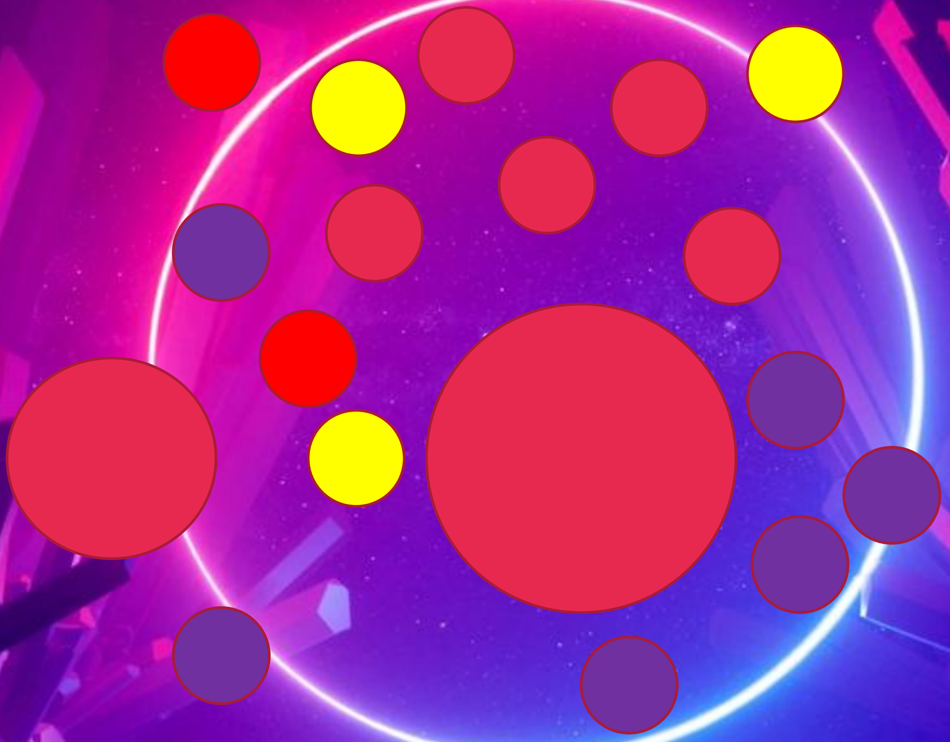


Crowding

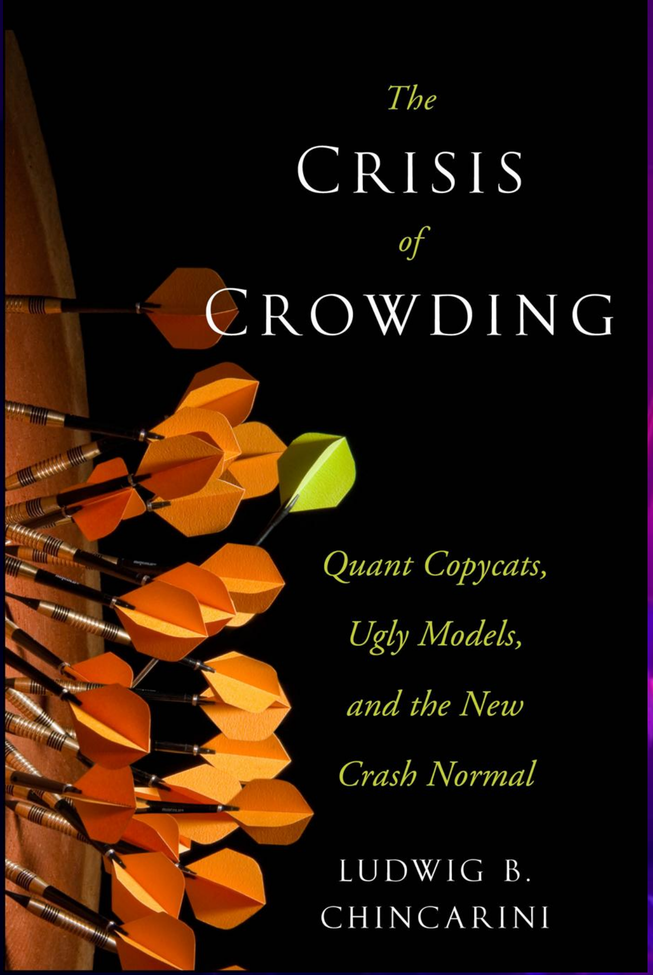
At Bloomberg Offices

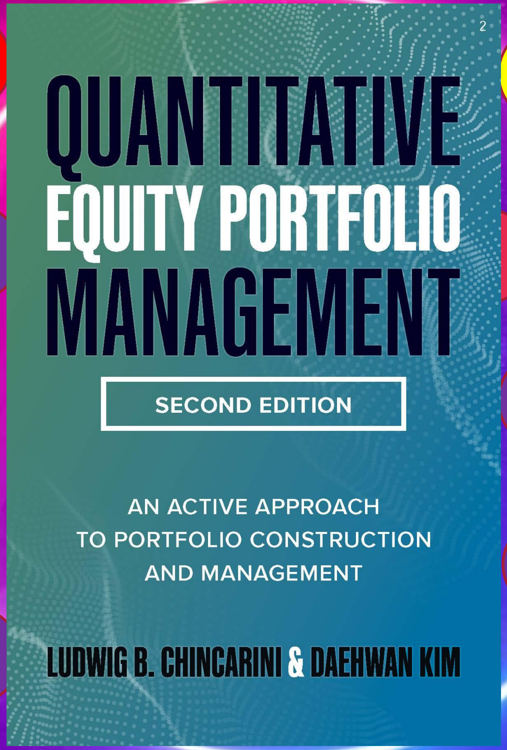
San Francisco, CA

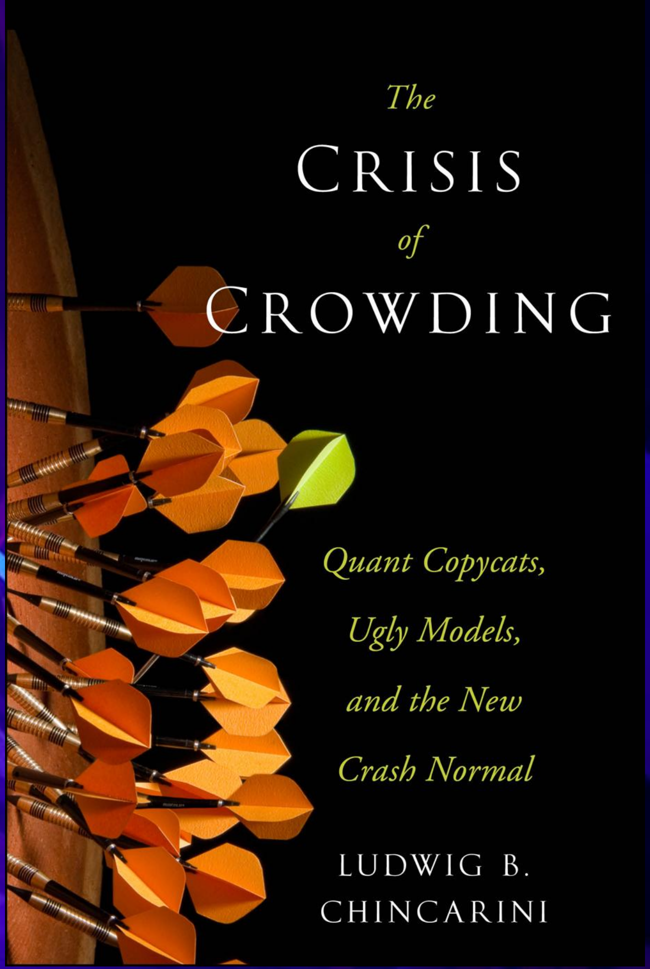
September 2, 2026

OCTOBER 17, 2024

LUDWIG CHINCARINI

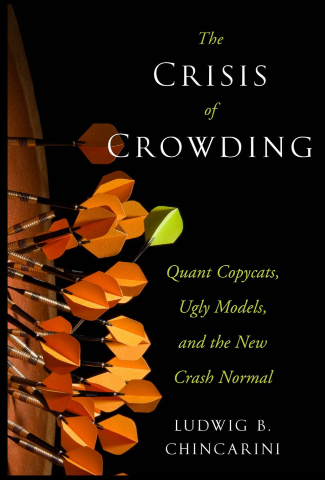






Thank you to Jose Menchero and everyone at Bloomberg.

