The Impact on Stock Returns of Crowding by Mutual Funds

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The roots of recent financial debacles—the 1987 market crash, the 1995 collapse of Barings Bank, the 1998 collapse of Long-Term Capital Management, the 2000 dot-com crash, and the 2007–2009 financial crisis—can be traced in part to crowding in the trading space, over-leveraging, and illiquidity.[1] As suggested by numerous studies (as well as anecdotal evidence), correlated trades, leverage, and illiquidity can interact to distort prices and adversely affect the subsequent performance of "crowded" investments. Our interest is in investigating the joint impact of correlated trades in conjunction with illiquidity on stock returns. We accomplish our objective by developing a new measure of crowding that captures the interaction of correlated trades and illiquidity, and use this metric to study the impact on stock returns of mutual funds crowding into equity markets.

Our interest in investigating the impact on stock returns of mutual funds crowding into equities is not accidental. Mutual funds as a group now holds a weighty fraction of equities. Recent data released by the Federal Reserve on September 16, 2016, shows that the share of open-end mutual fund equity holdings has increased from 7.3%, at the time of the 1987 market crash, to about 23.9% of the total capitalization of equity markets as of the second quarter of 2016.[2] These sizable equity holdings have enabled mutual funds to play an increasingly important role in setting stock prices. Evidence provided in Wermers [1999], Sias [2004], and Choi and Sias [2009] shows that mutual funds' sizable stake in equity investments, in conjunction with mutual fund managers' tendency to herd, can cause their trades to have a large impact on stock prices. Further, Sias, Turtle, and Zykaj [2016] find that equity mutual funds display a higher propensity than hedge funds to hold the same stocks. Taken together, these findings make mutual funds as a group an ideal candidate for investigating the impact of crowding on stock returns.

Our work focuses on documenting the potential financial gains that can be realized from investment strategies that exploit any distortions or inefficiencies caused by crowding. Our novel contribution is the development of a metric to measure the degree of crowding using low-frequency, public information. We think of crowding the same way we think of traffic congestion. Traffic congestion results whenever the traffic on the road exceeds the capacity of the roadway. In an analogous manner, when the ratio of investors' holdings to liquidity level for a stock exceeds the norm for this ratio, congestion, or crowding, happens.[3] Our crowding metric for a stock is obtained by dividing the percentage of shares held by equity mutual funds by the average share turnover for the stock.[4] A high (low) percentage of mutual fund holdings in a low- (high-) turnover stock is associated with a high (low) degree of crowding. Our crowding metric is therefore aimed at detecting crowding at the level of an individual stock and is not intended for detecting when a trading strategy is crowded.

The two papers that are closely related to our work are Cahan and Luo [2013] and Hong et al. [2015]. Unlike our work, which focuses on the impact of crowding by mutual funds into stock returns, Hong et al. study the consequences of crowding by hedge funds or arbitrageurs. They use the days to cover (DTC) metric, which is defined as the short ratio divided by the average daily turnover. Like our crowding measure, the DTC captures the costliness of exiting crowded trades. Cahan and Luo, instead of looking at crowding at the individual stock level as in our work, focus on developing a timely crowding measure using high-frequency intraday and daily data to discern if a trading strategy or factor is crowded. They develop two measures of crowding: The first measures crowding as the spread in shorting demand for stocks screened out by a given trading strategy. The second compares the 21-day mean pairwise correlation (MPC) for a portfolio of stocks identified for a given trading strategy to the distribution of the MPCs for 1,000 random portfolios. If the MPC for the former is higher than the latter, it indicates that the trading strategy under consideration is crowded. However, Cahan and Luo do not control for the effect of illiquidity on the cost of exiting crowded trades.

We construct our crowding measure, *Actratio*, using data on actively managed mutual funds because actively managed mutual funds are more likely than passive funds to employ short-term strategies that attempt to time the market and/or engage in security selection. To the extent that the fund managers observe similar information and use trading models that produce correlated trading signals, actively managed mutual funds will tend to crowd on similar stocks and create transitory distortions in prices. We use this crowding metric to discern if a stock is overcrowded or undercrowded, and we use this knowledge to design an investment strategy to extract excess returns from the price distortions induced by crowding. Our strategy is able to generate abnormal returns that are much larger than reported in the academic literature to date. A long–short trading strategy based on our crowding metric that goes long on the least crowded stocks and shorts the most crowded stocks can generate an annualized Daniel et al. [1997] characteristics-adjusted (henceforth, "DGTW-adjusted") abnormal return of 14.53%. When we apply such a strategy to a subset of stocks in the least and most crowded deciles, we can obtain a substantial DGTW-adjusted return as high as 38.46%. It is worth noting that the magnitude of the abnormal returns we report are more in line with the huge returns reported by practitioners. For example, in 2008, Systematic Alpha reported a return of 46%, while QCM (U.K.-based Quality Capital Management) reported a 60% return to their investors (Davis [2011]. These figures can hardly be reconciled with extant findings in academic literature and are viewed as suspect by academic researchers. Our results offer a partial explanation for the huge returns reported by practitioners.

Our robustness tests confirm that the abnormal returns generated by the trading strategy are not driven by time-varying expected returns. Although crowding and liquidity are correlated by construction, it is important to point out that results from our empirical analysis show that our crowding metric is more complex than a liquidity measure. Following the approach in Ibbotson et al. [2013], we provide evidence from a double sort by illiquidity and crowding to show that our crowding metric contains signals beyond what is conveyed in turnover.

DATA DESCRIPTION

Our data on mutual fund holdings come from the Thomson Reuters Mutual Fund Common Stock Holdings/Transactions database, CDA/Spectrum S12. This database contains information on quarterly equity holdings of mutual funds in the United States. Data on stock returns, stock prices, and trading volume are from the Center for Research in Security Prices (CRSP) monthly stock file. We further obtain accounting data from Compustat, and analyst forecast data from I/B/E/S. Our sample period is from the first quarter of 1981 to the fourth quarter of 2012.

