Crowding and Tail Risk in Momentum Returns

Pedro Barroso[1] Roger M. Edelen[2] Paul Karehnke[3]

[1]Universidade Católica Portuguesa

[2]Virginia Tech

[3]ESCP Business School

Conseil Scientifique de l'AMF - Séance du 2 février 2022

Is arbitrage destabilizing for financial markets?

"People who have argued that speculation can be destabilizing seldom realize that this is largely equivalent to saying that speculators lose money, since speculation can be destabilizing in general only if speculators sell when the currency is low in price and buy when it is high."
(Friedman, 1953, p. 175)

Arbitrage with crowding

- Crowding: inability to observe in real time how many peers are following the same strategy.
- Abreu and Brunnermeier (2003)
  Due to incomplete information about the action of peers, arbitrageurs may ride a bubble (destabilize) rather than trade against it (stabilize).
- Stein (2009)
  Crowding can induce arbitrageurs to push prices away from fundamental value.

Growing interest in crowding

- Firms have started to provide tools to institutional investors to identify the crowdedness of a trade.
  - Examples: MSCI crowding scores, Novus Crowding Index.

- Crowded trades are conjectured to have played an important role in crashes such as the ‘quant meltdown’ of 2007 (Khandani and Lo, 2007; Pedersen, 2009).

Momentum

- Momentum strategy:
  Buy winner stocks (i.e., stocks that have performed well over the past year) and sell looser stocks (i.e., stocks that have performed poorly over the past year).
  - Documented for US equity returns (Levy, 1967; Jegadeesh and Titman, 1993), most other countries (Rouwenhorst, 1998) and asset classes (Asness et al., 2013).
  - Related to gradual diffusion of information.
- A large body of literature shows that institutional investors are momentum traders (Lewellen, 2011; Edelen et al., 2016).
- Momentum has been a very profitable investment strategy but it is also known to be subject to infrequent and substantial crashes (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016).

We ask:

- What role does unknown competition in the momentum strategy — "crowding" — play in momentum crashes?

We ask:

- What role does unknown competition in the momentum strategy — "crowding" — play in momentum crashes?
- Several authors argue *indirectly* that it may be causal.

  $\Longrightarrow$ Hypothesis: Crowding-induced tail risk.

We ask:

- What role does unknown competition in the momentum strategy — "crowding" — play in momentum crashes?
- Several authors argue *indirectly* that it may be causal.

  $\Longrightarrow$ Hypothesis: Crowding-induced tail risk.

- We *directly* examine this hypothesis.
  - Theoretically: with a model of momentum trading and inability to observe momentum capital.
  - Empirically: using 13f holdings data to directly proxy for institutional momentum trading.

We find:

Theory

- Crowding-induced momentum crashes can arise when momentum investors follow linear trading strategies that ignore feedback effects.
- When momentum traders instead follow nonlinear trading strategies that account for possible feedback effects, no momentum crashes arise.
- In both cases, momentum returns negatively relate to crowd size.

Empirics

- Crowding negatively predicts the first moment.
- Consistent with the model's prediction under rational beliefs, crowding does not seem to predict tail risk.

Theory

Our theoretical setting

Initial conditions

- Homogeneous information; everybody holds the market.
- Three investor types: informed, momentum, and counterparty. All are risk averse and capital constrained.
- Three stock types: winner; loser; or neutral.

Two periods

- Portfolio formation period
  - Informed investors observe noisy signal of all stocks' type.
  - Market clears in a call auction.
- Evaluation period
  - Stock values are realized.
  - Information and holdings revert to a homogeneous state.

Investors

- **Informed investors**
  - Observe private signal of dividends for winners ($\delta/2$) and losers (-$\delta/2$).
  - Realized dividends add a noise component, ϵ;
    $\Rightarrow$ Informed leave some expected value on the table.

- **Momentum investors**
  - No private signals, but form $E_M(\delta|f)$ conditioning on f, the formation-period return differential, winners minus losers;
    $\Rightarrow$ Pick up some of the value informed investors leave behind.