1. Crowding



- *The Crisis of Crowding* by Ludwig Chincarini.

- The book tells the real stories of the financial crisis of 2008 and beyond how they are all connected by elements of crowding.

- The book is easy to read and informative with lots of interviews with insiders, including Goldman Sachs executives, Jimmy Cayne, Myron Scholes, John Meriwether, Vice Chairman of Citibank, government regulators, and others.

2. Intro to Crowding

How does crowding differ from herding?

They are similar. However, herding represents many similar investors following the same strategy and liquidity may not be fragile.

Crowding represents similar and/or different investors following the same or different, but correlated strategies to an extent that the opportunity or trading space is crowded/saturated. When the saturation is severe, the return and risk of the space is no longer determined by fundamentals, but determined by the behavior of the participants in the space. Exit is difficult. This makes all historical return and risk calculations less useful.

2. Intro to Crowding

Concepts Important to How Crowding Will Affect Markets:

1. Leverage – affects investor choices.
2. Liquidity – how much is on the other side in short period
3. Interdependence – investor 1's actions affect investor 2's actions
4. Types of Investors – how they will react to catalyst (depends on investor type)
5. Type of Catalyst

2. Intro to Crowding

Measuring Crowding Empirically

Return-Based Measures

- Can statistical characteristics of returns within an investment universe signal potential crowding?
- Timely and usually easy to get access to. Not clear its crowding.

Example 1: Take a factor (e.g. momentum), divide into deciles, compute cross-sectional residual return to each stock (i.e. Fama-French decoupled), then compute pair-wise correlation between stocks in each decile. If pair-wise correlation grows, maybe a signal that large portion of return movement is due to crowding by some group of investors following momentum.

Example 2: Recent large returns to a trade not explained by fundamentals.

2. Intro to Crowding

Measuring Crowding Empirically

Holding-Based Measures

- Can we detect crowding by measuring the holdings of an actual group of investors relative to the available liquidity in the market?
- Not as timely (delays in reporting) and difficult to gather.

Example 1: Take the individual holdings of all hedge fund managers of type A, the compute a similarity matrix and measure average similarity over time. Increased average similarity indicates crowding (with or without adjustment for correlation).

Example 2: Take the percentage of each stock owned by a group of hedge funds of type A and divide that by average share turnover. High values of this variable indicates stocks that might be crowded.

2. Intro to Crowding

How Crowding Typically Happens

1. Attractive Trading Opportunity Develops
2. Copycats rush to follow the leader (even if it's not their core business)
3. Herding occurs, but sometimes very hidden (not obvious)
4. The trading space becomes crowded
5. Not all crowded spaces are similar.
    a. 1 type of holder (all traders similar)
    b. N types of holders (different motivations and behaviors to risk)
    c. Holders can have exactly same position or slightly different positions, still leading to crowded behavior.
    d. Inadvertent Crowding (see Bruno, Chincarini & Ohara (2018)).
    e. Transaction costs and crowding (Chincarini (2017)).

Practitioners and **Academics** have written a lot since *The Crisis of Crowding*

3. Investment Banks Measure Crowding

Crowding measures and reports are regularly included in major bank reports, including Bank of America, Credit Suisse, Goldman Sachs, MSCI Barra, Bernstein, JP Morgan, IMF, Nomura, and others.

For more details, see my website: www.ludwigbc.com Go to Presentations

4. Academic Studies on Crowding

- Many articles and more at https://ludwigbc.com/presentations/slides-2/

as well as appendix to this presentation.

5. Early Studies

- Over the last few years, however, many quantitative types with similar ideas ... have emerged. The world is saturated with … [They] may not have estimated the effect that this could have on [their] strategies when other players were placing the same types of trades. In particular, a shock to the market, … could lead to a trigger effect, where all … began closing positions. … a self-fulfilling crisis emerged. …perhaps the correlation across strategies drastically changed because there were too many … playing the same game. …they must have underestimated this effect. "The Failure of Long-Term Capital Management," Chincarini (1998)

- David Rocker elaborated on the Long-Term Capital Management
- crisis with an article in Barron's in March 1999 entitled "A Crowded Trade".

- Years later, in 2004, in a speech to the Economic Club of New York in 2004, Timothy Geithner, then president of the Federal Reserve Bank of New York mentioned the idea of crowding. While there may well be more diversity in the types of strategies hedge funds follow, there is also considerable clustering, which raises the prospect of larger moves in some markets if conditions lead to a general withdrawal from these crowded trades. This was related mainly to the awareness that was brought from the LTCM crisis.

- At Presidential address, Sophisticated Investors and Market Efficiency, Stein (2009) attempts toy model of crowding.

6. Highlights of Chincarini's Recent Work

- Chincarini, Ludwig. "Transaction Costs and Crowding." Quantitative Finance, August 2017.
- Chincarini, Ludwig (w/ Sal Bruno and Frank Ohara). "Portfolio Construction and Crowding." Journal of Empirical Finance, March 9, 2018.
- Chincarini, Ludwig (w/ Fabio Moneta). "The Challenges of Oil Investing: Contango and the Financialization of Commodities" Energy Economics, Vol. 102, July 2021.
- Chincarini, Ludwig (w/ Fabio Moneta and Renato Le Paz). "Crowded Spaces and Anomalies" Journal of Banking and Finance, Forthcoming.
- Crowding in an Artificial World (2026)

6A. Transaction Costs and Crowding

A. How do transaction costs and crowding interact?

B. Was the quant crisis influenced by transaction cost considerations?

C. Do portfolio managers really consider transaction costs when building portfolios?

D. How is size of a portfolio and investment horizon related?

6A. Transaction Costs and Crowding

1. Crowding declines significantly from $500M to $5B and "no change" to $20B.

2. For market neutral portfolios also doesn't move much and is still less than "no cost" case.

3. Obviously, if individual managers are larger than $20B, transaction cost crowding could play a role.

4. Paper highlights how institutional features can subtlely create crowding in the financial system.

Suggestion for method to model any transaction impact costs for managers (in QEPM 2022 as well).

6B. Portfolio Construction and Crowding

- If portfolio managers use similar risk models, these risk models might cause positions to become crowded.
- Could occur if models are similar or even slightly different.

6B. Portfolio Construction and Crowding

- In order to examine whether risk-model induced crowding is an issue in the financial industry, we focus on the equity portfolio management world.

- We obtain risk model data from leading risk model providers – BARRA, Northfield, and Axioma.

- We also obtain fundamental and stock return data from Factset.

- Data from 1992 to 2013, but we present results only for 2006-2013.

6B. Portfolio Construction and Crowding

- Random: We generate 100 random alphas for each stock in 3000 stock universe every month. For each stock:

$$\alpha \sim N(0, \Sigma_{\alpha})$$

- Non-Random: We use three realistic models of portfolio alpha based on stock fundamentals
  - Value and Momentum
  - PEG
  - Aggregate Z-Score with many factors

6B. Portfolio Construction and Crowding

- **Step 1**: Match stocks from all 3 professional risk models.
- **Step 2**: Every month, create 100 random alphas or 3 non-random.
- **Step 3**: Construct portfolio optimization (a) Long Only; (b) Market Neutral w/o Liquidity; (c) Market Neutral w/ Liquidity. Constraints: Sectors, Beta, Max/Min weights, Dollar Neutral, Leverage=2.
- **Step 4**: Do this for all risk models and all portfolio construction techniques. *Includes OGARCH risk models*
- **Step 5**: Compare the resulting portfolios for crowding.

