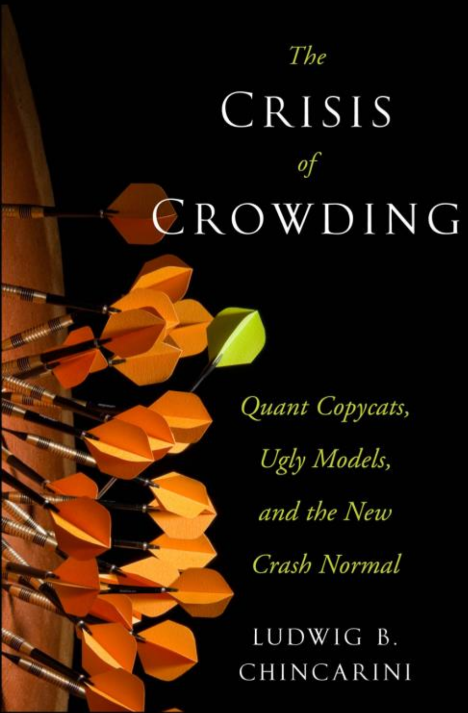
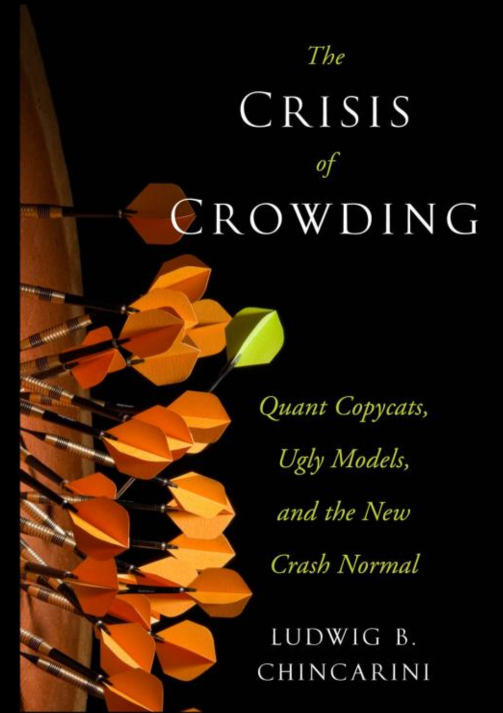


Crowding

December 19, 2018



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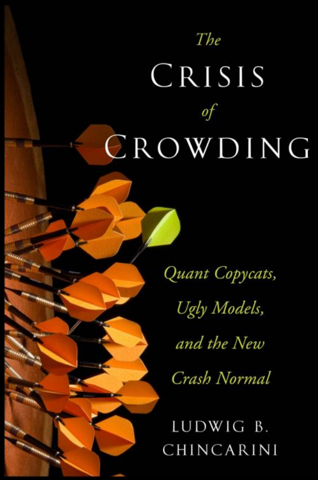
BLOOMBERG
DECEMBER 19, 2018

- Thank you Jose and Bloomberg for inviting me.



1. New Idea of 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** are Acknowledging this New Risk

3. Market Acknowledges 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

- Three areas of contribution:

    A. Portfolio Construction

        - Copycat Techniques

        - Copycat Alpha

    B. Impact of Crowding

    C. Implications

4. Academic Studies 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)

4. Academic Studies 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)

4. Academic Studies on Crowding

M. “Portfolio Construction and Crowding” Bruno, Chincarini, and Ohara (2018).

N. “Transaction Costs and Crowding” Chincarini (2017)

O. “The Impact on Stock Returns of Crowding by Mutual Funds,” Tay et al. (2017)

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)

4. Academic Studies on Crowding

S. “Omitted Risks or Crowded Strategies: Why Mutual Fund Comovement Predicts Future Performance” Chue (2015).

T. “Crowded Trades” Kinlaw, Kritzman, and Turkington (2018)

U. “Trading in Crowded Markets,” Gorban, Obizhaeva, and Wang (2018)

V. “The Equilibrium Consequences of Indexing,” Bondy and Garcaz (2018) – not on crowding, but related.

W. “Learning in Crowded Markets,” Kondory and Zawadowskiz (2016)

4. Academic Studies on Crowding

X. “Are Exchange-Traded Funds Harvesting Factor Premiums?” Blitz (2017)

Y. “Managing Risks Beyond Volatility,” Alighanbari, Doole, and Melas (2017)

Z. “Does Herding Behavior Reveal Skill? An Analysis of Mutual Fund Performance,” Jiang and Verardo (2018)

Transaction Costs & Crowding

5. 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?

5. Transaction Costs and Crowding

Methods

- Take typical data for portfolio construction and two reasonable transaction cost models.
- Simulate the creation of many portfolios based on a universe of 2000 stocks.
- Change the asset level of portfolios (since market impact depends on this)
- Examine how transaction costs influence the crowding of portfolios.

5. Transaction Costs and Crowding

Brief Answers

- This evidence doesn't seem to link transaction costs to crowding in quant crisis (unless managers did not explicitly consider them or ignored some constraints)
- Do portfolio managers (not just quants) really consider them explicitly and accurately?
- As a portfolio becomes larger, i.e. $20 million to $5 billion, the portfolio manager must gradually transform to a longer term investment horizon, otherwise violating reasonable constraints.