Investors

- **Informed investors**
  - Observe private signal of dividends for winners ($\delta/2$) and losers ($-\delta/2$).
  - Realized dividends add a noise component, ϵ;
    $\Rightarrow$ Informed leave some expected value on the table.

- **Momentum investors**
  - No private signals, but form $E_M(\delta|f)$ conditioning on f, the formation-period return differential, winners minus losers;
    $\Rightarrow$ Pick up some of the value informed investors leave behind.

We refer to

- δ as the "fundamental value" and
  f as the "price" of the momentum portfolio.
- $m = \delta - f$ is the momentum return (disregarding ϵ)

key variables

Investors

- Third investor type: **Counterparty investors**
  - Myopic beliefs: trade against deviation from historical value.
  - Essentially noise traders who facilitate market clearing.

Preferences and the investment opportunity set

- CRRA
  - Risk capacity proportional to wealth.
  - Essentially treat every dollar equally to give content to crowding.

Preferences and the investment opportunity set

- CRRA
  - Risk capacity proportional to wealth.
  - Essentially treat every dollar equally to give content to crowding.
- Three assets:
  - Market portfolio
  - **Momentum portfolio** $\longleftarrow$ *what we care about*
  - A risk-free investment.

Demands

- Investor i's demand for the momentum portfolio is

$$\frac{E_{type(i)}\left[m+\epsilon\right]}{\gamma Var_{type(i)}\left[m+\epsilon\right]}K_i.$$

Demands

- Investor i's demand for the momentum portfolio is

$$\frac{E_{type(i)}\left[m+\epsilon\right]}{\gamma Var_{type(i)}\left[m+\epsilon\right]}K_i.$$

- Beliefs of the three investor types:

$$\begin{aligned}
E_I\left[m|\delta,f\right] &= \delta - f, & Var_I\left[m|\delta,f\right] &= \sigma_\epsilon^2;\\
E_M\left[m|f\right] &= \delta^E - f, & Var_M\left[m|f\right] &= \delta^V + \sigma_\epsilon^2;\\
E_C\left[m|f\right] &= -f, & Var_C\left[m|f\right] &= \sigma_\delta^2 + \sigma_\epsilon^2.
\end{aligned}$$

- Solve for Momentum investors' beliefs.

(δ^E & δ^V: shorthand for momentum expectation and variance)

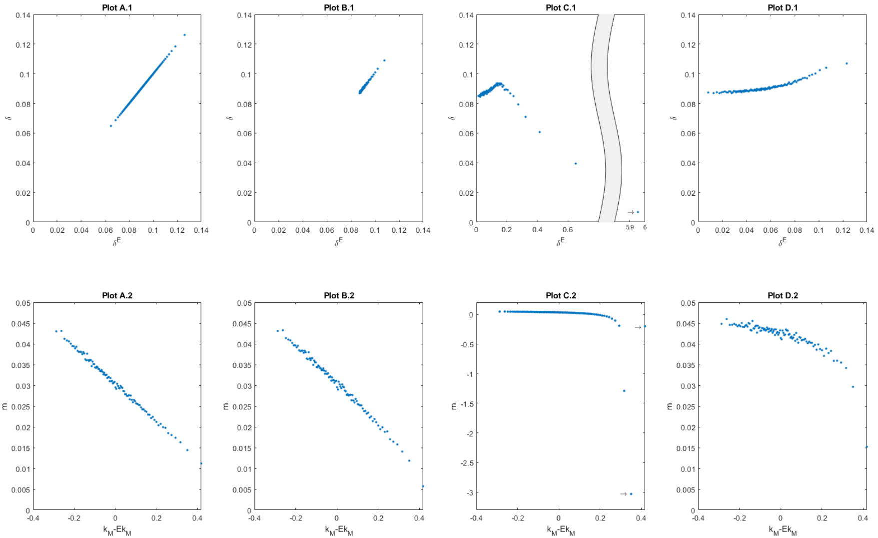
Market clearing

We consider four cases for momentum investors' beliefs.