6B. Portfolio Construction and Crowding

Summary:

1. Crowding occurs from the use of standard risk models in the industry – even when crowding is absent in alpha models.
2. Crowding seems to be more severe for long-only equity managers.
3. The OGARCH procedure we suggest reduces crowding amongst portfolio managers.
4. Crowding would be less in a financial system where there is a diversification of risk model usage.

6C. The Challenges of Oil Investing

Objective:

1. Are some of the peculiarities in the oil market caused by changes in the player composition and crowding?

6C. The Challenges of Oil Investing

Oil Market

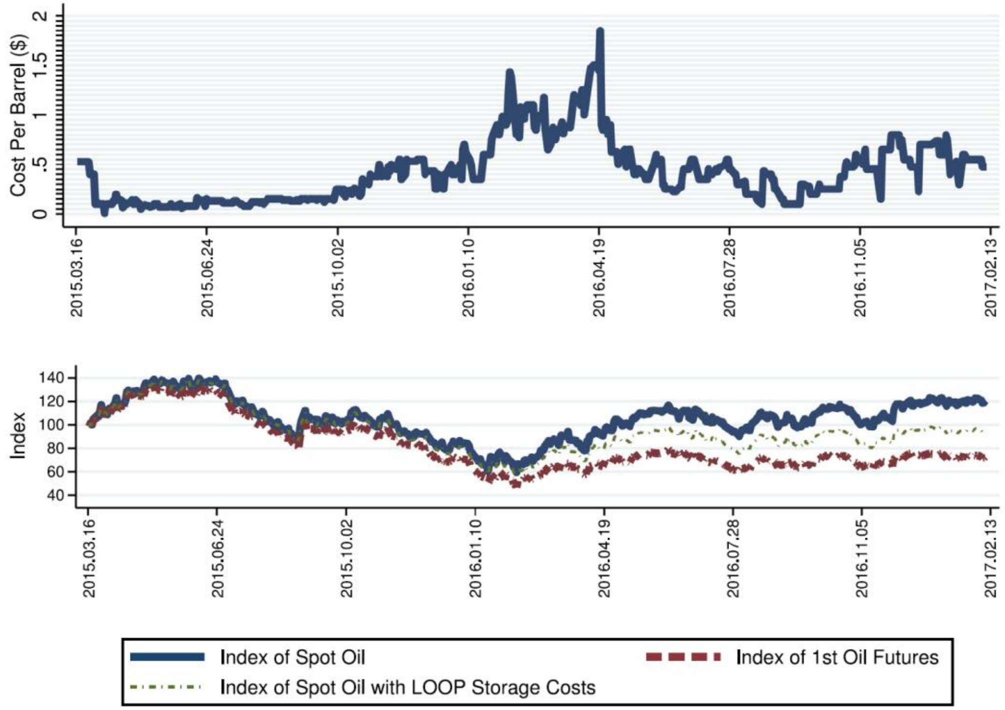


Fig. 1. LOOP Storage Costs and Spot Oil Adjusted for Storage Costs. The top figure shows the daily costs of storage of 1000 barrels of oil in dollars per barrel based on the nearest-term LOOP futures contract traded on the CME. The bottom figure shows an index of spot oil, spot oil adjusted for storage costs, and an index of rolling the nearest-term futures contract. All indices start at 100.

6C. The Challenges of Oil Investing

Oil Market

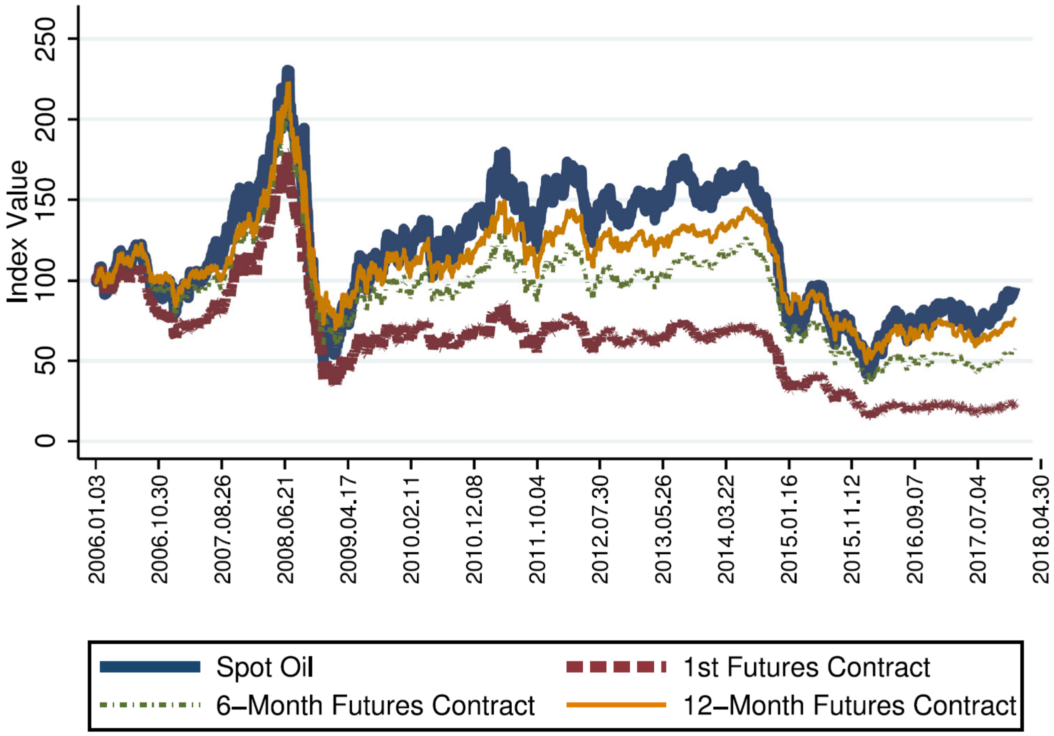


Fig. 2. Performance of Oil Futures and Spot Oil. This figure shows the cumulative returns of investing in spot oil and three rolling futures contracts; the 1-month, 6-month, and 12-month futures contracts. The strategy rolls futures on the expiration date of the front contract at closing futures prices. All indices start at 100.

6C. The Challenges of Oil Investing

Oil Market

We know that the difference in futures returns, r_f, and spot returns, r_s, is related to the cost of carry $\Psi_t = r_t + u_t - y_t$ and therefore to the interest rates, storage costs, and convenience yields (see Appendix E) according to the following equation:

$$r_{f,t} - r_{s,t} = (m-1)\Delta\Psi - \Psi_{t-1} = m\Delta\Psi - \Psi_t \tag{3}$$

where $\Delta\Psi = \Psi_t - \Psi_{t-1}$. We posit that the crowding of the futures market affects the commodity-price relationship through the variable, y, the convenience yield. Thus, in order to understand whether crowding might contribute to both contango and the tracking error between oil futures and spot oil, we estimate the following equation using weekly and daily data:

$$Y_t = \alpha + \gamma CROWD_{t-1} + \mathbf{\Lambda X}_{t-1} + Y_{t-1} + \epsilon_t \tag{4}$$

where Y_t is either the futures return, contango, or the difference between futures and spot returns.[31] $CROWD_{t-1}$ is a variety of proxies for crowding and $\mathbf{X}_{t-1}$ are control variables thought to affect the dependent variable.

6C. The Challenges of Oil Investing

Oil Market

Table 6
Proxy Measures of Crowding in the Oil Market.
Source: COT and Bloomberg.