We follow standard convention and limit our analysis to common stocks of firms incorporated in the United States (with CRSP share type code 10 or 11 only) and listed on NYSE, AMEX, or NASDAQ. Following Chen, Hong, and Stein [2002], we divide the stocks into quintiles based on NYSE breakpoints and keep only quintiles 2 through 5. In doing so, we exclude small-cap stocks that tend to be less liquid and have higher transaction costs. Our final sample is, therefore, comprised of relatively large stocks with market capitalization above the 20th percentile NYSE breakpoint. We categorize mutual funds into active funds and passive funds on the basis of their portfolio turnover following the approach of Yan and Zhang [2009] and focus on active funds for the reasons explained in the previous section. A fund is defined to be an active (passive) fund if its portfolio turnover is at the top (bottom) tercile portfolio turnover of all funds during a particular quarter.[5] Under current SEC rules, mutual funds have 60 days after their fiscal quarter-end to file their portfolio holdings through the EDGAR system. Given that mutual fund holdings information is available to the public with a lag of two quarters, we construct a quarterly crowding measure, denoted as *Actratio*, for each stock as the percentage of shares held by active mutual funds at the end of quarter $(t - 2)$ divided by the stock's average turnover during quarter $(t - 1)$. Even though there is significant lag in the data used, it is possible that the mispricing might persist for an extended time as explained in Stein [2009]. Stein points out that when investors are unable to observe arbitrage capacity and employ strategies that are not grounded on fundamentals, they can no longer rely on price signals to coordinate their trades. Hence, they will not know if they have undertraded or overtraded. Consequently, any distortion in price could potentially persist for an extended time. Stein further emphasizes that "[t]he problems associated with crowding and leverage that I identify persist even when arbitrageurs fully understand the structure of the world that they are operating in … Thus, any remaining inefficiencies cannot be said to be the result of one-time mistakes, but rather must be thought of as a more permanent part of the landscape." For this reason, even if the signal embedded in our crowding measure is based on lagged data, the information may not be fully priced in yet.

Our main objective is to test the profitability of trading against the crowding by mutual funds. In each quarter, we sort the stocks in our sample into deciles based on our crowding measure, *Actratio*. This quarterly sorting is implemented from the first quarter of 1981 through the fourth quarter of 2012. Decile 1 represents the least crowded decile, and Decile 10, the most crowded. Exhibit 1 presents summary statistics for the variables used in our analysis. All the variables are winsorized at 1% level to exclude the impact of outliers. On average the most crowded decile is about 26 times as crowded as the least crowded decile, based on the crowding measure, *Actratio*. A few important points stand out. First, turnover (*Turnover*) and issuance (*Issuing*) activities decrease monotonically with the degree of crowding while the percentage of shares held by mutual funds (*MFRatio*), book-to-market ratio (*BTM*), and stock price (*Price*) increase monotonically with the degree of crowding. Second, the mean and median market capitalization (*Mkt cap*) and the median of analyst coverage (*Analyst*) exhibit an inverted U-shaped pattern with an increase in the degree of crowding; Deciles 1 and 10 have lower market capitalization and less analyst coverage than the deciles in between.[6] The summary statistics suggest that, on average, the most crowded decile is comprised of less-liquid, smaller-cap value stocks that are heavily invested in by mutual funds; the least crowded decile is comprised of more-liquid, larger-cap growth stocks that receive the least investment from mutual funds. Last but foremost, we see that the monthly returns of the decile portfolios (*RET*) decrease monotonically with *Actratio*, ranging from 2.16% for stocks in the least crowded decile, to 0.86% for stocks in the most crowded decile. In other words, more-crowded stocks on average earn lower returns in each month than less-crowded ones. A long–short portfolio strategy that takes a long position in Decile 1 and a short position in Decile 10 provides an annualized rate of return of 15.6%. Our correlation analysis reveals a strong negative relationship between the level of crowding and return.[7]

INVESTMENT PERFORMANCE ANALYSIS OF THE CROWDING DECILE PORTFOLIOS

We now consider the buy-and-hold cumulative returns of the decile portfolios from January 1981 through December 2012. Beginning in March 1981, we compute our crowding metric, *Actratio*, and sort the stocks into deciles of crowdedness. We then buy-and-hold each decile portfolio and rebalance them quarterly. Specifically, at the end of each quarter, we re-sort the stocks using the latest *Actratio*, reformulate the decile portfolios, and hold the portfolios for another quarter. This process is repeated until the end of December 2012.

In Exhibit 2, we report the annualized return after adjusting for the effects of size, book-to-market, and momentum. To implement this control, we create portfolio benchmarks using a characteristics-based procedure similar to that of Daniel et al. [1997]. At the end of every quarter, we assign stocks to market-cap quintiles based