5. Transaction Costs and Crowding

Several contributions to the literature on crowding and liquidity

- First, it helps to clarify how transaction cost models contribute to crowding in the investment space.

- Second, it introduces a simple method for approximating several varieties of transaction costs that can be used in portfolio optimization. The approximation is very accurate and quite simple to use, and practitioners can use it to model a variety of complex transaction costs within a standard portfolio optimization framework.

5. Transaction Costs and Crowding

A. Empirical Strategy: Generate Alphas

- 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
  - Momentum
  - Beta

5. Transaction Costs and Crowding

A. Empirical Strategy: Construct Portfolios

- **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/ Liquidity. Constraints: Sectors, Beta, Max/Min weights, Dollar Neutral, Leverage=2.
- **Step 4**: Do this for all risk models and all portfolio construction techniques using transaction costs generated form different size portfolios (1B, 5B, and 20B)
- **Step 5**: Compute ex-post crowding of portfolios.

5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – 2 Models for Market Impact

$$tc_{it} = C_{it} + \left|\frac{100 s_{it}/2}{p_{it}}\right| + |c_{it}| \qquad (16)$$

where C_{it} is the percentage commission cost from the trade, s_{it} is the bid-ask spread of stock i at time t, p_{it} is the price of stock i at time t, and c_{it} is the market-impact costs for stock i at time t based on one of the two market impact models. These transaction costs, tc_{it} are in percentage points. Since

5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – Market Impact 1 (Almgren et al)

$$c_{it} = \frac{I}{2} + \mathrm{sgn}(n_{it})\eta\sigma_{it}\left|\frac{n_{it}}{V_{it}T}\right|^{3/5} \quad (14)$$

where $I = \gamma\sigma_{it}\frac{n_{it}}{V_{it}}\left(\frac{N_{it}}{V_{it}}\right)^{1/4}$, $\gamma = 0.314$, $\eta = 0.142$, σ_{it} is the daily volatility of stock return i at the beginning of month t, N_{it} is the total amount of shares outstanding in the security, V_{it} is the average daily trading volume of the stock (shares traded, not dollars traded), sgn() is a function that is -1 if shares are being sold and 1 is shares are being bought, T is the time interval in which the trade takes place in number of days, for this paper we use $T = 1$, and n_{it} represents the number of shares of the security the portfolio is trading.‡

5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – Market Impact 2 (Northfield)

(2015)). This model of market impact is estimated every month by Northfield with dynamically generated parameters for each stock. The model is of the form,

$$c_{it} = B_{it}|n_{it}| + C_{it}|n_{it}|^{0.5} \tag{15}$$

where B_{it} and C_{it} are parameters estimated by Northfield, n_{it} is the number of shares to be purchased for security i in month t, and c_{it} is expressed in terms of percentage price movement.§

5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – Example

For example, for December 2013, take two stocks, AT&T (Ticker Symbol: T), a very liquid stock, and AGL Resources (Ticker Symbol: GAS), a less liquid stock. AT&T for this particular period had a market capitalization of $183 billion, a stock price of $35.16, and a 10-day average daily trading volume of 18,930,000 shares. The spread was 1 cent or a 0.0284% spread. The trading costs in percentage terms for a 1% position in a $500 million portfolio was 0.0232%. That is, a $5 million trade of AT&T representing 142,000 shares would cost the trader $1,160. This does not represent commissions, it is simply the market impact and spread costs. AGL Resources for this particular period had a market capitalization of $5.6 billion, a stock price of $47.23, and a 10-day average daily trading volume of 490,000 shares. The spread was 2 cents or a 0.0423% spread. The trading costs in percentage terms for a 1% position in a $500 million portfolio was 0.1621%. That is, a $5 million trade of AGL Resources representing 105,865 shares would cost the trader $8,105.

5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – Approximation of Tcosts (to fit inside standard model)