Number	Measure	Computation	Purpose
1.	Volume as Fraction of Open Interest	$\frac{Volume}{OI}$	Measures whether an abnormal amount of volume is putting pressure on the futures market. Source: Exchanges and Bloomberg.
2.	Net Concentration of 4 Largest Players	$C_L^4 - C_S^4$	Measures the percentage of futures market long by top 4 participants minus the percentage of market short by same participants. Source: COT
3.	Net Concentration of 8 Largest Players	$C_L^8 - C_S^8$	Measures the percentage of futures market long by top 8 participants minus the percentage of market short by same participants. Source: COT
4.	Producer Pressure	$\frac{PL-PS}{OI}$	Measures the difference between producer longs minus producer shorts as a percentage of total open interest. Producer longs are defined to be producers, processors, merchants or dealers. Source: COT
5.	Money Manager Pressure	$\frac{MMCL-MMCS}{OI}$	Measures the difference between money manager longs minus money manager shorts as a percentage of total open interest. We exclude swap dealers and other reportables contained in the COT database. Source: COT
6.	Commercial Pressure	$\frac{CL-CS}{OI}$	Measures the difference between commercial longs minus commercial shorts as a percentage of total open interest. Commercial longs are defined to entities involved in businesses that require futures or options for hedging as per form CFTC Form 40. Source: COT
7.	Non-Commercial Pressure	$\frac{NCL-NCS}{OI}$	Measures the difference between non-commercial longs minus non-commercial shorts as a percentage of total open interest. Non-Commercial longs are defined as those that are not commercial. We exclude swap dealers and other reportables contained in the COT database. Source: COT
8.	ETP Fund Flows as Fraction of Open Interest	$\frac{\text{ETP flows}}{OI}$	Measures the total net flows in the four largest ETPs (USO, OIL, USO, and DBO) that invest in oil futures divided by total open interest converted in dollar values. Source: Bloomberg
9.	Change in AUM	ΔAUM	Measures the total change in assets under management (in millions of U.S. dollars) of the four largest ETPs (USO, OIL, USO, and DBO) that invest in oil futures. Source: Bloomberg
10.	Change in AUM as Fraction of Open Interest	$\frac{\Delta AUM}{OI}$	Measures the total change in assets under management of the four largest ETPs (USO, OIL, USO, and DBO) that invest in oil futures divided by total open interest converted in dollar values. Source: Bloomberg

Note: The table presents some of the proxy variables used to measure crowding in the oil market. For the variable volume as fraction of open interest we use average daily trading volume for the last 20 trading days in the daily analyses.

6C. The Challenges of Oil Investing

- Crowding and Financialization of oil marke has impact on futures prices and may be cause of distortions of futures prices.

4. Conclusion

In recent years, investing in oil futures has underperformed a hypothetical benchmark of spot oil, leading to frustration among some oil investors. In this paper, we show that the drag from investing in oil futures is related to contango. We provide evidence that the crowding and financialization of commodities have an impact on futures prices and might contribute to the contango and a distortion of the relationship between oil futures and spot returns. We also provide support that there has been an impact of changes in passive investing capital on futures prices. The futures markets play a very important role in price discovery and price signaling concerning aggregate demand and supply of commodities, which is used by market participants such as producers and corporations using commodities. Sockin and Xiong (2015) provide a theoretical model that highlights that due to informational frictions, investment flow can affect futures prices and feed back to commodity supply and demand and spot prices. Hence, distortions in the futures market, which we at least partially attribute to the increase in capital to oil ETPs, can affect the real economy.

6D. Crowded Spaces and Anomalies

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)

6D. Crowded Spaces and Anomalies

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.

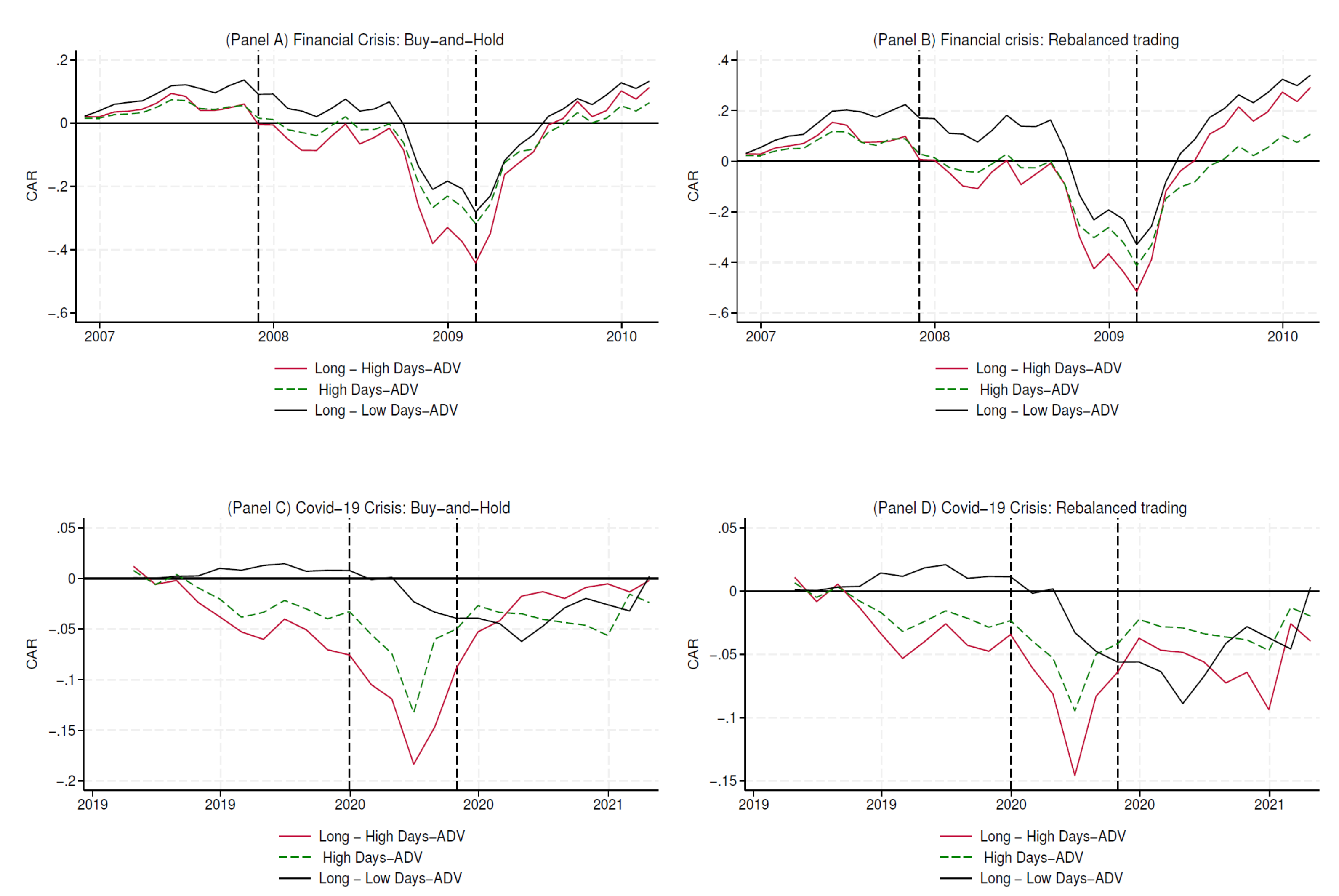
6D. Crowded Spaces and Anomalies

- 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

6D. Crowded Spaces and Anomalies



6E. Crowding in the Artificial World

- This paper was written with the use of AI.
- **Question**: If we lived in a world where portfolio managers used AI to build alpha-models, would it be crowded?
- Would the crowding cause problems for such a world?
- Are there potential mitigation procedures?

6E. Crowding in the Artificial World

- Part 1: We give four AI agents access to financial data (returns and financial factors). We ask them to find the best alpha strategy in a sample of data and compute the performance in-sample and out-of-sample. Some basic portfolio constraints (market neutral), leverage<2, and absolute weight constraints.