- **Known capital** (yields linear beliefs)
- **Rational beliefs**:
  Conjecture a relation between f and δ that generates demands that cause f to relate to δ as conjectured.
- **Myopic beliefs**:
  Unknown capital, but that uncertainty is ignored
  (follow a linear strategy, as above)
- **Optimal linear**:
  Grid search over linear slopes to maximize the average utility in 100,000 simulations.

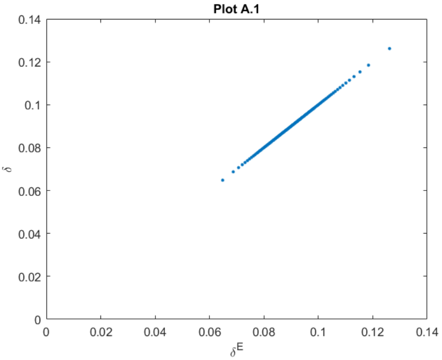
Plot actual δ vs. beliefs... 100,000 simulations

Known capital | Rational beliefs | Myopic beliefs | Optimal linear



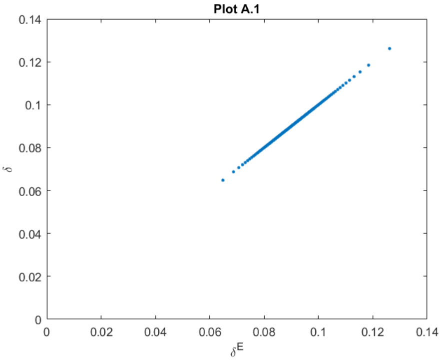
Plot actual δ vs. beliefs... 100,000 simulations

Known capital

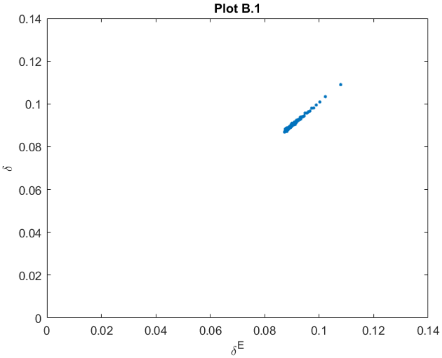


Plot actual δ vs. beliefs... 100,000 simulations

Known capital

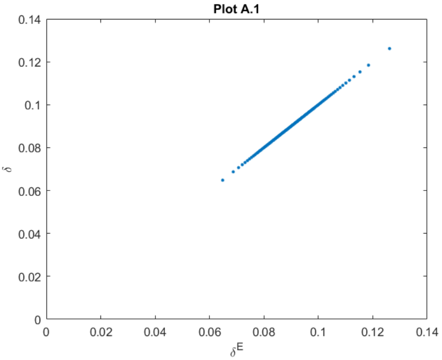


Rational beliefs



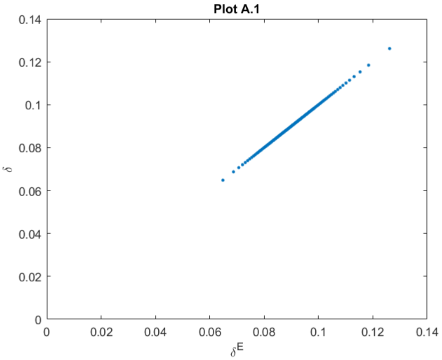
Plot actual δ vs. beliefs... 100,000 simulations