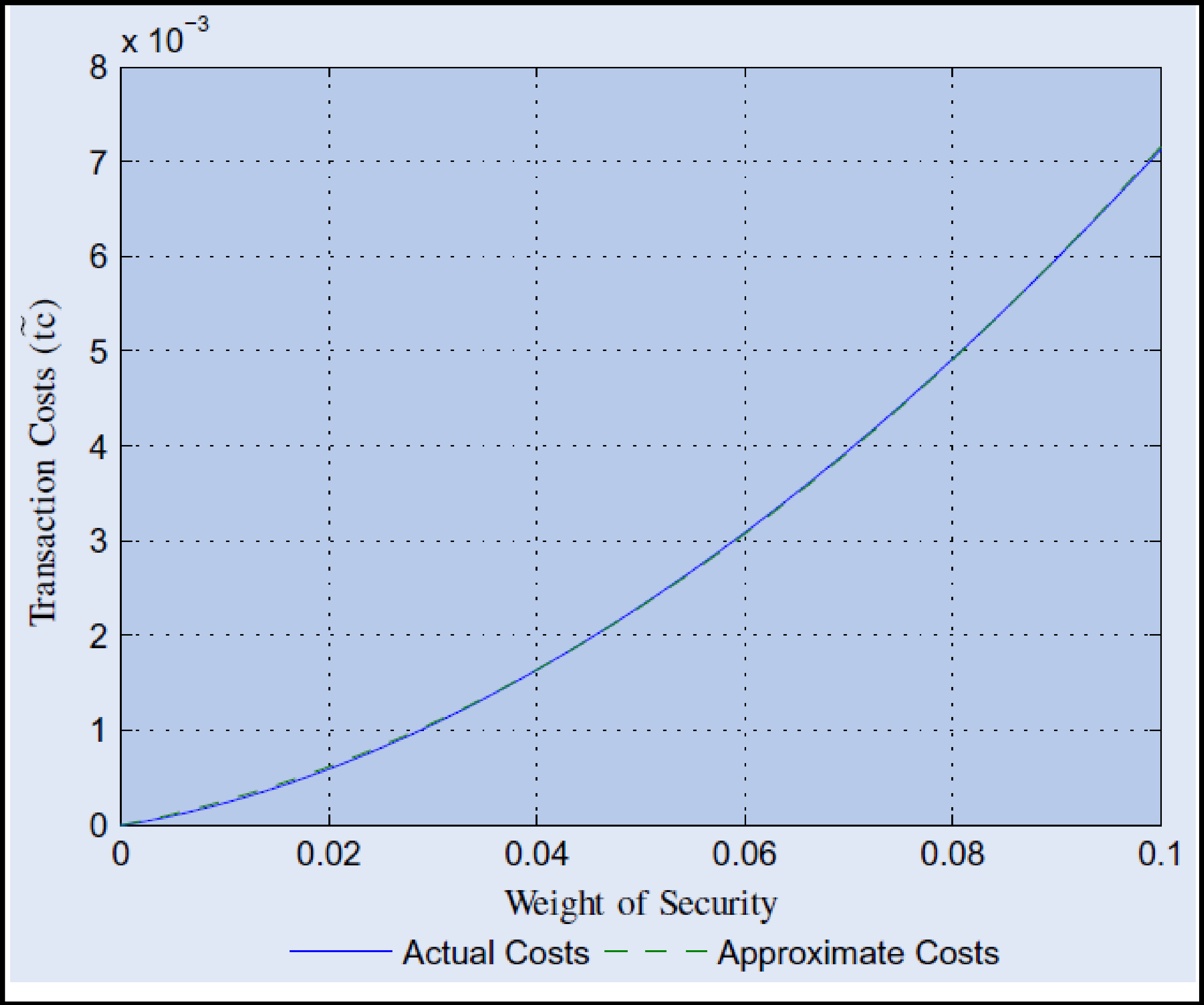
First, the transaction costs are computed for each stock in the portfolio by varying the portfolio weight of each stock from zero to 0.10 (the maximum possible value for any stock in the portfolio) for each net asset level. Second, a regression is run on each stock of the following form:

$$\widetilde{tc}_{it} = a_{it} w_{it} + b_{it} w_{it}^2 \tag{17}$$

where $\widetilde{tc}_{it}$ is a vector of net transaction costs from the transaction model corresponding to each stock's particular weight, a_{it} and b_{it} are parameters estimated from the linear regression.† That is, $\widetilde{tc}_{it}$ represents the percentage transaction cost of each stock multiplied by the stock's weight, w_{it}, representing the net transaction cost impact of each stock at each weight to the entire portfolio.

5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – Approx Method – high R2



5. Transaction Costs and Crowding

A. Empirical Strategy: Transaction Costs – With Approx can fit into standard optimization problem (see Appendix of paper)

$$\min_{\mathbf{x}} \frac{1}{2}\mathbf{x}'\mathbf{Q}\mathbf{x} + \mathbf{x}'\mathbf{c} \quad s.t. \quad \mathbf{A}'\mathbf{x} \leq \mathbf{b} \tag{B1}$$

$$\mathbf{l}'\mathbf{x} + \mathbf{x}'\mathbf{Q}^*\mathbf{x} \leq \mathbf{r} \tag{B2}$$

$$\mathbf{lb} \leq \mathbf{x} \leq \mathbf{ub} \tag{B3}$$

$$\mathbf{A} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ [\,] & & & \end{bmatrix} \tag{B4}$$

$$\mathbf{b} = \begin{bmatrix} 1 \\ [\,] \end{bmatrix} \tag{B5}$$

$$\mathbf{Q} = 2\mathbf{\Sigma} \tag{B6}$$

$$\mathbf{Q}^* = \begin{bmatrix} \hat{\beta}_1 & 0 & \dots & 0 \\ 0 & \hat{\beta}_2 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \hat{\beta}_N \end{bmatrix} \tag{B7}$$

and $\mathbf{l} = -\tilde{\mu}$, $\tilde{\mu} = \mu - \hat{\alpha}$, $\mathbf{c} = \mathbf{0}$, and $r = -\mu^T$, where $\tilde{\mu}$ is a vector of the expected returns of each stock minus the constant estimate in the transaction cost regression, μ is the expected return of each stock, μ^T is the desired target of after transaction costs expected return for the portfolio to match, and $\hat{\beta}_i$ is the coefficient estimate from the transaction cost regression for stock i.

