Crowded Trading

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Role of Institutional Investors (French, 2008)

	Direct Holdings	Open-end Funds	CEFs	ETFs	DB Plans	DC Plans	ESOPs	Public Funds	Nonprofits	Banks and Insurance	Hedge Funds	Foreign Investors	Foreign Holdings
1980	47.9	4.6	0.5	0.0	18.1	3.9	2.8	4.4	8.3	9.4	0.0	7.6	2.0
1981	45.9	4.4	0.5	0.0	19.0	3.7	3.5	5.1	7.9	10.1	0.0	8.1	1.9
1982	42.4	5.0	0.4	0.0	21.1	3.5	4.6	5.5	7.2	10.2	0.0	8.2	1.7
1983	39.5	6.3	0.4	0.0	21.4	3.4	5.0	6.7	6.7	10.5	0.0	8.4	2.2
1984	37.3	7.0	0.3	0.0	21.8	3.0	6.7	7.4	6.3	10.2	0.0	8.4	2.2
1985	35.4	7.6	0.3	0.0	22.5	3.3	7.7	7.2	6.0	10.1	0.0	8.4	2.9
1986	37.4	9.4	0.4	0.0	20.3	2.6	6.6	7.6	6.2	9.4	0.0	9.7	4.1
1987	36.1	10.4	0.6	0.0	18.4	3.9	6.9	8.5	6.0	9.3	0.0	9.9	5.2
1988	39.3	9.6	0.7	0.0	15.5	3.8	6.1	9.5	6.5	8.9	0.0	10.2	6.4
1989	38.3	10.3	0.7	0.0	14.8	3.7	6.6	9.9	7.2	8.5	0.0	10.6	7.8
1990	35.4	10.5	0.9	0.0	15.3	4.3	6.4	11.1	7.6	8.2	0.3	10.1	8.5
1991	35.0	10.4	0.9	0.0	15.5	4.0	6.9	11.8	6.3	8.7	0.4	9.3	9.1
1992	33.0	12.4	0.9	0.0	14.9	3.8	7.4	11.9	6.5	8.6	0.5	9.0	9.4
1993	29.7	15.7	0.9	0.0	14.4	4.1	7.4	11.8	6.1	9.1	0.8	8.6	13.7
1994	26.8	17.9	1.0	0.0	14.1	4.3	6.9	11.9	6.8	9.5	0.8	8.9	15.4
1995	26.7	19.6	1.1	0.0	13.2	4.1	6.3	12.3	6.6	9.5	0.7	9.2	14.7
1996	27.2	22.2	1.1	0.0	11.5	3.9	5.4	12.1	6.5	9.3	0.8	8.8	14.8
1997	29.5	23.4	1.0	0.1	9.8	3.9	4.4	11.7	6.1	9.3	0.8	9.4	13.6
1998	30.2	24.3	1.0	0.2	9.2	4.3	4.0	11.1	5.8	9.4	0.7	10.4	13.9
1999	36.0	24.7	0.8	0.2	7.4	3.5	3.1	9.9	4.9	8.9	0.6	10.3	14.3
2000	36.2	24.4	0.6	0.5	8.1	3.6	2.6	9.5	4.6	9.1	0.7	10.8	13.7
2001	36.0	23.6	0.5	0.7	8.8	3.5	3.0	10.0	4.0	9.2	0.8	11.4	13.1
2002	32.1	23.7	0.5	1.1	9.9	3.6	3.0	10.8	3.6	10.5	1.3	12.3	14.5
2003	29.9	25.5	0.6	1.2	9.8	3.7	3.2	11.0	3.4	10.4	1.3	13.2	16.8
2004	27.1	27.6	0.8	1.6	9.7	3.9	3.1	11.0	3.1	10.7	1.4	13.6	18.6
2005	26.1	28.8	0.9	2.0	9.1	3.9	3.0	10.9	2.9	10.8	1.5	14.0	22.3
2006	24.2	30.5	1.0	2.5	8.6	4.0	2.8	10.7	2.6	11.2	1.9	15.1	25.3
2007	21.5	32.4	1.1	3.0	8.5	3.8	2.8	10.6	2.3	11.8	2.2	16.3	27.2

General trend: individual investors are supplanted by institutions

Implications for Market Efficiency

- The common view is that individuals are naive investors while institutions (e.g., hedge funds) are rational arbitrageurs
- These data seem to suggest that
  - we are converging to a world in which the smart-money trades intensively against each other
  - with the dumb money playing a much-diminished role
- So, basic economic logic suggests that
  - as more money is brought to bear against a given trading opportunity
  - any predictable excess returns must be reduced