Known capital

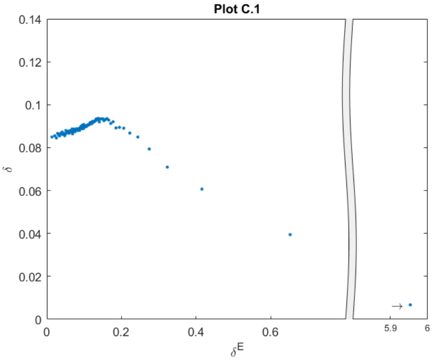


Plot actual δ vs. beliefs... 100,000 simulations

Known capital

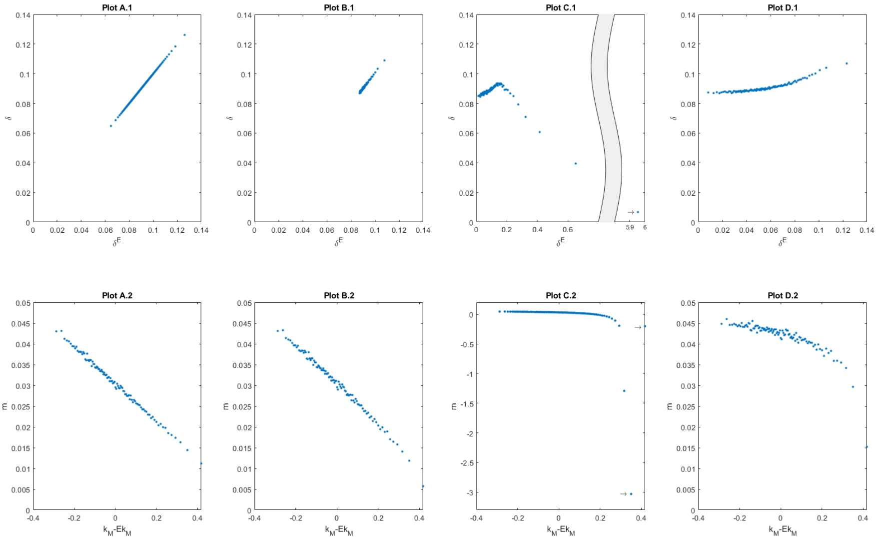


Myopic beliefs



Plot actual δ vs. beliefs... 100,000 simulations

Known capital | Rational beliefs | Myopic beliefs | Optimal linear



Simulated momentum returns

Belief spec.	known	rational	myopic	optimal linear
λ^{-1}			1.50	1.12
Expected momentum returns m				
mean	3.0%	3.0%	-2.4%	4.2%
stdev	1.4%	1.6%	174.2%	2.0%
skew	0.6	0.4	-151.3	-0.3
kurt	3.1	3.0	29218.7	10.8
min	0.05%	-2.55%	-38957.17%	-53.10%
max	10.26%	11.53%	13.16%	13.28%
Realized momentum returns $m + \epsilon$				
mean profit	3.65%	3.44%	-4863.08%	0.65%
cer(2)	2.62%	2.53%	-100.00%	0.74%
cer(4)	1.30%	1.25%	-100.00%	0.37%
cer(10)	0.52%	0.50%	-100.00%	0.15%

Model conclusions

- There is a theoretical basis for crowding-induced momentum crashes...

  ...if and only if momentum investors hold myopic beliefs.

- Momentum returns negatively relate to realized crowd size.

Empirical analysis

Proxies for momentum investing from 13f data

- Quarterly portfolio holdings data from 6,360 institutions in the period of 1980-2015.
  - Source: Form 13f that all institutional investment managers with at least \$100 million in assets under management are required to file.

- Following Grinblatt et al. (1995) we calculate the following score:

$$\mathtt{SCORE}_{i,q} = \sum_{j=1}^{J} (\omega_{i,j,q} - \omega_{i,j,q-1})\, r_{j,q-1}, \tag{1}$$

  where $r_{j,q}$ is the quarter q return on stock j and ω is a relative portfolio weight computed holding prices fixed.
- Institution i is a momentum investor in quarter q if it has a positive SCORE from equation (1) in each quarter $q-3$ through q.
  $\Rightarrow$ We denote this $\mathbb{1}_{\mathtt{MOM}_{i,q}}$, where $\mathbb{1}$ is the indicator function.

Transition probabilities: Momentum investors and stocks

Institutions' type					
	probabilities			likelihood	
	$q+1$	$q+4$	All q	$q+1$	$q+4$
$\texttt{SCORE}_{i,q} = 1$	0.54	0.54	0.45	1.20	1.19
$\mathbb{1}_{\texttt{MOM}_{i,q}} = 1$	0.71	0.34	0.10	7.05	3.32

Stock returns							
	$q+1$			$q+4$			All q
	Win	mid	Los	Win	mid	Los	
Winner	0.56	0.42	0.02	0.16	0.60	0.23	0.13
mid	0.08	0.82	0.09	0.12	0.74	0.14	0.67
Loser	0.02	0.33	0.65	0.17	0.52	0.31	0.19

$\Rightarrow$ Momentum type persists; more than the underlying momentum stock classification.