5. Transaction Costs and Crowding

A. Empirical Strategy: Measuring Crowding

1. Cosine Similarity amongst portfolios.

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

$$S = \left(H'H\right) \circ \hat{\hat{H}}$$

2. Crowding

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

3. Ratio of Crowding Before and After Construction

$$\Omega = \frac{\sum_{i=1}^{m} \sum_{j=1}^{m} S_{p:i,j} - m}{\sum_{i=1}^{m} \sum_{j=1}^{m} S_{\alpha:i,j} - m}$$

5. Transaction Costs and Crowding

A. Empirical Strategy: Another Measure?

4. Correlation Adjusted Crowding

$$C^* = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} S^*_{p:i,j} - m}{m^2 - m}$$

Question: Any insights???

$$S^* = (H'CCH) \circ \bar{\bar{H}} \tag{44}$$

where $\circ$ represents the Hadamard product or the element-by-element multiplication of the matrices, and

$$\bar{\bar{H}} = \begin{bmatrix} \frac{1}{\bar{h}_{11}} & \frac{1}{\bar{h}_{12}} & \cdots & \frac{1}{\bar{h}_{1M}} \\ \ldots & \ldots & \ldots & \ldots \\ \frac{1}{\bar{h}_{M1}} & \frac{1}{\bar{h}_{M2}} & \cdots & \frac{1}{\bar{h}_{MM}} \end{bmatrix} \tag{45}$$

and $\bar{H} = |C'H||CH|$, where $||$ contains the Euclidean norm of each manager's correlation-adjusted weight vector, H is the manager holdings matrix, and C is the correlation matrix of securities.

5. Transaction Costs and Crowding

B. Results

Table 2. Summary of crowding from random alpha models and transaction costs from March 2009 to 2013.

	Risk model 1						Risk model 2						Risk model 3					
	C	Omega	SR	Max	Min	$\bar{N}$	C	Omega	SR	Max	Min	$\bar{N}$	C	Omega	SR	Max	Min	$\bar{N}$
Alpha	0.00																	
Long-only																		
MN NTC	−0.00	27.11	−42.646	0.006	−0.006	747	−0.00	55.14	−60.02	0.008	−0.008	731	−0.00	62.98	−32.70	0.008	−0.01	736
LONG NTC	0.37	−19958.74	−1.123	0.090	0.000	44	0.41	−24910.52	−8.03	0.087	0.000	48	0.39	−21522.80	−4.13	0.092	0.00	46
Port. Size ($500M)																		
MN TC1	−0.00	26.23	−7.132	0.007	−0.008	663	−0.00	27.70	−6.66	0.009	−0.009	652	−0.00	57.83	−6.51	0.010	−0.01	652
LONG TC1	0.32	−17843.58	0.794	0.090	0.000	50	0.27***	−16434.66	0.32	0.085	0.000	66	0.31**	−16026.43	0.53	0.091	0.00	56
Port. Size ($5B)																		
MN TC1	−0.00	26.74	−14.669	0.009	−0.009	594	−0.00	19.87	−13.70	0.012	−0.012	588	−0.00	51.50	−13.61	0.012	−0.01	586
LONG TC1	0.29***	−15581.70	0.167	0.088	0.000	77	0.25***	−13758.30	−0.08	0.082	0.000	106	0.27***	−14462.44	−0.04	0.088	0.00	92
Port. Size ($20B)																		
MN TC1	−0.00	40.62	−22.275	0.013	−0.013	122	−0.00	27.97	−20.73	0.015	−0.016	503	−0.00	45.28	−21.27	0.015	−0.02	502
LONG TC1	0.38	−6862.70	−0.491	0.082	0.000	122	0.32***	−7217.42	−0.66	0.075	0.000	159	0.36	−6539.03	−0.66	0.082	0.00	144
Port. Size ($500M)																		
MN TC2	−0.00	29.83	−7.346	0.007	−0.007	655	−0.00	45.16	−6.44	0.009	−0.009	644	−0.00	60.42	−6.73	0.010	−0.01	644
LONG TC2	0.34	−17964.16	0.960	0.091	0.000	43	0.33***	−20577.48	0.51	0.088	0.000	47	0.33	−16635.14	0.80	0.093	0.00	44
Port. Size ($5B)																		
MN TC2	−0.00	28.76	−13.438	0.009	−0.009	591	−0.00	30.47	−11.91	0.011	−0.011	583	−0.00	58.93	−12.31	0.011	−0.01	581
LONG TC2	0.30**	−16088.35	0.558	0.091	0.000	45	0.27***	−16026.43	0.06	0.086	0.000	52	0.28***	−14002.91	0.30	0.092	0.00	47
Port. Size ($20B)																		
MN TC2	−0.00	28.39	−19.124	0.010	−0.010	513	−0.00	1.88	−17.08	0.013	−0.013	506	−0.00	56.05	−17.56	0.014	−0.01	506
LONG TC2	0.26***	−14485.43	0.157	0.091	0.000	49	0.22***	−12348.61	−0.25	0.086	0.000	59	0.24***	−13175.77	−0.12	0.091	0.00	53

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.