Implications for Market Efficiency

- Does this imply that the financial market is becoming more efficient? In the sense that
  - prices, on average, wind up closer to fundamental values
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- Does this imply that the financial market is becoming more efficient? In the sense that
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- The answer is, unfortunately, *Not Necessarily*
- The reason is that, in the process of pursuing a given trading strategy, arbitrageurs inflict negative **externalities** on one another

One Such Externality: Crowded Trading

- For a broad class of quantitative trading strategies, for each individual arbitrageur, he cannot know in real time exactly
  - how many other arbitrageurs are using the same model
  - how many other arbitrageurs are taking the same positions
- This inability of traders to condition their behavior on current market-wide arbitrage capacity creates a coordination problem
  - sometimes there is too much arbitrage activity in a strategy
  - sometimes there is too little arbitrage activity
- This can result in prices being pushed further away from fundamentals

Price Momentum as an Example

- Historical returns over 10% per year, across asset classes, markets
  - Some investors underreact to information
  - Smart investors exploit such underreaction by trading in the direction of past stock returns

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- Key issue: Momentum traders are simply chasing past returns without forming an independent estimate of the fundamental value
- Imagine that the stock price has risen 10% in the past year
  1. should be 20%, but some investors have underreacted
  2. should be 10%, but other momentum traders have already piled in

- Consequently, from individual momentum traders' perspective
  - hard to know amount of activity already in the strategy
  - hard to know when to stop investing

The Coordination Problem

- **Too little arbitrage activity:** Momentum reflects underreaction as arbitrage pushes prices toward fundamental value
- **Too much arbitrage activity:** Prices overshoot and then revert as crowded arbitrage pushes prices away from fundamental value

- Whether momentum is an underreaction or overreaction phenomenon should vary through time, crucially depending on the size of the "momentum crowd"

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- **Too little arbitrage activity:** Momentum reflects underreaction as arbitrage pushes prices toward fundamental value
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- Whether momentum is an underreaction or overreaction phenomenon should vary through time, crucially depending on the size of the "momentum crowd"

- However, measuring the intensity of momentum trading in the market is challenging (unknown composition, capital, strategies)

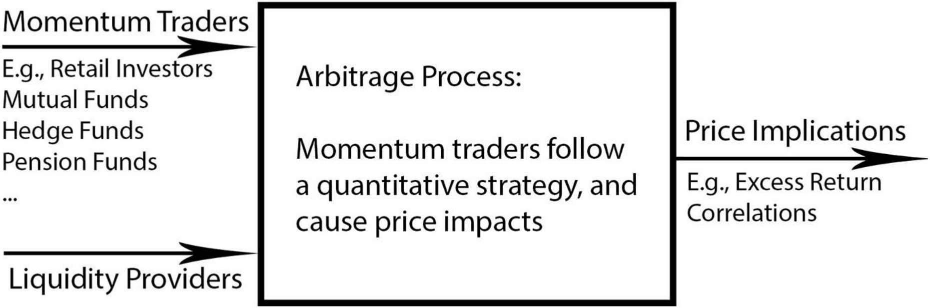
Our Approach

Lou and Polk (2015a,b) propose a new measure of the size of "momentum crowd" by exploiting a simple fact

- Momentum traders follow a quantitative strategy
- They buy a portfolio of winners and sell a portfolio of losers at each point in time for diversification and hedging purposes
- Momentum trading can generate excess return comovement among momentum stocks at relative high frequencies

We link time variation in the excess comovement of momentum stocks to time variation in momentum trading and to time variation in key characteristics of momentum returns

Our Approach



The Timing of Momentum Strategies

Formation Period (Year 0)

- When the momentum characteristic is measured
- Sort stocks into decile portfolios
- Ranges from three months to one year

Holding Period (Year 1)

- When capital is invested in momentum
- Ranges from one month to one year

Post-holding Period (the "long-run") **(Years 2-3)**

- To detect any reversal in momentum profits
- Years two to three following the formation period

Comovement of Momentum Stocks

We define **comomentum** as the average pairwise correlation of daily/weekly Fama-French (1993) three-factor residuals for winner/loser decile stocks in the ranking period

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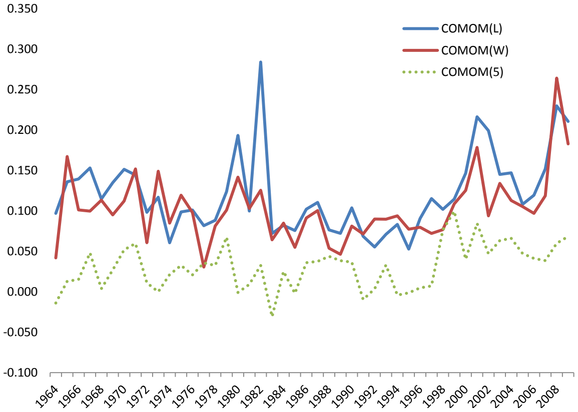
- Robust to measuring residual correlations between winners and losers
- Robust to using daily returns or a six-month window
- Robust to using characteristic-adjusted returns
- Robust to a variety of industry controls
- Robust to measuring in the holding period (and predicting just the post-holding returns)