B. AI Agents and the Information Environment

The four agents are commercial large language models operating in agentic coding harnesses: ChatGPT 5.6 Sol through codex-cli 0.148.0 (Agent 1), Claude Fable 5 through claude-code 2.1.241 (Agent 2), DeepSeek V4 Pro through reasonix v1.31.3 (Agent 3), and Gemini 3.7 Flash through antigravity 1.1.19 (Agent 4). The labels are the providers' public model names; the sessions accessed the models through an API proxy under the provider model identifiers `openai/gpt-5.6-sol`, `anthropic/claude-fable-5`, `deepseek/deepseek-v4-pro`, and `gemini/gemini-3.7-flash`, in August 2026. Each agent is a single realized session of a stochastic system, not a

6E. Crowding in the Artificial World

- Strategy Choices:

Frozen Strategy Definitions and Construction Rules

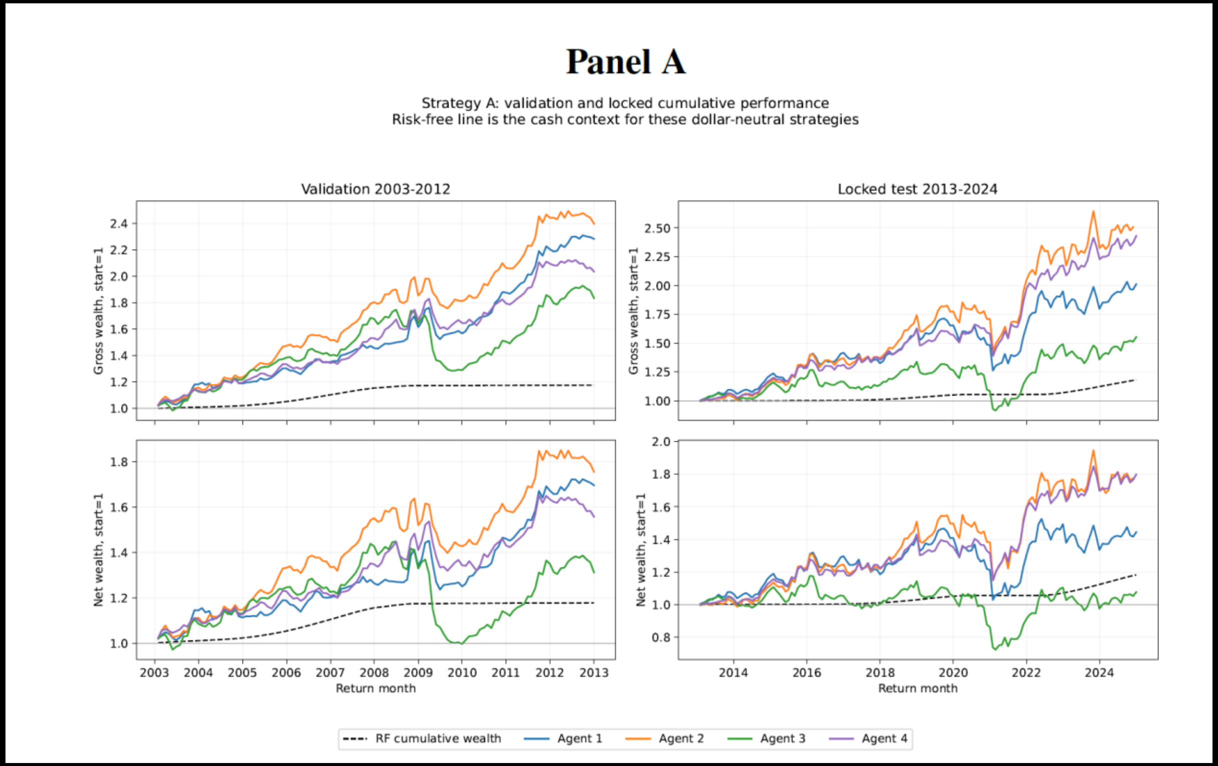
All values are taken directly from the frozen locked-run and measure tables in the archived workflow record; no value is recomputed.

This table reports the eight frozen strategy specifications, as locked before the opening of the January 2013–December 2024 locked test period. Signals are Open Source Asset Pricing (OSAP) predictors; orientation gives the sign applied to each signal in the composite. All strategies share the protocol-mandated constraints: dollar-neutral long and short legs scaled to +1 and −1, position weights capped at $|w| \leq 5\%$ with within-leg redistribution, at least 100 names per leg, a \$5 minimum price screen, and monthly rebalancing at month-end formation with returns earned in the following month. Agents 1 and 3 froze identical specifications for Strategies A and B; SHA-256 hashes of the frozen specification files are archived in the workflow record. The selected signals are: AnnouncementReturn, the cumulative return around earnings announcements; CBOperProf, cash-based operating profitability; dNoa, the change in net operating assets (selected with negative orientation); DelFINL, the change in net financial liabilities (negative orientation); and EarningsSurprise, standardized unexpected earnings. In the combination rules, "Development-Sharpe-weighted" means that component ranks are weighted by each signal's standalone development-period Sharpe ratio, fixed at the freeze. The trade-suppression rules reduce turnover by retaining incumbent positions: Agent 2's no-trade band (3.0) admits a new position only at the decile cutoff but holds an incumbent security while its composite rank remains within 3.0 times the entry decile (the top or bottom 30% of the ranking); Agent 4's hysteresis buffer (15%) likewise admits at the decile cutoff and holds an incumbent while its composite score remains within 15 percentile points of the entry cutoff.

Agent	Strategy	Signals (orientation)	Combination rule	Leg cutoffs	Within-leg weighting	Trade-suppression rule
1	A = B	AnnouncementReturn (+), CBOperProf (+), dNoa (−)	Equal average of oriented cross-sectional percentile ranks	Top/bottom decile	Equal	None
2	A	CBOperProf (+), AnnouncementReturn (+), DelFINL (−)	Development-Sharpe-weighted average of oriented ranks	Top/bottom decile	Equal	None
2	B	CBOperProf (+), AnnouncementReturn (+), dNoa (−)	Development-Sharpe-weighted average of oriented ranks	Top/bottom decile	Equal	No-trade band (3.0)
3	A = B	AnnouncementReturn (+), CBOperProf (+), DelFINL (−), EarningsSurprise (+)	Equal average of oriented ranks	Top/bottom decile	Equal	None
4	A	CBOperProf (+), AnnouncementReturn (+)	Linear score weights on oriented percentile ranks	Top/bottom quintile	Score-proportional	None
4	B	CBOperProf (+), AnnouncementReturn (+)	Linear score weights on oriented percentile ranks	Top/bottom decile	Equal	Hysteresis buffer (15%)

6E. Crowding in the Artificial World

- In-Sample: 1980-2002. Out-of-Sample: 2003-2012. Locked Period: 2013-2024.



6E. Crowding in the Artificial World

Table II

Strategy Performance in the Validation and Locked Test Periods

This table reports annualized performance of the eight frozen strategies in the validation period (January 2003–December 2012, 120 months) and the locked test period (January 2013–December 2024, 144 months; 143 for Agent 2, for which one locked month is infeasible under its frozen construction and is disclosed under the frozen attrition rule). Gross returns are before transaction costs; net returns subtract effective-cost estimates from the Hasbrouck (2009) trading-cost model, applied to turnover measured against prior-month weights drifted by realized returns (Section II.C). Volatility (vol.) is the annualized standard deviation of monthly returns. Sharpe ratios are monthly mean over monthly standard deviation, annualized by $\sqrt{12}$, with no risk-free adjustment (dollar-neutral portfolios). Maximum drawdown (Max. DD) is the largest peak-to-trough decline of the cumulative arithmetic return path over the period. Turnover is annualized one-sided turnover; Cost is the annualized average transaction-cost drag. Agents 1 and 3 hold identical A and B strategies; their rows are repeated for completeness.