Exhibit 1
Summary Statistics

Crowding Deciles	1	2	3	4	5	6	7	8	9	10
Actratio	0.010	0.013	0.020	0.028	0.035	0.045	0.056	0.072	0.101	0.258
RET (Mean, in %)	2.162	1.765	1.466	1.483	1.357	1.264	1.131	1.113	1.047	0.864
RET (Std. dev.)	0.081	0.071	0.066	0.062	0.059	0.056	0.053	0.053	0.052	0.056
No. MFs (Active)	46.977	73.908	87.017	95.286	100.656	106.665	106.297	106.960	94.022	52.453
MFRatio (Mean)	0.074	0.117	0.135	0.146	0.155	0.163	0.170	0.177	0.185	0.178
MFRatio (Median)	0.028	0.070	0.092	0.106	0.116	0.127	0.135	0.146	0.153	0.146
Number of Stocks	357.161	321.508	319.867	319.486	319.034	318.836	317.657	317.663	317.072	317.250
Mkt Cap (Mean)	1,207.635	1,200.060	1,433.870	1,532.816	1,625.736	1,719.793	1,731.025	1,750.323	1,492.034	767.319
Mkt Cap (Median)	197.542	264.955	325.656	360.873	386.154	389.340	381.733	354.721	273.660	136.752
BTM (Mean)	0.613	0.609	0.613	0.624	0.637	0.646	0.664	0.677	0.717	0.806
BTM (Median)	0.475	0.484	0.501	0.516	0.533	0.548	0.565	0.581	0.616	0.696
Price (Mean)	7.824	8.385	9.643	10.753	11.826	12.649	13.741	14.509	15.150	21.322
Price (Median)	4.792	5.874	7.348	8.590	9.569	10.430	11.486	12.045	12.174	12.476
Turnover (Mean)	4.055	4.141	3.820	3.478	3.214	2.972	2.750	2.496	2.162	1.715
Turnover (Median)	2.963	3.185	3.028	2.811	2.628	2.447	2.279	2.065	1.771	1.241
Volume (Mean, MM)	14.348	14.318	13.519	12.501	11.591	11.179	10.203	9.663	8.155	5.620
Volume (Median, MM)	2.643	2.818	3.010	2.906	2.833	2.710	2.425	2.108	1.554	0.728
Analyst (Mean)	8.15	9.44	10.05	10.17	10.29	10.39	10.17	9.88	8.89	6.59
Analyst (Median)	5.00	7.00	8.00	8.00	8.00	8.00	8.00	8.00	7.00	5.00
Issuing (Median)	0.013	0.011	0.009	0.008	0.007	0.006	0.006	0.005	0.004	0.003

Notes: This table reports the pooled means and medians for the characteristics of the decile portfolios. The sample includes all the common stocks (with share code 10 or 11) traded on NYSE, AMEX, and Nasdaq with market capitalization above the 20th percentile NYSE breakpoint. Actratio *is the percentage of shares held by active mutual funds at the end of quarter (t − 2) divided by the stock's average turnover during quarter (*t *− 1). Decile portfolios are formed based on* Actratio *and quarterly rebalanced.* RET *is the equally weighted decile monthly return.* No. MF (Active) *is the numbers of active funds owning a stock.* MFRatio *is the number of a stock's shares held by mutual funds scaled by its total shares outstanding in quarter (*t *− 1).* Number of stocks *is the average number of stocks in each decile.* Mkt Cap *is a stock's inflation-adjusted (1982–1984 as the based year) market capitalization ($ millions) at the end of quarter (*t *− 1).* BTM *is the book-to-market ratio at the end of year (s − 1).* Price *is the inflation-adjusted (1982–1984 as the based year) stock price at the end of quarter (*t *− 1).* Turnover *is the monthly trading volume of a stock scaled by its total shares outstanding, measured in the last month of quarter (*t *− 1).* Volume *is the number of stocks traded in the last month of quarter (*t *− 1).* Analyst *is the number of analysts following a stock during the year before the portfolio formation.* Issuing *is the issuance activity for a firm, measured as log (adjusted Shares$_{t-1}$) − log (Adjusted Shares$_{t-5}$). The reported values are the mean by default.*

on NYSE breakpoints. Within each size quintile, stocks are further ranked into subquintiles, based on their book-to-market ratios. This yields a total of 25 groups of stocks, which are further ranked into momentum quintiles each quarter, based on their raw returns over the prior 12 months, resulting in a total of 125 portfolio groups. The equal-weighted holding-period return for each of the 125 benchmark portfolios is then calculated, and the DGTW-adjusted return for a stock is defined as its holding-period return for that stock in excess of the holding-period return on the benchmark portfolio to which it belongs.

As can be seen in Exhibit 2, the DGTW-adjusted returns exhibit a pattern similar to the one observed in Exhibit 1, in that portfolio returns decrease monotonically from the least crowded Decile 1 to the most crowded Decile 10. The magnitude of the DGTW-adjusted returns is statistically and economically significant. Note that a trading strategy (P1–P10) that takes a long position in a portfolio containing Decile 1 stocks and a short position in a portfolio with Decile 10 stocks generates an annualized raw return as high as 14.53% over the period 1981–2012.[8] We further divide the sample into six subperiods: 1981 to the dot-com bubble buildup (1981–1994), the dot-com bubble (1995–1998), the dot-com crash (1999–2001), the subsequent bull market (2002–2006), the global financial crisis (2007–2008), and post–global financial crisis (2009–2012). We find the DGTW-adjusted returns continue to be statistically significant in all subperiods. What we find surprising, however, is that most of the abnormal returns are driven by the least crowded stocks.[9]

EXHIBIT 2
Buy-and-Hold Cumulative Returns of the Decile Portfolios

	DGTW-Adjusted Return						
Crowding Deciles	**Entire Period (1981–2012)**	**Pre-Bubble (1981–1994)**	**Tech Bubble (1995–1998)**	**Bubble Burst (1999–2001)**	**Post-Bubble (2002–2006)**	**Global Financial Crisis (2007–2008)**	**Post Crisis (2009–2012)**
Low	13.22	7.53	20.81	24.77	18.32	6.58	15.24
2	8.69	5.25	13.19	23.90	8.71	5.38	7.49
3	5.55	3.25	8.33	11.75	6.54	5.63	5.17
4	5.40	2.99	6.36	14.29	6.08	4.51	6.17
5	4.01	3.06	4.25	7.91	4.14	3.57	4.31
6	3.20	2.09	1.95	7.57	3.98	4.44	3.52
7	1.84	1.20	1.10	4.72	1.98	7.02	0.04
8	1.32	1.89	0.31	1.73	0.35	1.39	1.24
9	0.62	1.54	–1.02	0.04	1.08	–1.01	–0.20
High	–1.31	–0.92	–2.14	–2.01	–1.25	–4.08	0.08
t-statistics (Low-High)	**(8.29)**	**(6.59)**	**(5.36)**	**(2.70)**	**(5.08)**	**(1.92)**	**(2.54)**