5. Transaction Costs and Crowding

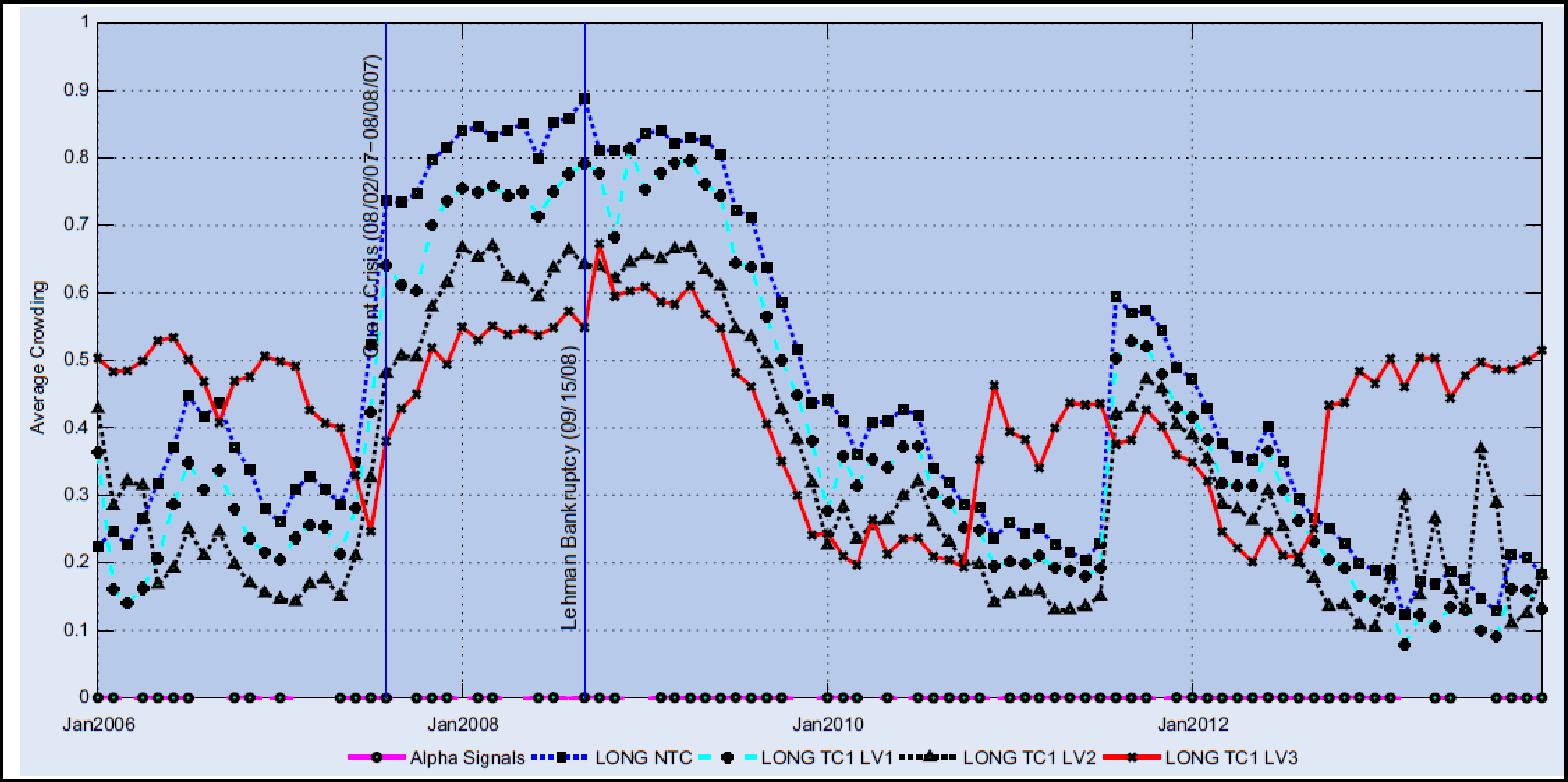
B. Results

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.

5. Transaction Costs and Crowding

Results



5. Transaction Costs and Crowding

C. Future Research

1. There are many extensions to this paper including size of stock universe and ratio of portfolio size to average volume in the universe.

2. Also relationship between size of portfolio and type of strategy available. For example, larger portfolio may force horizon of investor to change.

5. Transaction Costs and Crowding
Summary

- If you would like copies of the published papers, I can send them to you (or check www.ludwigbc.com). **Please give me your card after the talk**.