Momentum crowd

- We focus on three measures of crowd size (i.e., proxies for k_M):
  - `CNT`: (relative) number of institutions following a momentum strategy.
  - `AUM`: relative assets under management of momentum institutions.
  - `TRD`: trading (more precisely, quarterly change in holdings) of momentum institutions.
- Presentation focuses on these measures computed at the factor-level; results using security level measures are in paper and very similar.

Crowding and momentum returns

- Three specifications of the crowding variables:
  - $\Delta\texttt{CROWD}_q$ is the change in the variable.
  - $\texttt{CROWD}_{q\text{-}1}$ is the level of the variable.
  - $\texttt{CROWD\_EVOL}_q$ is the GARCH(1,1) volatility of residual crowding.
- We control for known predictors of momentum returns:
  - Dynamic betas (Grundy and Martin, 2001).
  - Momentum's volatility computed with daily returns in the previous quarter (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016).

Crowding and momentum returns

The dependent variable is the quarterly return of momentum.

Model:	cumulative returns			dynamic FF3		
Crowding measure:	AUM	TRD	CNT	AUM	TRD	CNT
ΔCROWD$_q$	-0.19*	-0.33	-0.29	-0.21***	-0.34*	-0.33*
	(-1.94)	(-1.51)	(-1.36)	(-2.64)	(-1.94)	(-1.84)
CROWD$_{q\text{-}1}$	-0.23***	-0.44**	-0.50***	-0.24***	-0.34*	-0.58***
	(-3.83)	(-2.10)	(-3.39)	(-4.32)	(-1.87)	(-4.35)
CROWD_EVOL$_q$	2.79*	2.21	4.55**	3.06**	2.30	6.60***
	(1.83)	(1.06)	(2.27)	(2.47)	(1.31)	(3.75)
Realized vol.	-0.29	-0.31*	-0.30	-0.27***	-0.28**	-0.25**
of Mom rets.	(-1.61)	(-1.75)	(-1.56)	(-2.62)	(-2.54)	(-2.21)
Adj-rsquare	16.6%	9.0%	12.0%	40.7%	31.8%	37.7%

The controls for the dynamic FF3 are not tabulated.

Predicting momentum crashes

The table contains the coefficients of probit models for the chance of a crash (5% and 10% left tails).

Tail:	5% left tail			10% left tail		
Crowding measure:	AUM	TRD	CNT	AUM	TRD	CNT
$\Delta\mathtt{CROWD}_q$	8.4	12.3	19.2	11.7**	6.7	16.5
	(1.49)	(1.15)	(1.17)	(2.40)	(0.71)	(1.32)
$\mathtt{CROWD}_{q\text{-}1}$	7.2	14.4	24.5*	10.4***	15.4	21.6**
	(1.55)	(1.00)	(1.79)	(2.68)	(1.25)	(2.22)
$\mathtt{CROWD\_EVOL}_q$	-1.4	43.2	-213.3	-11.3	20.7	-187.7
	(-0.02)	(0.41)	(-1.09)	(-0.17)	(0.23)	(-1.35)
Realized vol.	10.1***	9.9***	10.8***	11.5***	11.6***	11.6***
of Mom rets.	(3.22)	(3.18)	(3.10)	(3.96)	(3.60)	(3.78)

Predicting momentum crashes

The table contains the coefficients of probit models for the chance of a crash (5% and 10% left tails). Square brackets indicate Wald test for difference in tails [p-values].