Notes: This table presents the buy-and-hold cumulative returns for the decile portfolios. We form a hypothetical portfolio based on Actratio *at the beginning of March 1981 and hold it until the end of December 2012, with quarterly rebalancing. Each figure stands for the compound annualized return by holding and rebalancing this portfolio for the entire sample period or its subsample periods. Equally weighted DGTW-adjusted returns are reported. The* t*-statistics for the long/short strategy (Low-High) are computed from the quarterly holding period returns over the sample period.*

ALTERNATIVE RISK-ADJUSTED PERFORMANCE: CARHART [1997] FOUR-FACTOR MODEL

In this section, we consider an alternative way to adjust the returns for risk and stock characteristics. Exhibit 3 presents the results from running the Carhart [1997] four-factor model to control for commonality associated with market movement, firm size, value/growth characteristics, and momentum. We find, after adjusting for the market risk, size, value, and momentum, that the abnormal returns (alphas) decrease with mutual fund crowding. Specifically, the alphas are positive for lower-decile (less-crowded) portfolios and negative for higher-decile (more-crowded) portfolios. Translating the figures into the returns of a hedge portfolio with a long position in Decile 1 portfolio and a short position in Decile 10 portfolio generates an annualized abnormal return as high as 17.28%.

INVESTMENT PERFORMANCE WITH SMALLER PORTFOLIOS

Exhibit 1 shows that there are on average about 357 stocks in Decile 1 and 317 stocks in Decile 10, both of which are relatively large portfolios to manage for the long–short strategy proposed in the prior two sections. Here we dissect the data further to see if it would still be possible to generate large abnormal returns with smaller portfolios. In the course of our experimentation, we shed further light on the characteristics of the stocks that are driving the abnormal returns in our long–short strategy. The procedure is similar to what we explained in the previous section, except that we further sort the stocks in Decile 1 and in Decile 10 separately by their market capitalization. Our intent is to investigate the abnormal returns that could be generated using a subset of the stocks sorted by market cap in Decile 1 and Decile 10.

We find that in general a strategy that is long the smaller-cap stocks in Decile 1 and short the larger-cap stocks in Decile 10 generates even larger abnormal returns than reported in the previous two sections.[10] Exhibit 4 presents the results for two strategies. The first strategy takes a long position in the lower 50th percentile stocks (by market cap) in Decile 1 and a short position in the upper 50th percentile stocks (by market cap) in Decile 10. This strategy employs half as many stocks as the strategy described in the previous section. The second strategy is similar but replaces the stocks

EXHIBIT 3
Carhart [1997] Four-factor Model

Crowding Deciles	Low	2	3	4	5	6	7	8	9	High
MKT_RF	1.20***	1.14***	1.14***	1.10***	1.08***	1.06***	1.03***	1.04***	1.00***	1.01***
	(24.98)	(38.11)	(50.26)	(57.60)	(64.06)	(51.61)	(59.06)	(39.39)	(39.98)	(36.47)
SMB	1.04***	0.98***	0.86***	0.76***	0.67***	0.59***	0.52***	0.50***	0.55***	0.69***
	(13.00)	(21.10)	(28.62)	(26.63)	(16.72)	(8.71)	(9.14)	(7.92)	(8.56)	(11.21)
HML	–0.16	–0.14**	–0.03	0.05	0.15***	0.20***	0.27***	0.32***	0.39***	0.37***
	(–1.47)	(–2.31)	(–0.75)	(1.56)	(5.41)	(5.26)	(6.77)	(6.61)	(8.16)	(7.59)
UMD	–0.38***	–0.21***	–0.18***	–0.19***	–0.19***	–0.18***	–0.15***	–0.15***	–0.18***	–0.23***
	(–3.30)	(–3.72)	(–4.99)	(–9.15)	(–8.87)	(–8.17)	(–7.19)	(–5.41)	(–6.35)	(–8.84)
Constant	1.26***	0.80***	0.45***	0.48***	0.34***	0.24***	0.09	0.05	–0.01	–0.18**
	(5.37)	(5.73)	(5.09)	(6.77)	(5.57)	(3.99)	(1.40)	(0.59)	(–0.14)	(–2.05)
Observations	384	384	384	384	384	384	384	384	384	384
R^2	0.86	0.93	0.95	0.97	0.96	0.97	0.96	0.96	0.95	0.95

*Notes: This table presents the abnormal returns using the Carhart [1997] four-factor model to control for market risk, size, value, and momentum effect. Results are based on equally weighted returns of the decile portfolios. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.*

by those stocks from the first quartile of Decile 1 for the long position and those from the fourth quartile of Decile 10 for the short position. Since the second strategy uses a quarter of the stocks in each decile, there is on average about 89 and 79 stocks respectively for the long and short positions. Both strategies produce much larger abnormal returns than what we have seen in Exhibit 2. The first and second equally weighted strategies generate a DGTW-adjusted abnormal return of 26.87% and 38.46%, respectively. These returns are statistically significant at 1%. The abnormal returns from the value-weighted strategies are slightly smaller but are also statistically significant at 1%.[11]

Similar to what we reported earlier, most of the abnormal returns come from the long position in the least crowded stocks. These stocks are generally covered by fewer analysts, owned by fewer actively managed mutual funds, and have slightly higher turnover. The implication is that there is limited information about these stocks and mutual funds are not paying much attention to them. The higher abnormal returns therefore can be construed as a compensation for the uncertainty surrounding these stocks due to the lack of attention and a scarcity of information about the stock intrinsic risk. Our findings are consistent with recent empirical evidence in Fang, Peress, and Zheng [2014]. They find that funds that have the highest propensity to buy media-covered stocks underperform funds that have the lowest propensity to do so.