- Chincarini, Ludwig B. "Transaction Costs and Crowding". *Quantitative Finance, 2017*

- Bruno, Salvatore, Chincarini, Ludwig B., and Frank Ohara. "Portfolio Construction and Crowding." *Journal of Empirical Finance, 2018*

Crowded Thoughts

6. Crowded Thoughts

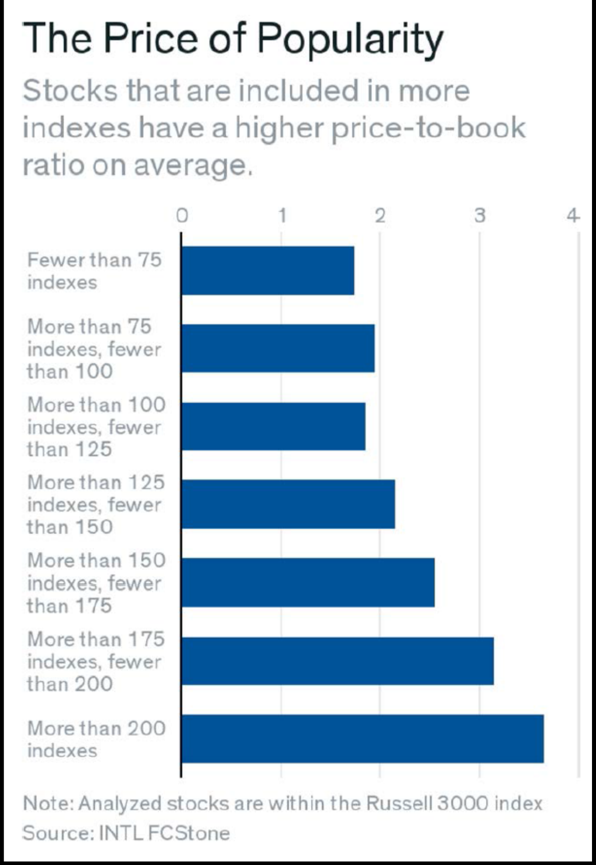
A. More studies showing that crowded space lead to inferior returns.

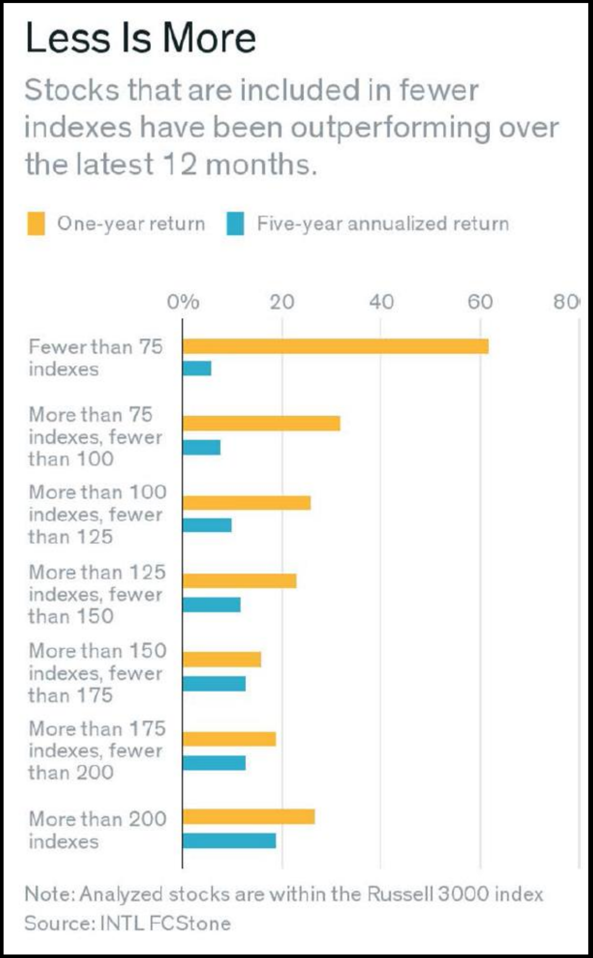
Our new, dynamic measure of fund-level herding captures the tendency of fund managers to follow the trades of the institutional crowd. We find that herding funds underperform their antiherding peers by over 2% per year. Differences in

skill drive this performance gap: Antiherding funds make superior investment decisions even on stocks not heavily traded by institutions, and can anticipate the trades of the crowd… Jiang and Verrado (2018)