Tail:	5% left tail			10% left tail		
Crowding measure:	AUM	TRD	CNT	AUM	TRD	CNT
ΔCROWD$_q$	8.4	12.3	19.2	11.7**	6.7	16.5
	(1.49)	(1.15)	(1.17)	(2.40)	(0.71)	(1.32)
	[0.35]	[0.92]	[0.60]	[0.25]	[0.57]	[0.91]
CROWD$_{q\text{-}1}$	7.2	14.4	24.5*	10.4***	15.4	21.6**
	(1.55)	(1.00)	(1.79)	(2.68)	(1.25)	(2.22)
	[0.86]	[0.81]	[0.98]	[0.35]	[0.66]	[0.93]
CROWD_EVOL$_q$	-1.4	43.2	-213.3	-11.3	20.7	-187.7
	(-0.02)	(0.41)	(-1.09)	(-0.17)	(0.23)	(-1.35)
	[0.29]	[0.43]	[0.48]	[0.14]	[0.30]	[0.92]
Realized vol. of Mom rets.	10.1***	9.9***	10.8***	11.5***	11.6***	11.6***
	(3.22)	(3.18)	(3.10)	(3.96)	(3.60)	(3.78)
	[0.00]***	[0.00]***	[0.00]***	[0.00]***	[0.00]***	[0.00]***

⇒ Only “Realized vol. of Mom rets” predicts the left tail reliably.

Higher moments of momentum returns: Tercile portfolios, sort on [column header], T1 low

	CROWD			ΔCROWD			Realized vol. of Mom rets.
	AUM	TRD	CNT	AUM	TRD	CNT	
Volatility							
T1	23.8	25.7	32.3	26.0	27.0	25.7	15.3
T2	28.0	22.3	26.8	20.7	26.4	26.3	17.4
T3	25.8	29.5	16.5	30.2	24.6	25.9	38.3
	(0.40)	(0.74)	(-3.63)***	(0.77)	(-0.51)	(0.04)	(5.62)***
Skewness							
T1	-1.8	-1.5	-1.7	-1.8	-1.5	-1.8	-0.3
T2	-1.6	-0.7	-1.1	-0.5	-1.6	-1.2	-0.3
T3	-1.1	-1.8	-0.6	-1.5	-1.4	-1.5	-1.2
	(0.57)	(-0.26)	(1.83)*	(0.25)	(0.03)	(0.24)	(-2.06)**
Kurtosis							
T1	14.6	10.8	10.6	15.1	9.5	15.4	4.0
T2	11.5	4.9	8.1	5.8	13.6	9.0	4.0
T3	8.9	12.6	4.7	9.2	11.2	10.5	6.7
	(-1.11)	(0.37)	(-2.77)***	(-1.32)	(0.40)	(-0.97)	(2.29)**

Higher moments of momentum returns: Tercile portfolios, sort on [column header], T1 low

	CROWD			ΔCROWD			Realized vol. of Mom rets.
	AUM	TRD	CNT	AUM	TRD	CNT	
Volatility							
T1	23.8	25.7	32.3	26.0	27.0	25.7	15.3
T2	28.0	22.3	26.8	20.7	26.4	26.3	17.4
T3	25.8	29.5	16.5	30.2	24.6	25.9	38.3
	(0.40)	(0.74)	(-3.63)***	(0.77)	(-0.51)	(0.04)	(5.62)***
Skewness							
T1	-1.8	-1.5	-1.7	-1.8	-1.5	-1.8	-0.3
T2	-1.6	-0.7	-1.1	-0.5	-1.6	-1.2	-0.3
T3	-1.1	-1.8	-0.6	-1.5	-1.4	-1.5	-1.2
	(0.57)	(-0.26)	(1.83)*	(0.25)	(0.03)	(0.24)	(-2.06)**
Kurtosis							
T1	14.6	10.8	10.6	15.1	9.5	15.4	4.0
T2	11.5	4.9	8.1	5.8	13.6	9.0	4.0
T3	8.9	12.6	4.7	9.2	11.2	10.5	6.7
	(-1.11)	(0.37)	(-2.77)***	(-1.32)	(0.40)	(-0.97)	(2.29)**

⇒ High CROWD followed by lower vol, less left-skew & less kurtosis

Crowding and momentum volatility

Dependent variable is realized volatility of momentum returns or residuals from the dynamic FF3 model.