SHORT-SALES CONSTRAINTS AND TRANSACTION COSTS

In this section, we discuss how frictions such as short-sales constraints and transaction costs may affect our trading strategy returns. There are two reasons why short sales constraints should not be of concern for our crowding-based strategy. First, most of the abnormal returns from our strategy arise from the long position rather than the short position. In Exhibit 2, we can see that the DGTW-adjusted return of Decile 1 (the long leg) is 13.22%, whereas the DGTW-adjusted return of Decile 10 (the short leg) is only −1.31%. In Exhibit 4, where we present investment performance results for smaller portfolios, we also find the DGTW-adjusted return for the long position to be a lot larger than for the short position. For instance, for the strategy that goes long the first quartile of stocks in Decile 1 and short the fourth quartile in Decile 10, the long position produces a DGTW-adjusted return of 33.6% versus −4.8% for the short position. Second, our sample is comprised of relatively large stocks with market capitalization above the 20th percentile NYSE breakpoint. Hanson and Sunderam [2014] have shown that the average short interest ratio has increased over the years with stocks in NYSE deciles 2 to 5 experiencing a fourfold or fivefold increase since 1991. This evidence suggests that it should not be difficult to short the stocks in our sample. For the above reasons, short-sales constraints should not have a significant impact on the profitability of our crowding-based trading strategy.

EXHIBIT 4

Long the Least Crowded Small Stocks and Short the Most Crowded Big Stocks

Panel A

	50th Percentile Equal Weighted	50th Percentile Value Weighted	25th Percentile Equal Weighted	25th Percentile Value Weighted
Long Small Stocks in Decile 1	22.259%	14.063%	33.603%	27.418%
Short Big Stocks in Decile 10	–4.613%	–4.700%	–4.858%	–4.859%
Long–short strategy return	26.872%	18.763%	38.461%	32.277%
t-statistics (long/short strategy)	(7.29)	(8.91)	(7.40)	(9.05)

Panel B

	Decile 1 Lower 50th Percentile		Decile 10 Upper 50th Percentile		Decile 1 Lower 25th Percentile		Decile 10 Upper 25th Percentile	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
MFRatio	0.047	0.017	0.192	0.160	0.032	0.013	0.207	0.182
Mkt Cap ($MM)	87.363	67.502	1,467.578	388.306	38.276	32.143	2,692.631	939.287
Turnover	3.352	2.321	1.999	1.532	2.911	2.007	2.183	1.764
Volume ($MM)	6.190	1.202	8.699	1.356	4.432	0.911	17.211	3.139
#Analyst	4.156	3.000	8.461	7.000	3.010	2.000	12.470	11.000

Notes: Exhibit 4 presents the buy-and-hold cumulative returns of the strategy to long the least crowded (Decile 1) small stocks and short the most crowded (Decile 10) big stocks. Small stocks are defined as the lower 25% (or 50%) percentile by inflation-adjusted market capitalization in Decile 1; Big stocks are defined as the upper 25% (or 50%) percentile by inflation-adjusted market capitalization in Decile 10. The trading strategy starts at the beginning of March 1981 and ends in December 2012 with quarterly rebalancing. Both equally and value-weighted returns are reported. The figure stands for the compound annualized DGTW-adjusted return. The t*-statistics for the long/short strategy are computed from the quarterly holding period returns over the sample period.*

Next, we turn our attention to how short-selling costs and transaction costs may affect our returns. Following Ibbotson et al. [2013], we compute migration probability of stocks between different deciles in consecutive quarters in Exhibit 5, measuring how likely a stock in one decile is to migrate to a different decile in the next quarter. Our results indicate that stocks in Decile 1 and Decile 10 are "sticky," in that 78.50% of the stocks in Decile 1 and 81.76% of the stocks in Decile 10 portfolios tend to stay in the same decile in the following quarter. Considering that the portfolios are rebalanced four times annually, most of the stocks will need to be traded only once or twice a year.[12] We use a conservative estimate of 75 basis points as the short-selling and transaction costs for the stocks in Decile 10. Specifically, we assume a 25-basis-point short-selling cost (see D'Avolio [2002]; Lynch and Balduzzi [2000]) plus a 50-basis-point transaction cost (Balduzzi and Lynch [1999]) for each transaction. The 50 basis points is the upper limit for transaction costs estimated by Balduzzi and Lynch. Given that most of the stocks need to be traded only once or twice a year, the total short-selling and transaction costs should be between 0.75% (0.75% × 1) and 1.5% (0.75 × 2%) per annum. Therefore, even after taking into account the transaction costs, our crowding-based strategy still generates substantial abnormal returns.

ROBUSTNESS TO TIME-VARYING EXPECTED RETURNS

The evidence presented so far suggests we can earn relatively substantial risk-adjusted returns with trading strategies that exploit the disequilibrium caused by crowding by mutual funds. However, the substantial abnormal returns we observe could have been driven by changes in time-varying expected returns that we have yet to control for. To investigate whether this might be the case, we follow Chordia and Shivakumar [2002] by including macroeconomic variables such as a recession dummy, liquidity risk, and default risk, in our regression analyses. Our recession dummy variable reflects the recessionary periods identified by NBER. We use the liquidity factor proposed by Pastor and Stambaugh [2003] to proxy for liquidity risk and yield spread between BAA and AAA corporate bonds as a measure of default risk.