6. Crowded Thoughts

A. More studies showing that crowded space lead to inferior returns.





Source: Barrons 08/16/2018

7. Crowded Thoughts

B. Crowding in Other Markets? Oil Market (Chincarini & Moneta (2018)

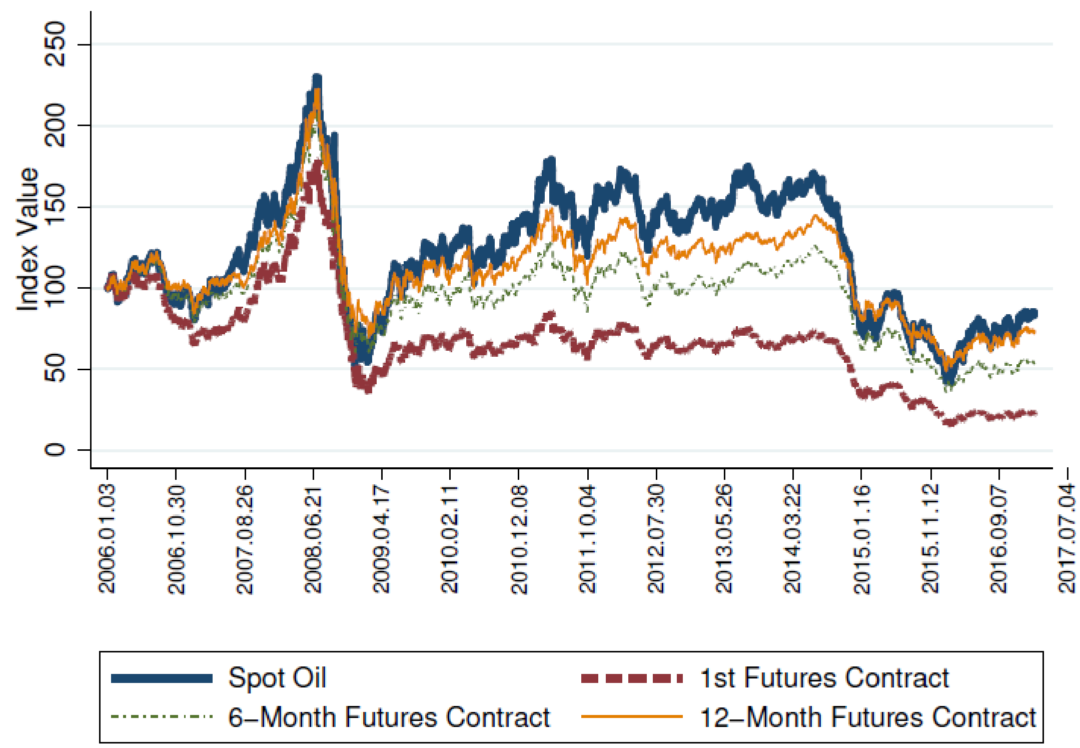


Figure 1: Indices of Oil Futures with Varying Rolls and Spot Oil. This figure shows the cumulative returns of investing in spot oil and three rolling futures contracts; the 1-month, 6-month, and 12-month futures contracts. The strategy rolls futures on the expiration date at closing futures prices. All indices start at 100.

7. Crowded Thoughts

B. Crowding in Other Markets? Oil Market

Table 2: Summary Statistics about Contango and Backwardation in the Oil Market

Strategy	Contango (%) Mean	Median	S.D.	Max	Min	Days	nobs	Avg. Volume
Investment Period: 1994 - December 2005								
Fut1Roll0	-2.43	-0.53	54	5.63	-24.11	42	3001	67242
Fut2Roll0	-4.46	-2.28	15	0.95	-1.32	42	3001	43821
Fut6Roll0	-5.62	-5.44	11	0.39	-0.59	31	3001	2488
Fut12Roll0	-5.34	-5.34	9	0.22	-0.31	28	3001	640
Investment Period: 2006 - February 10, 2017								
Fut1Roll0	2.10	0.36	16	1.99	-3.52	56	2797	298998
Fut2Roll0	7.03	4.34	12	1.34	-0.53	82	2797	135657
Fut6Roll0	5.10	4.59	8	0.54	-0.17	77	2797	14461
Fut12Roll0	3.07	3.19	6	0.29	-0.11	74	2797	4190

Note: The table presents the various statistics with respect to the contango in the futures market. For each futures contract, the first number indicates the specific futures contract, either 1, 2, 6, or 12 depending on whether the nearest-term, 2nd, 6th, or 12th contract is used. The second number represents the roll date. Thus, a "0" indicates the contract was theoretically rolled on the expiration date. Mean represents the annualized mean daily contango in percentage terms for the particular contract and roll. Median represents the annualized median contango, S.D. represents the standard deviation of daily contango annualized by multiplying by $\sqrt{250}$ in percentage terms, Max and Min represent the maximum and minimum annualized daily contango. Days represents the percentage of days that the market is in contango as opposed to backwardation. nobs represents the number of daily observations used for the calculations, and Avg. Volume represents the average daily volume of the representative contracts. Contango is calculated daily as $C^{i}_{t,d} = F^{i}_{t,d,m} - F^{*}_{t,d,d}$, where a positive value indicates contango and a negative value indicates backwardation in the market.