Panel A: Validation period (2003–2012)

Agent	Strategy	Gross mean	Net mean	Gross vol.	Gross Sharpe	Net Sharpe	Gross max. DD	Net max. DD	Turnover	Cost
1	A	8.52%	5.53%	6.93%	1.23	0.80	−13.50%	−14.83%	7.41	2.99%
1	B	8.52%	5.53%	6.93%	1.23	0.80	−13.50%	−14.83%	7.41	2.99%
2	A	9.04%	5.90%	7.39%	1.22	0.80	−11.89%	−14.70%	7.76	3.14%
2	B	6.87%	4.96%	6.24%	1.10	0.80	−13.73%	−14.57%	4.63	1.91%
3	A	6.44%	3.07%	8.40%	0.77	0.36	−26.38%	−31.22%	8.74	3.37%
3	B	6.44%	3.07%	8.40%	0.77	0.36	−26.38%	−31.22%	8.74	3.37%
4	A	7.34%	4.64%	6.52%	1.13	0.71	−12.67%	−14.17%	6.72	2.70%
4	B	8.41%	6.08%	7.38%	1.14	0.82	−14.27%	−15.52%	5.60	2.34%

Panel B: Locked test period (2013–2024)

Agent	Strategy	Gross mean	Net mean	Gross vol.	Gross Sharpe	Net Sharpe	Gross max. DD	Net max. DD	Turnover	Cost
1	A	6.41%	3.65%	10.69%	0.60	0.34	−26.37%	−29.95%	7.63	2.76%
1	B	6.41%	3.65%	10.69%	0.60	0.34	−26.37%	−29.95%	7.63	2.76%
2	A	8.46%	5.56%	11.98%	0.71	0.46	−23.18%	−26.06%	7.91	2.90%
2	B	5.91%	4.19%	10.42%	0.57	0.40	−25.08%	−27.55%	4.66	1.73%
3	A	4.28%	1.23%	11.02%	0.39	0.11	−31.69%	−38.63%	9.03	3.05%
3	B	4.28%	1.23%	11.02%	0.39	0.11	−31.69%	−38.63%	9.03	3.05%
4	A	7.88%	5.36%	9.56%	0.82	0.56	−16.46%	−19.60%	6.82	2.52%
4	B	10.08%	7.82%	11.61%	0.87	0.67	−21.05%	−22.34%	5.73	2.26%

6E. Crowding in the Artificial World

Table III

Factor-Adjusted Performance

This table reports annualized alphas (Panels A and B) and factor loadings (Panels C and D) from regressions of monthly strategy returns on the Fama–French three-factor model (FF3; Fama and French, 1993) and on the Fama–French five factors plus momentum (FF6), in the validation and locked test periods. t-statistics, in brackets, use heteroskedasticity- and autocorrelation-consistent (HAC) standard errors with six lags. The factors are MKT (market excess return), SMB (small minus big, size), HML (high minus low, value), RMW (robust minus weak, profitability), CMA (conservative minus aggressive, investment), and MOM (momentum); FF3 uses MKT, SMB, and HML only. The validation sample is 120 months for both models. The locked-period FF6 sample is 142 months because the momentum factor is unavailable for November–December 2024; FF3 requires no momentum factor, so its locked sample is 144 months (143 for Agent 2, whose one infeasible locked month is disclosed under the frozen attrition rule). Panels C and D report loadings from the gross-return FF6 regressions; the corresponding net-return loadings differ from the gross loadings by at most 0.02 in every cell and are omitted. Agents 1 and 3 hold identical A and B strategies; their rows are repeated for completeness. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Panel A: Gross returns

Agent	Strategy	Model	Validation α	Locked α	Validation adj. R^2	Locked adj. R^2
1	A	FF3	9.92%*** [5.63]	7.55%*** [3.08]	0.15	0.30
1	A	FF6	9.34%*** [5.56]	4.90%** [2.51]	0.30	0.44
1	B	FF3	9.92%*** [5.63]	7.55%*** [3.08]	0.15	0.30
1	B	FF6	9.34%*** [5.56]	4.90%** [2.51]	0.30	0.44
2	A	FF3	11.01%*** [5.87]	9.99%*** [4.36]	0.29	0.30
2	A	FF6	10.80%*** [5.85]	7.19%*** [3.89]	0.32	0.49
2	B	FF3	8.10%*** [5.41]	6.95%*** [3.13]	0.14	0.37
2	B	FF6	7.86%*** [4.67]	4.53%** [2.57]	0.25	0.51
3	A	FF3	8.04%*** [2.73]	5.33%** [2.02]	0.18	0.31
3	A	FF6	7.93%*** [3.77]	2.07% [1.01]	0.45	0.50
3	B	FF3	8.04%*** [2.73]	5.33%** [2.02]	0.18	0.31
3	B	FF6	7.93%*** [3.77]	2.07% [1.01]	0.45	0.50
4	A	FF3	9.17%*** [6.39]	7.64%*** [4.19]	0.38	0.28
4	A	FF6	9.13%*** [5.73]	5.13%*** [3.54]	0.40	0.52
4	B	FF3	10.39%*** [6.64]	9.57%*** [4.33]	0.34	0.32
4	B	FF6	10.19%*** [6.10]	6.86%*** [3.74]	0.36	0.55

6E. Crowding in the Artificial World

- Do the chosen portfolios lead to crowding? (We measure crowding against a random benchmark).

6E. Crowding in the Artificial World

C.1. Similarity Measures

Measures operate at four layers. Throughout, m and n index strategies under the same objective (A or B), t indexes formation months, and i indexes securities in the common eligible universe U of 126 signals' investable cross-section.

Signal choice. For strategies m and n with selected signal sets $S_m, S_n \subseteq U$, signal overlap is the Jaccard index

$$J_{mn} = \frac{|S_m \cap S_n|}{|S_m \cup S_n|},$$

computed both on signal identities and on the signals' OSAP economic-family classifications (the family-level index applies the same formula to multisets of family labels). The system-level statistic is the mean of J_{mn} over the six agent pairs.

Security rankings. Ranking similarity is the cross-sectional Spearman rank correlation, each formation month, between two strategies' composite scores over the common set of eligible securities with valid scores for both; the reported statistic averages over pairs and months.

Holdings. The principal holdings measure is the signed cosine similarity between full portfolio weight vectors,

$$H_{mn,t} = \frac{\sum_i w_{i,m,t}\, w_{i,n,t}}{\sqrt{\sum_i w_{i,m,t}^2}\sqrt{\sum_i w_{i,n,t}^2}} \in [-1, 1],$$

6E. Crowding in the Artificial World

with opposite-side positions in the same security scored as offsetting rather than crowded exposure. Aggregation is month-first: the cross-pair mean is computed each month, then averaged over months within the evaluation period. Supplementary leg overlaps normalize each leg to unit gross weight and report the fraction held in common at the smaller of the two weights, separately for long and short legs.

Desired trades. Using the drifted-weight convention of Section II.C, strategy m's desired trade in security i at rebalance t is

$$\Delta_{i,m,t} = w_{i,m,t} - \tilde{w}_{i,m,t},$$

where $\tilde{w}_{i,m,t}$ is the return-drifted weight carried from $t-1$. The principal trade measure is same-direction overlap,

$$SD_{mn,t} = \frac{\sum_i \min(\Delta^+_{i,m,t}, \Delta^+_{i,n,t}) + \sum_i \min(\Delta^-_{i,m,t}, \Delta^-_{i,n,t})}{\min\left(\sum_i |\Delta_{i,m,t}|,\ \sum_i |\Delta_{i,n,t}|\right)} \in [0,1],$$

where Δ^+ and Δ^- denote the positive and negative parts (desired buys and sells in absolute value). Opposite-direction overlap OD applies the same construction to buy-against-sell coincidences, and the signed trade cosine T applies the cosine formula to the vectors $\Delta_{\cdot,m,t}$ and $\Delta_{\cdot,n,t}$.