Comomentum Time Series



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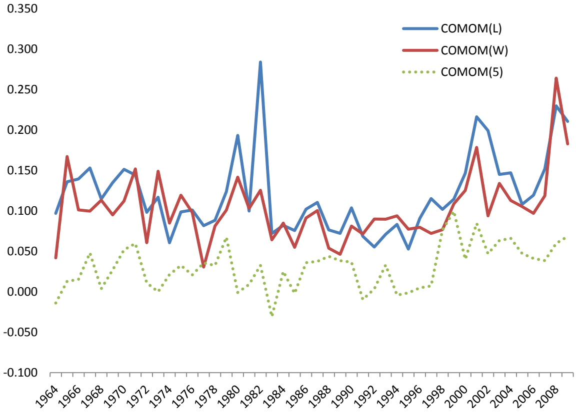
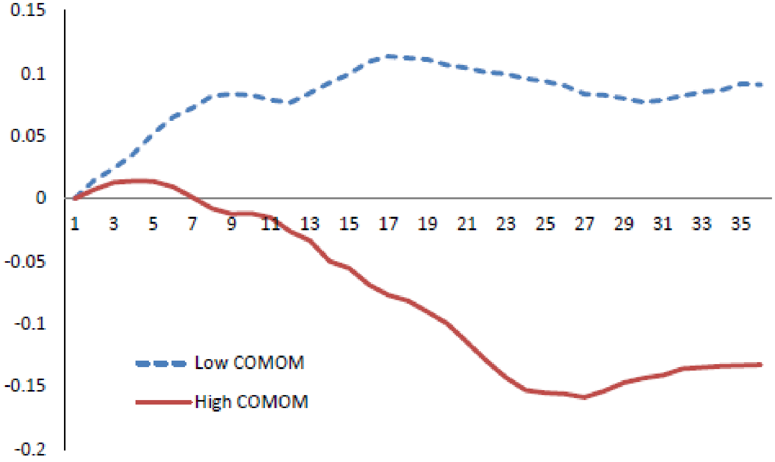


Comomentum is correlated with existing (noisy) measures of arbitrage activity, e.g., AUM of hedge funds, borrowing costs