7. Crowded Thoughts

B. Crowding in Other Markets? Oil Market (Preliminary results)

Table 11: Returns of Futures Conditional on Crowding at time t

Decile	Return of 1st Futures minus Spot				Return of 2nd Futures minus Spot				Return of Average Futures minus Spot			
	1w	1m	3m	6m	1w	1m	3m	6m	1w	1m	3m	6m
Net Concentration of Four Major Players												
Lowest	0.004	0.018	0.063	0.132	0.004	0.017	0.060	0.121	0.005	0.019	0.060	0.124
	(1.410)	(3.245)	(6.410)	(8.705)	(1.556)	(3.285)	(6.762)	(8.658)	(2.306)	(4.992)	(8.893)	(10.088)
2	-0.003	-0.004	-0.005	0.021	-0.002	-0.001	-0.004	0.018	-0.002	0.000	0.005	0.024
	(-0.935)	(-0.556)	(-0.462)	(1.323)	(-0.902)	(-0.179)	(-0.367)	(1.215)	(-0.824)	(0.056)	(0.540)	(1.976)
3	0.005	0.008	0.043	0.077	0.005	0.008	0.037	0.063	0.004	0.008	0.030	0.052
	(1.456)	(1.430)	(4.213)	(4.692)	(1.724)	(1.548)	(3.851)	(4.237)	(1.812)	(1.797)	(3.663)	(4.152)
4	0.004	0.020	0.049	0.059	0.003	0.017	0.041	0.048	0.003	0.015	0.040	0.053
	(1.325)	(2.979)	(3.953)	(2.929)	(0.950)	(2.765)	(3.677)	(2.680)	(1.103)	(3.175)	(4.365)	(3.565)
Highest	-0.000	-0.001	-0.010	0.001	-0.001	-0.004	-0.011	0.004	-0.000	-0.002	-0.003	0.021
	(-0.012)	(-0.080)	(-0.651)	(0.058)	(-0.175)	(-0.554)	(-0.856)	(0.224)	(-0.017)	(-0.310)	(-0.328)	(1.471)
Low-High	0.004	0.019	0.073	0.131	0.005	0.021	0.071	0.117	0.005	0.020	0.063	0.103
	(0.906)	(2.054)	(4.147)	(5.161)	(1.147)	(2.474)	(4.554)	(5.254)	(1.359)	(3.050)	(5.078)	(5.541)
Volume / Open Interest												
Lowest	0.005	0.016	0.063	0.098	0.005	0.011	0.054	0.089	0.004	0.008	0.043	0.074
	(1.684)	(2.656)	(5.357)	(5.146)	(1.597)	(2.040)	(5.248)	(5.372)	(1.853)	(2.109)	(5.541)	(5.793)
2	-0.001	-0.001	0.012	0.062	-0.000	0.002	0.013	0.062	-0.000	0.003	0.017	0.061
	(-0.450)	(-0.247)	(1.068)	(3.626)	(-0.129)	(0.343)	(1.419)	(4.222)	(-0.021)	(0.900)	(2.366)	(5.282)
3	0.003	0.023	0.054	0.095	0.004	0.022	0.049	0.087	0.004	0.020	0.049	0.090
	(1.095)	(4.147)	(5.161)	(5.718)	(1.298)	(4.119)	(4.943)	(5.630)	(1.668)	(4.869)	(5.773)	(6.690)
4	0.001	-0.003	0.004	0.032	0.000	-0.003	0.002	0.020	0.001	-0.000	0.009	0.033
	(0.200)	(-0.392)	(0.282)	(1.791)	(0.046)	(-0.512)	(0.159)	(1.259)	(0.237)	(-0.022)	(0.898)	(2.349)
Highest	0.003	0.007	0.007	0.001	0.001	0.006	0.004	-0.005	0.002	0.008	0.014	0.016
	(0.749)	(0.943)	(0.539)	(0.059)	(0.429)	(0.878)	(0.373)	(-0.332)	(0.631)	(1.476)	(1.355)	(1.072)
Low-High	0.002	0.010	0.056	0.097	0.003	0.006	0.050	0.094	0.002	0.000	0.029	0.058
	(0.517)	(1.024)	(3.226)	(3.722)	(0.712)	(0.649)	(3.174)	(4.044)	(0.607)	(0.049)	(2.322)	(2.995)
Net Non-Commercial Positions / Open Interest												
Lowest	0.004	0.012	0.039	0.057	0.004	0.011	0.037	0.057	0.002	0.008	0.028	0.052
	(1.345)	(1.680)	(2.846)	(2.848)	(1.311)	(1.802)	(3.099)	(3.395)	(1.063)	(1.651)	(3.104)	(4.148)
2	0.003	0.019	0.033	0.077	0.002	0.015	0.023	0.060	0.003	0.014	0.027	0.068
	(0.976)	(2.788)	(2.491)	(3.885)	(0.643)	(2.331)	(1.930)	(3.388)	(1.080)	(2.657)	(2.651)	(4.477)
3	0.006	0.022	0.067	0.129	0.006	0.020	0.060	0.114	0.006	0.020	0.061	0.114
	(1.860)	(3.475)	(6.394)	(7.985)	(2.087)	(3.476)	(6.254)	(7.742)	(2.364)	(4.459)	(7.649)	(9.163)
4	-0.001	0.002	0.057	0.119	-0.001	0.004	0.058	0.114	0.001	0.007	0.057	0.109
	(-0.340)	(0.409)	(6.288)	(8.431)	(-0.222)	(0.751)	(6.882)	(8.903)	(0.223)	(1.704)	(8.267)	(9.987)
Highest	-0.003	-0.014	-0.061	-0.106	-0.002	-0.013	-0.059	-0.104	-0.001	-0.009	-0.045	-0.081
	(-1.006)	(-2.480)	(-6.170)	(-8.102)	(-0.924)	(-2.443)	(-6.133)	(-8.046)	(-0.645)	(-2.032)	(-5.484)	(-7.268)
Low-High	0.007	0.025	0.101	0.163	0.006	0.024	0.096	0.161	0.004	0.017	0.072	0.133
	(1.676)	(2.843)	(5.849)	(6.671)	(1.596)	(2.943)	(6.229)	(7.451)	(1.210)	(2.600)	(5.977)	(7.849)

Thank you

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