EXHIBIT 5
Migration of Stocks' Crowding Deciles One Quarter after Portfolio Formation

	Quarter ($t+1$) Crowding Deciles										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total**
Quarter (t) Crowding Deciles											
1	78.50	13.49	2.89	1.51	0.94	0.73	0.53	0.48	0.42	0.52	100
2	11.04	66.42	15.82	3.57	1.42	0.73	0.46	0.24	0.16	0.15	100
3	2.16	14.43	58.96	17.12	4.19	1.68	0.80	0.32	0.16	0.19	100
4	1.19	2.67	16.29	53.96	18.21	4.82	1.69	0.72	0.31	0.15	100
5	0.88	1.13	3.16	17.68	51.01	18.64	5.03	1.71	0.59	0.18	100
6	0.67	0.53	1.25	3.66	18.47	49.37	19.40	4.88	1.38	0.38	100
7	0.47	0.33	0.50	1.35	4.07	19.09	49.48	19.73	4.17	0.81	100
8	0.42	0.26	0.33	0.55	1.26	3.94	19.35	52.62	19.03	2.25	100
9	0.49	0.13	0.22	0.26	0.46	1.10	3.46	18.36	61.25	14.27	100
10	0.72	0.17	0.17	0.17	0.24	0.34	0.54	1.93	13.97	81.76	100
Total	9.23	9.91	10.01	10.06	10.11	10.11	10.13	10.16	10.20	10.07	100

Notes: This table illustrates the migration of stocks' crowding deciles between adjacent quarters. The table shows how likely a stock in one decile (denoted by the number in the row of decile) migrates to another decile (denoted by the number in the column of decile) in the next quarter.

Panel A in Exhibit 6 reports the results from including the recession dummy variable in the cross-sectional regression. Likewise, Panels B and C in Exhibit 6 report the results from including the liquidity risk variable and the default risk, respectively, in the cross-sectional regressions. Our results in Panel A indicate that there is very little exposure to the recession dummy variable. Most importantly, the intercepts are still statistically and economically significant for the lowest decile and highest decile, similar to our findings in previous sections. The results in Panel B and Panel C are similar to those in Panel A. Although there is a mild risk exposure to default risk and liquidity risk, the risk-adjusted alphas do not change materially. It is evident that the abnormal returns generated from our trading strategy are not driven by time-varying expected returns.

COMPARISON OF THE CROWDING MEASURE WITH LIQUIDITY MEASURE

Ibbotson et al. [2013], Nguyen et al. [2007], and Datar, Naik, and Radcliffe [1998] have demonstrated that liquidity as proxied by turnover is a robust factor in asset pricing. This section provides evidence to show that our crowding measure is an improvement over liquidity. We follow the approach in Ibbotson et al. [2013] and do a double sort of our sample by illiquidity as proxied by 1/turnover and crowding measures. We first sort the sample into quintiles by illiquidity, and within each quintile we further sort the stocks into quintile by crowding. Exhibit 7 presents the results of our analysis in terms of raw returns and DGTW-adjusted returns. Our analysis shows that after sorting by illiquidity there remains a huge spread between the least and most crowded quintile stocks within each illiquidity quintile. For the least illiquid quintile, the crowdedness spread measured in raw return is 25.29% (21.52 + 3.77) and in DGTW-adjusted return is 15.54% (11.32 + 4.22); the spreads are statistically significant at 1% (t-statistic = 3.22 and 5.96 for the raw returns and DGTW-adjusted returns, respectively). For the most illiquid quintile, the same spread is 9.97% (22.09 − 12.12) and 7.67% (4.56 + 3.11), respectively; the spreads are statistically significant at 5% and 1% (t-statistic = 2.21 and 4.05, respectively).[13] The evidence suggests that our crowding measure conveys important signals beyond what is embedded in turnover.[14]

CONCLUSION

The recent financial debacles can be traced in part to crowding in the trading space. Such crowding behavior distorts prices and destabilizes securities markets. We show that it is possible to earn relatively large

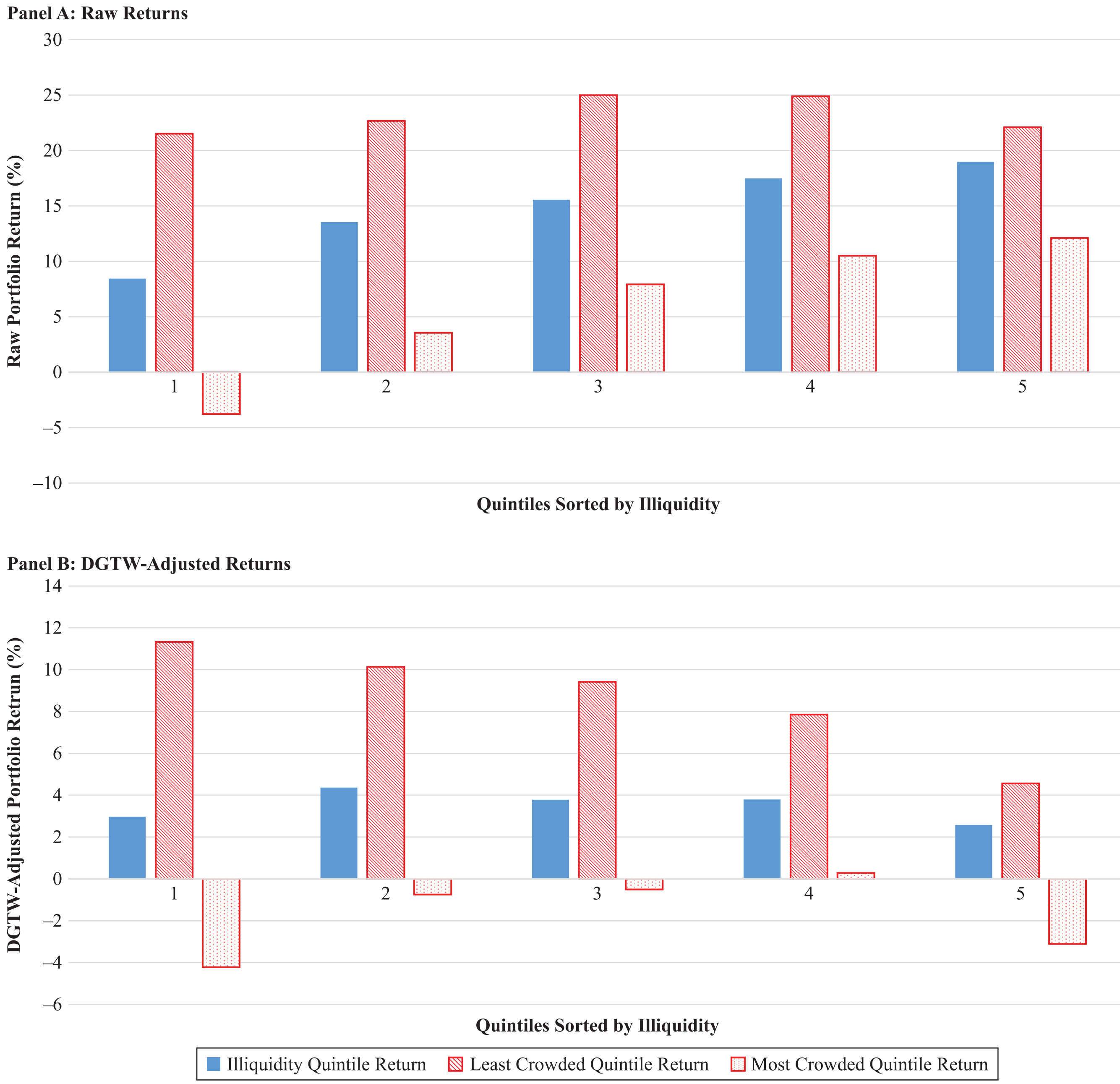
Exhibit 6
Recession/Liquidity/Default Risk