Model:	raw returns			dynamic FF3 residuals		
Crowding measure:	AUM	TRD	CNT	AUM	TRD	CNT
$\Delta\mathtt{CROWD}_q$	0.06	-0.04	-0.06	0.03	-0.10	-0.05
	(0.84)	(-0.21)	(-0.40)	(0.65)	(-0.72)	(-0.51)
$\mathtt{CROWD}_{q\text{-}1}$	-0.04	-0.15	-0.05	-0.06**	-0.18*	-0.10
	(-1.37)	(-1.32)	(-0.46)	(-2.24)	(-1.82)	(-1.21)
$\mathtt{CROWD\_EVOL}_q$	-0.14	-0.46	-1.71	0.12	-0.13	-0.75
	(-0.12)	(-0.34)	(-0.95)	(0.14)	(-0.12)	(-0.56)
Realized vol.	0.80***	0.80***	0.77***	0.77***	0.77***	0.74***
of Mom rets.	(8.84)	(8.64)	(9.15)	(8.83)	(8.42)	(9.10)
Adj-rsquare	63.3%	63.1%	63.5%	59.4%	59.2%	59.5%

Crowding and momentum volatility

Dependent variable is realized volatility of momentum returns or residuals from the dynamic FF3 model.

Model:	raw returns			dynamic FF3 residuals		
Crowding measure:	AUM	TRD	CNT	AUM	TRD	CNT
ΔCROWD_q	0.06	-0.04	-0.06	0.03	-0.10	-0.05
	(0.84)	(-0.21)	(-0.40)	(0.65)	(-0.72)	(-0.51)
$\text{CROWD}_{q\text{-}1}$	-0.04	-0.15	-0.05	-0.06**	-0.18*	-0.10
	(-1.37)	(-1.32)	(-0.46)	(-2.24)	(-1.82)	(-1.21)
CROWD_EVOL_q	-0.14	-0.46	-1.71	0.12	-0.13	-0.75
	(-0.12)	(-0.34)	(-0.95)	(0.14)	(-0.12)	(-0.56)
Realized vol.	0.80***	0.80***	0.77***	0.77***	0.77***	0.74***
of Mom rets.	(8.84)	(8.64)	(9.15)	(8.83)	(8.42)	(9.10)
Adj-rsquare	63.3%	63.1%	63.5%	59.4%	59.2%	59.5%

$\Rightarrow$ No evidence that crowding positively predicts volatility.

Determinants of crowding

Dependent variables are crowding measures.
Regress on past characteristics of momentum returns.

Crowding measure:	AUM	TRD	CNT
$1YR\_RET_{q\text{-}1}$	0.72**	0.25***	0.41***
	(2.57)	(3.40)	(2.69)
$1YR\_RET_{q\text{-}5}$	0.92***	0.40***	0.52***
	(3.22)	(3.93)	(2.94)
$1YR\_VOL_{q\text{-}1}$	-0.28*	-0.20***	-0.36***
	(-1.94)	(-3.31)	(-4.50)
$1YR\_VOL_{q\text{-}5}$	0.41*	0.07	0.18**
	(1.90)	(1.34)	(2.33)
Adj-rsquare	10.9%	20.1%	19.1%

Determinants of crowding

Dependent variables are crowding measures.
Regress on past characteristics of momentum returns.

Crowding measure:	AUM	TRD	CNT
$1YR\_RET_{q\text{-}1}$	0.72**	0.25***	0.41***
	(2.57)	(3.40)	(2.69)
$1YR\_RET_{q\text{-}5}$	0.92***	0.40***	0.52***
	(3.22)	(3.93)	(2.94)
$1YR\_VOL_{q\text{-}1}$	-0.28*	-0.20***	-0.36***
	(-1.94)	(-3.31)	(-4.50)
$1YR\_VOL_{q\text{-}5}$	0.41*	0.07	0.18**
	(1.90)	(1.34)	(2.33)
Adj-rsquare	10.9%	20.1%	19.1%

$\Rightarrow$ Crowding relates negatively to past momentum volatility and positively to past returns.