Liquidity-scaled common trading. Hypothetical capital is allocated equally across the four agents. For each security and month, the *common* component of desired buying is the portion of aggregate desired buying contributed by two or more strategies (zero when all buying in the security comes from a single strategy), and symmetrically for selling. The measure divides each security's common trade dollars by the security's formation-month dollar volume and sums across securities:

$$P_t = \frac{1}{K}\sum_i \frac{\text{CommonBuy}_{i,t} + \text{CommonSell}_{i,t}}{\text{DollarVolume}_{i,t}},$$

expressed per dollar of total system capital K; the measure is linear in K, so results at fixed AUM levels are deterministic rescalings. The unscaled companion, common trade per dollar of capital, omits the dollar-volume denominator. P is a sum of trading-to-volume ratios under an

6E. Crowding in the Artificial World

Table VI

Crowding Measures Relative to Frozen Benchmarks

This table compares the observed principal crowding measures with two frozen randomization benchmarks in both evaluation periods. The standardized benchmark (pre-specified in the measurement protocol) redraws signal sets and builds all benchmark portfolios under a single common construction; the agent-matched benchmark (specified post hoc but frozen before locked-sample access) redraws signal sets while holding each agent's own frozen construction code fixed. The principal measures are defined in Table V: H is the signed holdings cosine, SD the same-direction desired-trade overlap, and P the liquidity-scaled common trading per dollar of capital (reported $\times 10^{-6}$); Obj. denotes the strategy objective (A, gross Sharpe; B, net Sharpe). Each benchmark uses 1,000 frozen draws per objective; for the agent-matched liquidity-scaled common trading measure P in the locked test period, 869 draws are feasible (draws with no common trading in a month are infeasible for the dollar-volume denominator). Std. diff. is the standardized difference (observed − null mean)/null SD; the percentile is the observed value's location in the null distribution; the upper-tail p-value is computed with the add-one estimator (one plus the number of draws at or above the observed value, divided by one plus the number of draws). Panel C reports the protocol-defined classification (Appendix C.4): *elevated under both* if the observed value lies in the 5% upper tail of both null distributions, *elevated under one* if in the upper tail of exactly one; the 5% thresholds are nominal and unadjusted for the multiplicity of measures, objectives, periods, and benchmarks.

Panel A: Standardized-construction benchmark

Period	Obj.	Measure	Observed	Null mean	Null SD	Std. diff.	Percentile	Upper-tail p
Validation	A	H	0.596	0.456	0.066	2.13	0.976	0.025
Validation	A	SD	0.439	0.649	0.028	−7.34	0.000	1.000
Validation	A	P ($\times 10^{-6}$)	8.94	11.87	0.77	−3.83	0.000	1.000
Validation	B	H	0.571	0.452	0.065	1.85	0.964	0.037
Validation	B	SD	0.477	0.653	0.027	−6.49	0.000	1.000
Validation	B	P ($\times 10^{-6}$)	7.10	12.23	0.87	−5.88	0.000	1.000
Locked test	A	H	0.588	0.469	0.068	1.74	0.956	0.045
Locked test	A	SD	0.432	0.655	0.028	−7.88	0.000	1.000
Locked test	A	P ($\times 10^{-6}$)	3.31	3.60	0.36	−0.80	0.208	0.792
Locked test	B	H	0.561	0.464	0.066	1.47	0.928	0.073
Locked test	B	SD	0.465	0.659	0.027	−7.15	0.000	1.000
Locked test	B	P ($\times 10^{-6}$)	2.54	3.70	0.38	−3.05	0.000	1.000

Panel B: Agent-matched construction benchmark

Period	Obj.	Measure	Observed	Null mean	Null SD	Std. diff.	Percentile	Upper-tail p
Validation	A	H	0.596	0.330	0.047	5.71	1.000	0.001
Validation	A	SD	0.439	0.268	0.033	5.28	1.000	0.001
Validation	A	P ($\times 10^{-6}$)	8.94	4.13	1.95	2.46	0.976	0.025
Validation	B	H	0.571	0.317	0.048	5.33	1.000	0.001
Validation	B	SD	0.477	0.290	0.038	4.99	0.999	0.002
Validation	B	P ($\times 10^{-6}$)	7.10	3.65	1.72	2.01	0.965	0.036
Locked test	A	H	0.588	0.347	0.050	4.78	1.000	0.001
Locked test	A	SD	0.432	0.274	0.035	4.45	1.000	0.001
Locked test	A	P ($\times 10^{-6}$)	3.31	1.42	0.60	3.16	0.997	0.005
Locked test	B	H	0.561	0.333	0.050	4.55	1.000	0.001
Locked test	B	SD	0.465	0.297	0.041	4.14	0.997	0.004
Locked test	B	P ($\times 10^{-6}$)	2.54	1.28	0.53	2.38	0.984	0.017

Panel C: Classification by benchmark construction

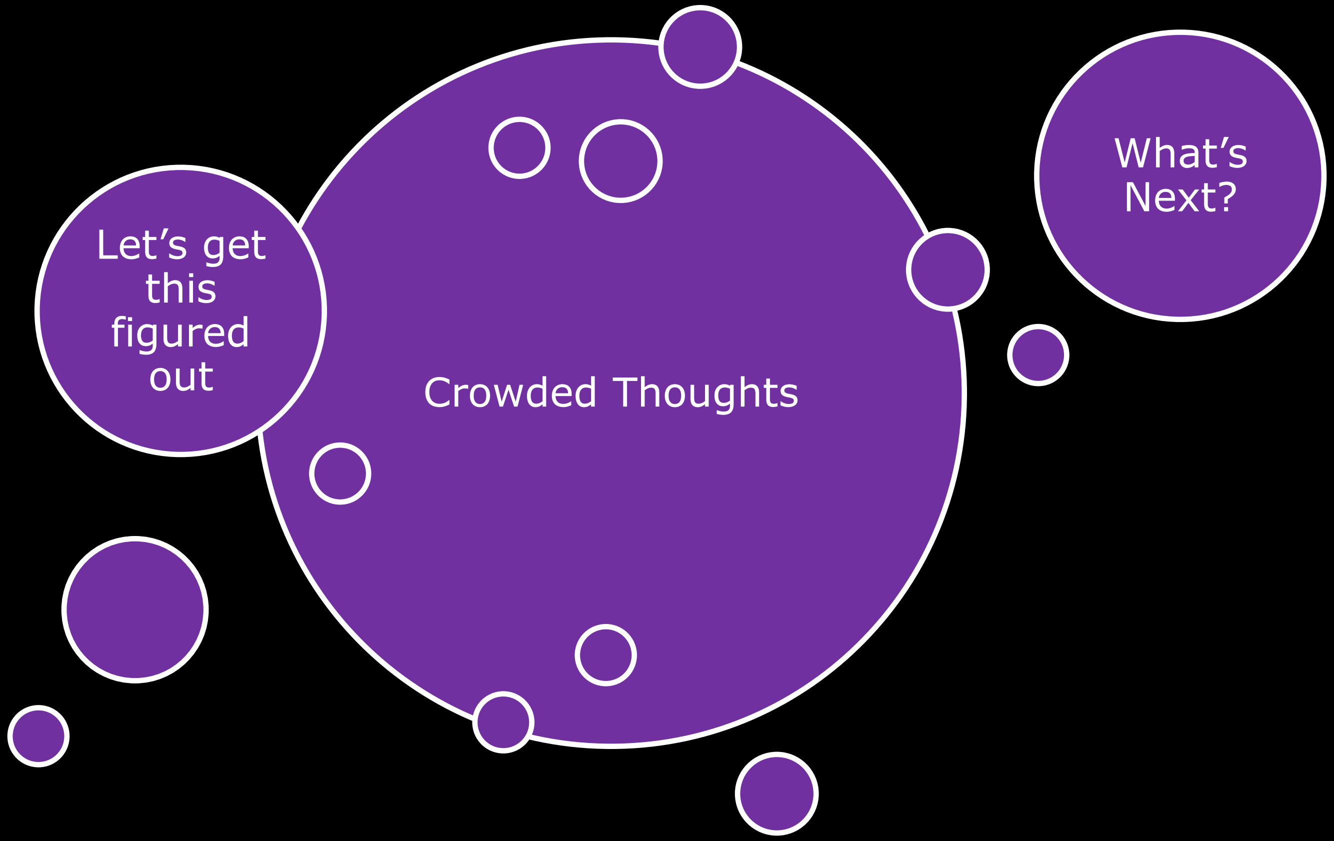
Objective	Measure	Validation	Locked test	Stability
A	H	Elevated under both	Elevated under both	Unchanged
A	SD	Elevated under one	Elevated under one	Unchanged
A	P	Elevated under one	Elevated under one	Unchanged
B	H	Elevated under both	Elevated under one	Changed
B	SD	Elevated under one	Elevated under one	Unchanged
B	P	Elevated under one	Elevated under one	Unchanged