Forecasting Momentum Returns

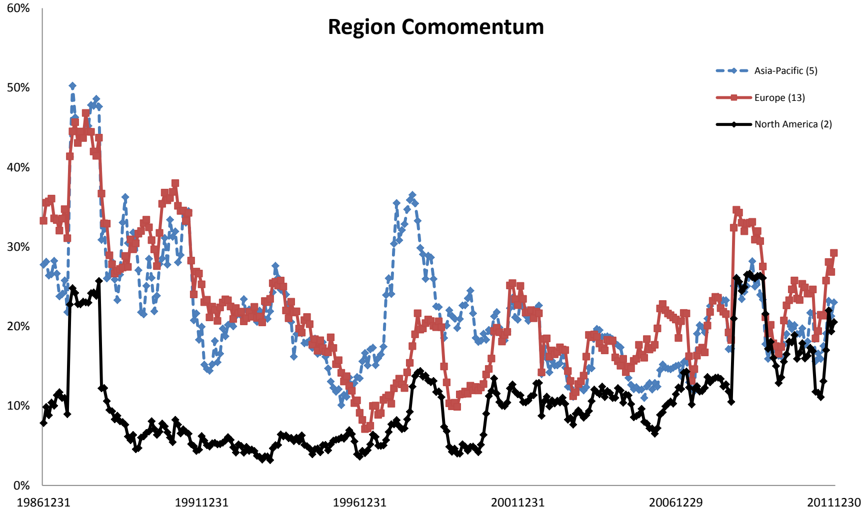


Comomentum Everywhere

Country	No months	CoefEst1	CoefEst2	Country	No months	CoefEst1	CoefEst2
AUS	302	-0.0494	-0.0351	GBR	300	-0.0501	**-0.0402**
		(-0.94)	(-0.48)			(-1.87)	(-2.11)
AUT	302	-0.0581	-0.0866	HKG	300	**-0.0646**	**-0.0796**
		(-1.76)	(-1.17)			(-3.77)	(-2.21)
BEL	300	**-0.1025**	-0.0946	ITA	300	-0.0108	-0.0239
		(-2.40)	(-1.95)			(-0.43)	(-0.73)
CAN	336	**-0.1652**	**-0.1341**	JPN	300	-0.0564	**-0.0535**
		(-2.70)	(-2.31)			(-1.63)	(-2.54)
CHE	300	-0.0347	**-0.0753**	NLD	300	**-0.0801**	**-0.0805**
		(-1.53)	(-2.35)			(-2.47)	(-2.02)
DEU	300	-0.0546	-0.0957	NOR	297	-0.0096	-0.1090
		(-1.72)	(-1.82)			(-0.16)	(-1.58)
DNK	300	-0.0248	-0.0200	NZL	271	**-0.0879**	-0.0462
		(-1.06)	(-0.63)			(-2.15)	(-1.67)
ESP	300	-0.0097	-0.0075	SGP	300	**-0.0791**	**-0.1189**
		(-0.28)	(-0.20)			(-2.36)	(-3.86)
FIN	300	-0.0110	-0.0046	SWE	300	-0.0107	-0.0091
		(-0.29)	(-0.12)			(-0.29)	(-0.11)
FRA	300	**-0.0725**	-0.0486	WLD	300	**-0.0851**	**-0.0569**
		(-2.06)	(-1.13)			(-2.60)	(-2.68)

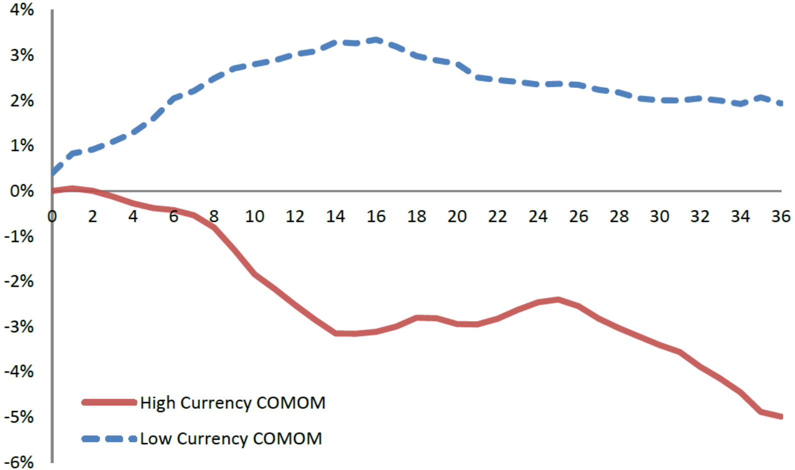
International results are consistent with the US findings

Comomentum Everywhere

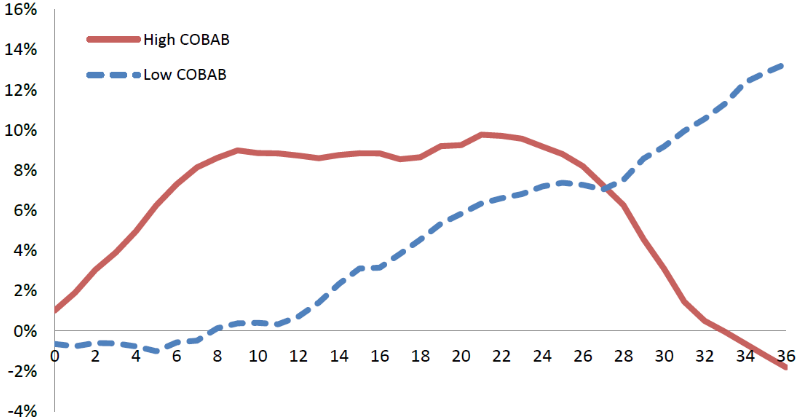


Arbitrage activity has become more integrated over the last 20 years

Forecasting Buy-and-hold Currency Momentum Returns



Forecasting Buy-and-hold Beta Arbitrage Returns



To Sum Up

- Focus on just one externality – crowded trading by smart money
  - Propose a novel approach to measuring intensity of arbitrage activity based on high-frequency excess return comovement
  - Our results, collectively, suggest that "smart money" can be destabilizing when arbitrage trading becomes crowded

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- Focus on just one externality – crowded trading by smart money
  - Propose a novel approach to measuring intensity of arbitrage activity based on high-frequency excess return comovement
  - Our results, collectively, suggest that "smart money" can be destabilizing when arbitrage trading becomes crowded
- There are other negative externalities that arbitrageurs may inflict upon one another, e.g.,
  - most arbitrageurs have short-term, performance-sensitive capital (due to investor capital flows or margin trading)
  - a few arbitrageurs' pulling out of a strategy can trigger a widespread sell-off, leading to sudden price drops and liquidity dry-ups