Crowding Deciles	Low	2	3	4	5	6	7	8	9	High
Panel A: Recession										
MKT_RF	1.18***	1.16***	1.10***	1.08***	1.04***	1.01***	0.99***	0.97***	0.95***	1.09***
	(33.81)	(24.06)	(29.21)	(42.96)	(70.25)	(58.48)	(48.19)	(37.00)	(41.33)	(32.21)
SMB	0.22***	0.48***	0.27***	0.19***	0.08***	0.02	–0.07*	–0.12**	–0.04	0.07
	(3.81)	(4.97)	(3.49)	(4.37)	(3.02)	(0.76)	(–1.68)	(–2.54)	(–1.15)	(1.08)
HML	–0.07	–0.38***	–0.20***	–0.10**	0.01	0.12***	0.16***	0.16***	0.22***	0.30***
	(–1.36)	(–4.46)	(–3.37)	(–2.58)	(0.41)	(4.35)	(4.25)	(3.24)	(4.66)	(5.89)
Recession	–0.25	–1.60**	–0.55	–0.42	–0.35	0.01	–0.08	0.02	0.24	–0.36
	(–0.41)	(–2.11)	(–1.16)	(–1.24)	(–1.59)	(0.04)	(–0.21)	(0.04)	(0.57)	(–0.96)
Constant	0.65***	0.72***	0.16	0.16*	–0.02	–0.07	–0.17**	–0.16*	–0.27***	–0.54***
	(5.04)	(4.39)	(1.38)	(1.85)	(–0.29)	(–1.11)	(–2.57)	(–1.90)	(–3.15)	(–5.29)
Observations	384	384	384	384	384	384	384	384	384	384
R^2	0.86	0.85	0.89	0.92	0.95	0.94	0.93	0.89	0.88	0.89
Panel B: Liquidity										
MKT_RF	1.19***	1.18***	1.12***	1.08***	1.03***	1.01***	0.99***	0.97***	0.95***	1.09***
	(34.59)	(25.43)	(32.49)	(44.40)	(69.87)	(58.57)	(46.33)	(39.43)	(41.05)	(30.73)
SMB	0.21***	0.47***	0.26***	0.19***	0.08***	0.02	–0.07*	–0.12**	–0.04	0.07
	(3.78)	(4.74)	(3.47)	(4.26)	(2.80)	(0.77)	(–1.73)	(–2.56)	(–1.10)	(1.05)
HML	–0.07	–0.37***	–0.20***	–0.10**	0.01	0.12***	0.16***	0.16***	0.22***	0.30***
	(–1.33)	(–4.22)	(–3.23)	(–2.54)	(0.38)	(4.33)	(4.23)	(3.26)	(4.59)	(5.84)
Liquidity	–0.95	–2.50	–3.79*	0.85	1.47	0.70	0.28	–0.27	0.25	0.84
	(–0.33)	(–0.73)	(–1.83)	(0.45)	(1.21)	(0.63)	(0.26)	(–0.15)	(0.15)	(0.55)
Constant	0.60***	0.50***	0.00	0.15	–0.01	–0.04	–0.17**	–0.17**	–0.25***	–0.55***
	(4.46)	(3.00)	(0.04)	(1.57)	(–0.16)	(–0.78)	(–2.41)	(–2.03)	(–2.74)	(–5.32)
Observations	384	384	384	384	384	384	384	384	384	384
R^2	0.86	0.85	0.89	0.92	0.95	0.94	0.93	0.89	0.88	0.89
Panel C: Default Risk										
MKT_RF	1.18***	1.16***	1.10***	1.08***	1.04***	1.01***	0.99***	0.97***	0.95***	1.09***
	(33.44)	(23.87)	(29.27)	(42.24)	(69.64)	(57.47)	(48.14)	(37.21)	(41.20)	(32.64)
SMB	0.22***	0.48***	0.27***	0.19***	0.08***	0.02	–0.07*	–0.12***	–0.04	0.07
	(3.77)	(4.95)	(3.52)	(4.51)	(2.88)	(0.70)	(–1.73)	(–2.63)	(–1.22)	(1.07)
HML	–0.07	–0.37***	–0.20***	–0.10**	0.01	0.12***	0.16***	0.16***	0.22***	0.30***
	(–1.35)	(–4.46)	(–3.39)	(–2.54)	(0.45)	(4.41)	(4.29)	(3.29)	(4.69)	(5.98)
Default Risk	–0.18	–0.88**	–0.46*	–0.35*	–0.03	0.10	0.03	0.18	0.27	–0.19
	(–0.56)	(–2.09)	(–1.79)	(–1.75)	(–0.27)	(0.62)	(0.13)	(0.60)	(1.01)	(–0.82)
Constant	0.82**	1.55***	0.62*	0.51**	–0.01	–0.18	–0.21	–0.36	–0.55**	–0.35
	(2.29)	(3.30)	(1.93)	(2.24)	(–0.08)	(–0.98)	(–0.88)	(–1.16)	(–1.99)	(–1.30)
Observations	384	384	384	384	384	384	384	384	384	384
R^2	0.86	0.85	0.89	0.92	0.95	0.94	0.93	0.89	0.88	0.89