Conclusion

Conclusion

- Model of crowding with momentum investors who attempt to infer informed investors' private signal from prices shows:
  - Crowding is not a viable explanation for momentum crashes in general.
  - Crowding with myopic momentum investors can provide that prediction.
- Crowding matters (first moment) and high crowding negatively predicts returns.
- The crowd seems to react to *and anticipate* higher moments of momentum (volatility, skewness, kurtosis).

  → Consistent with model's prediction:
  uncertain crowding need not generate tail risk...

  → and empirically *does not* seem to generate tail risk.

+ ++

Thank you very much for your attention.

Bibliography I

D. Abreu and M. K. Brunnermeier. Bubbles and crashes. *Econometrica*, 71(1):173–204, 2003.

C. S. Asness, T. J. Moskowitz, and L. H. Pedersen. Value and momentum everywhere. *The Journal of Finance*, 68(3):929–985, 2013.

P. Barroso and P. Santa-Clara. Momentum has its moments. *Journal of Financial Economics*, 116(1):111–120, 2015.

K. Daniel and T. J. Moskowitz. Momentum crashes. *Journal of Financial Economics*, 122(2):221–247, 2016.

K. Daniel, R. Jagannathan, and S. Kim. A hidden markov model of momentum. Working Paper, 2019. URL `http://www.kentdaniel.net/papers/unpublished/djk_20190217.pdf`.

Bibliography II

R. M. Edelen, O. S. Ince, and G. B. Kadlec. Institutional investors and stock return anomalies. *Journal of Financial Economics*, 119 (3):472–488, 2016.

M. Friedman. *Essays in Positive Economics*. University of Chicago Press, Chicago, 1953.

M. Grinblatt, S. Titman, and R. Wermers. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American Economic Review*, 85(5):1088–1105, 1995.

B. D. Grundy and J. S. M. Martin. Understanding the nature of the risks and the source of the rewards to momentum investing. *The Review of Financial Studies*, 14(1):29–78, 2001.

Bibliography III

N. Jegadeesh and S. Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91, 1993.

A. E. Khandani and A. W. Lo. What happened to the quants in august 2007? *Journal of Investment Management*, 5(4):29–78, 2007.

R. A. Levy. Relative strength as a criterion for investment selection. *The Journal of Finance*, 22(4):595–610, 1967.

J. Lewellen. Institutional investors and the limits of arbitrage. *Journal of Financial Economics*, 102(1):62–80, 2011.

R. C. Merton. On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2):449–470, 1974.

L. H. Pedersen. When everyone runs for the exit. *The International Journal of Central Banking*, 5:177–199, 2009.

Bibliography IV

K. G. Rouwenhorst. International momentum strategies. *The Journal of Finance*, 53(1):267–284, 1998.

J. C. Stein. Presidential address: Sophisticated investors and market efficiency. *The Journal of Finance*, 64(4):1517–1548, 2009.

What is a plausible explanation for momentum crashes?

- A plausible explanation for momentum crashes is proposed by Daniel et al. (2019) using the logic of Merton's (1974) model in which equity is a call option on the assets of a firm.
- Following large negative market returns, the effective leverage of the firms on the short side of the momentum strategy (the past-loser firms) becomes extreme.
- These stocks then exhibit the convex payoff structure associated with call options.
- When the market recovers, the convexity of the payoff leads to large positive returns on loser stocks and dramatic losses in the momentum strategy (which shorts the losers).

back

Regulatory or other actionable implications

- Holdings disclosure simplifies and improves information inference from prices for market participants.
- Return-chasing strategies have a large potential to destabilize; they need to be accompanied with some form of risk management strategy (e.g., scale down positions when volatility increases).

Regulatory or other actionable implications

- Holdings disclosure simplifies and improves information inference from prices for market participants.
- Return-chasing strategies have a large potential to destabilize; they need to be accompanied with some form of risk management strategy (e.g., scale down positions when volatility increases).
- Data used in the study has significant advantages (long period & all large institutions) but also drawbacks (quarterly & at the institution level); more frequent holdings and fund level data could be an interesting object of future study.

back