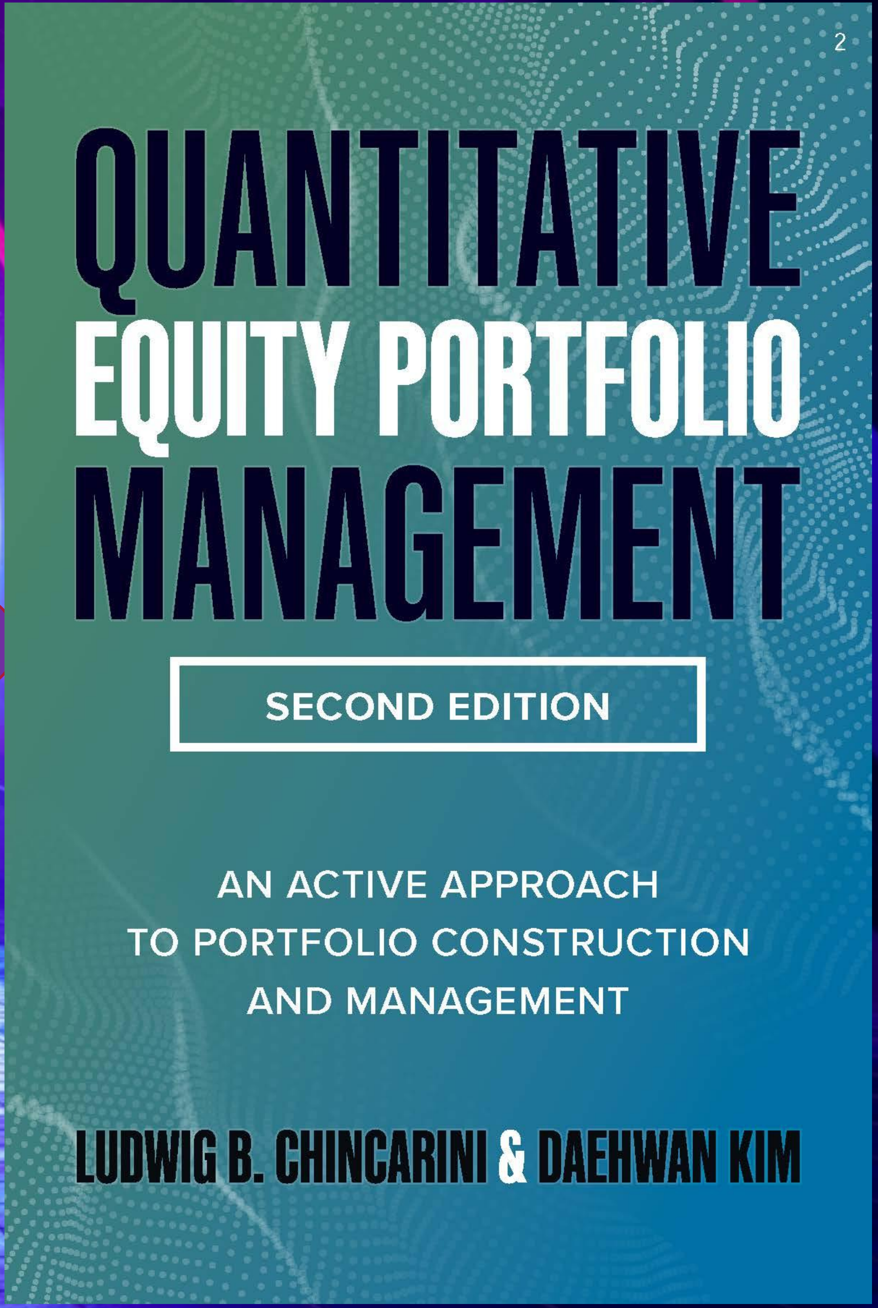
• 6E. Crowding in the Artificial World

- We also asked AI to build a model of crowding, which we are still analyzing for accuracy, but hopefully it will be useable.

- **Thank you for listening. ☺**

- THANK YOU – GRAZIE - DANKE


Let’s get this figured out
Crowded Thoughts
What’s Next?



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

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

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.

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

Appendix A: Recent New Research on Crowding

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

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

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

Appendix A: Recent New Research on Crowding

10. "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.

11. "The Mismatch Between Mutual Fund Scale and Skill," Song, Yang. Journal of Finance, October 2020.

12. "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.

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

Appendix A: Recent New Research on Crowding

14. “Crowding and Tail Risk in Momentum Returns,” Barroso, Edelen, and Karehn, JFQA, June 2022.

15. “Is There Too Much Benchmarking in Asset Management? Anil K Kashyap, Natalia Kovrijnykh, Jian Li, and Anna Pavlova. American Economic Review, 2023.

16. “Is There a “Crowded Trade” Basis for Push Back Against ESG Investing?” Dan diBartolomeo and William Zieff. Northfield Publication, December 2022.

17. “Crowding and Liquidity Shocks.” Hector Chan and Tony Tan,” Journal of Portfolio Management, February 2023.

Appendix A: Recent New Research on Crowding

18. "Learning in Crowded Markets," Journal of Economic Theory, Kondor and Zawadowski. September 2, 2019.

19. "Systemic Risk in Financial Networks: A Survey
," Jackson and Pernoud. Working Paper, December 2020. *Note*: Not directly about crowding, but has many elements that may be useful in understanding crowding.

20. "Crowded Trades, Market Clustering, and Price Instability" Kralingen, Garlaschelli, Scholtus 4, and Lelyveld. *Entropy*, 2021.

21. Kang, Wenjin and Rouwenhorst, K. Geert and Tang, Ke, Crowding and Factor Returns (March 13, 2021). Available at SSRN: https://ssrn.com/abstract=3803954 or http://dx.doi.org/10.2139/ssrn.3803954

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22. "Factor Crowding and Liquidity Exhaustion," Journal of Financial Research, Marks and Shang. Spring, 2019.

23. Harvey, Campbell R. and Liu, Yan and Tan, Eric K. M. and Zhu, Min, Crowding: Evidence from Fund Managerial Structure (April 9, 2021). Available at SSRN: https://ssrn.com/abstract=3554636 or http://dx.doi.org/10.2139/ssrn.3554636

24. Arnott, Robert D. and Harvey, Campbell R. and Kalesnik, Vitali and Linnainmaa, Juhani T., Alice's Adventures in Factorland: Three Blunders That Plague Factor Investing (April 10, 2019). Available at SSRN: https://ssrn.com/abstract=3331680 or http://dx.doi.org/10.2139/ssrn.3331680

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25. “What happens with more funds than stocks? Analysis of Crowding in Style Factors and Individual Equities,” Journal of Investment Management, Madhaven, Sobczyk, and Ang. 2021.

26. “Co-Impact: Crowding Effects in Institutional Trading Activity,” Quantitative Finance, Bucci, Mastromatteo, Eisler, Lillo, Bouchaud, and Lehallealysis.   2020.

27. “Trade Less and Exit Overcrowded Markets,” Review of Finance, Dyako, Jiang, and Verbeek.   2019.

Appendix A: Recent New Research on Crowding

28. Chincarini, Ludwig (w/ Fabio Moneta). "The Challenges of Oil Investing: Contango and the Financialization of Commodities" Energy Economics, Vol. 102, July 2021.

29. Chincarini, Ludwig (w/ Fabio Moneta and Renato Le Paz). "Crowded Spaces and Anomalies" Journal of Banking and Finance, Forthcoming.

30. Kyle, Albert S. & Obizhaeva, Anna A. & Wang, Yajun, 2026. "Trading in Crowded Markets," Journal of Financial and Quantitative Analysis, Cambridge University Press, vol. 61(1), pages 137-175, February.

Appendix B: 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 B: 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 B: 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 B: 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 B: 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 B: 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)