*Notes: This table presents abnormal returns after controlling for macroeconomic variables in the framework of the Fama–French three-factor model. Panel A controls for recession, Panel B for liquidity risk, and Panel C for default risk. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.*

Exhibit 7

Comparison of Illiquidity Quintile Portfolios and Illiquidity-Crowding Double-Sorted Portfolios



Notes: Exhibit 7 compares illiquidity portfolios and illiquidity-crowding double-sorted portfolios. The sample is first sorted into quintiles by illiquidity as proxied by 1/turnover. Within each illiquidity quintile, the sample is further sorted into quintiles, using our crowding measure. The lowest illiquidity is labeled Quintile 1 and the highest illiquidity is labeled Quintile 5.

abnormal returns by exploiting the disequilibrium caused by crowding. To measure crowdedness, we create a crowding measure by dividing the percentage of shares held by mutual funds by the average turnover of a stock. We then investigate the impact on stock returns of crowding by mutual funds for the period from the first quarter of 1981 through the fourth quarter of 2012. We find a strong negative association between our crowding measure and two-quarters-ahead quarterly returns. Using our crowding measure, we develop a trading strategy that is long the least crowded stocks and short the most crowded stocks to exploit the price distortions due to crowding. This long–short strategy earns an annualized rate of return of 18.57% for equally weighted portfolios. Even after we control for size, book-to-market, and momentum using a procedure prescribed by Daniel et al. [1997], the long–short strategy still generates a substantial annualized return of 14.53%. Using other common methods to control for risk produces annualized alphas of 17.28% (for the Carhart four-factor model). For pragmatic portfolio management reasons, we apply the long–short strategy to smaller portfolios that invest in a subset of the stocks in Decile 1 and Decile 10 and find that such a strategy produces even larger abnormal returns. The annualized DGTW-adjusted abnormal returns attainable are as high as 38.46%. We confirm that the abnormal returns are not driven by time-varying expected returns. Surprisingly, the abnormal returns can mostly be attributed to the least crowded stocks, which have characteristics resembling stocks neglected by mutual funds. We also demonstrate that our crowding measure is an improvement over the illiquidity measure and conveys important signals beyond what is embedded in turnover.

ENDNOTES

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[1]See, e.g., Gromb and Vayanos [2002]; Khandani and Lo [2007]; Brunnermeier [2009]; Stein [2009]; Adler [2012, 2014]; Chincarini [2012]; Cahan and Luo [2013]; and Hong et al. [2015].

[2]http://www.federalreserve.gov/releases/z1/current/accessible/l223.htm.

[3]We are interested in holdings arising from tactical trading strategies that need to be unwound over a short time frame as opposed to long-term investment strategies. Hence, we focus on the holdings of actively managed mutual funds.

[4]Our crowding metric bears some resemblance to how crowding is conceived in Stein [2009]. Stein thinks of crowding as the size of correlated trades relative to marketwide arbitrage capacity, and we measure crowding by looking at investors' holdings relative to the contemporaneous liquidity level. Another work in the same spirit, which looks beyond correlated trades and attempts to measure whether selling or buying is excessive, is Lakonishok, Shleifer, and Vishny [1992].

[5]The mean portfolio turnover of active funds is 0.07689 and the mean portfolio turnover of passive funds is 0.00343. The difference is statistically significant.

[6]*Mkt cap* and *Price* are inflation-adjusted using 1982–1984 as the base year. Inflation data is retrieved from the Bureau of Labor Statistics website: www.bls.gov.

[7]Our correlation analysis between the dependent variable and the independent and control variables is available in the online Appendix.

[8]The annualized raw return of the (P1–P10) trading strategy is 18.57%. The raw portfolio returns are available in the online Appendix.

[9]The reported *t*-statistics are from testing the difference in means of the quarterly holding period returns between Decile 1 and Decile 10. The results are consistent with the primary results. Particularly, the mean quarterly raw return of Decile 1 is 7.49% whereas the mean quarterly raw return of Decile 10 is 2.60%; the difference is statistically significant at 1% (*t*-statistic = 2.74) (Results are available in the online Appendix). The mean quarterly DGTW-adjusted return of Decile 1 is 2.70%, whereas the mean quarterly DGTW-adjusted return of Decile 10 is −1.02%; the difference is statistically significant at 1% (*t*-statistic = 8.29).

[10]We want to emphasize again that we have already excluded from our sample those stocks with market capitalization below the 20th percentile NYSE breakpoint, so the stocks in the sample are not that small.

[11]We perform the same difference in means analysis as in Exhibit 2 to gauge the statistical significance of the profitability of the long–short strategy.

[12]Based on a probability of 80% for stocks in Decile 1 or Decile 10 to migrate to another decile, 40.96% of the stocks do not migrate at all; 40.96% migrate once; 15.36% migrate twice; 2.56% migrate three times; 0.16% migrate four times a year.

[13]Tabulated results are available upon request.

[14]Furthermore, from results not tabulated in this article, we find that our crowding measure, *Actratio*, is still statistically significant after incorporating the various relevant controls including the liquidity measure (turnover) in our Fama–MacBeth [1973] regression analysis to predict a stock's future quarterly returns.

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