Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Hedge Fund Crowds and Mispricing

Richard Sias, H. J. Turtle, Blerina Zykaj

MANAGEMENT SCIENCE
Vol. 62, No. 3, March 2016, pp. 764–784
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2014.2131

Hedge Fund Crowds and Mispricing

Richard Sias
Department of Finance, Eller College of Management, University of Arizona, Tucson, Arizona 85721,
sias@eller.arizona.edu

H. J. Turtle
Department of Finance and Real Estate, College of Business, Colorado State University, Fort Collins, Colorado 80523,
harry.turtle@business.colostate.edu

Blerina Zykaj
Department of Finance, College of Business Administration, University of Toledo, Toledo, Ohio 43606,
blerina.zykaj@utoledo.edu

Recent models and the popular press suggest that large groups of hedge funds follow similar strategies resulting in crowded equity positions that destabilize markets. Inconsistent with this assertion, we find that hedge fund equity portfolios are remarkably independent. Moreover, when hedge funds do buy and sell the same stocks, their demand shocks are, on average, positively related to subsequent raw and risk-adjusted returns. Even in periods of extreme market stress, we find no evidence that hedge fund demand shocks are inversely related to subsequent returns. Our results have important implications for the ongoing debate regarding hedge fund regulation.

Keywords: hedge funds; crowds; market efficiency
History: Received April 7, 2014; accepted November 24, 2014, by Wei Jiang, finance. Published online in *Articles in Advance* June 24, 2015.

> Hedge funds are crowding into more of the same trades these days, amplifying market swings during crises and unnerving investors. Such trading has stoked market jitters in recent months and helped to diminish the impact of corporate fundamentals on stock-market movements. (Strasburg and Pulliam 2011)

1. Introduction

Hedge fund assets under management grew more than 1,420% between the end of 1997 and 2012 (from $118 billion to $1.8 trillion; figures from Barclay Hedge[1]). Stein (2009, p. 1517) points out that the dramatic growth in these "prototypical sophisticated investors" could result in two negative externalities associated with hedge fund crowds. First, if hedge funds crowd into strategies that are not anchored to fundamental value, they can drive prices from value when there is uncertainty about the level of arbitrage capital; for example, too many "arbitrageurs" following a momentum strategy could drive prices from value even if momentum initially results from underreaction. Second, the negative externalities of crowded hedge fund portfolios are exacerbated in a funding crisis—if a shock forces a fund to delever and sell securities held in common with other hedge funds, this causes a negative return shock to other hedge funds holding the same stocks. As a result, other hedge funds will be forced to delever, driving even further negative return shocks and deleveraging, i.e., a "fire sale spillover" (Stein 2009, p. 1542). Pedersen (2009) and Adrian and Brunnermeier (2011) also emphasize the importance of portfolio overlap as a potential linkage in hedge fund contagion.

A number of previous studies posit that hedge fund crowds play a meaningful role in destabilizing markets. Studies speculate that hedge fund crowding was a key contributor to the 1998 financial crisis (e.g., Kyle and Xiong 2001, Gromb and Vayanos 2002), the 2007 "quant crisis" (e.g., Khandani and Lo 2011, Brunnermeier 2009), and the 2008–2009 financial crisis (e.g., Acharya et al. 2009, Pedersen 2009).

These concerns are echoed by the popular press (e.g., see introductory quote), regulators, and hedge fund managers themselves. For instance, the European Central Bank (2006, p. 142) claims, "In addition to potentially high leverage, the increasingly similar positioning of individual hedge funds within broad hedge fund investment strategies is another major risk for financial stability which warrants close monitoring despite the essential lack of any possible remedies" and Daniel Loeb (Third Point, LLC founder) writes in his June 2010 investor letter,

[1] See http://www.barclayhedge.com/research/indices/ghs/mum/Hedge_Fund.html (last accessed May 28, 2015).

"Please note that we will no longer discuss investments made prior to our public 13F filings. We have found that discussing our ideas may result in 'piling on' by other hedge funds who may subsequently sell at inopportune times resulting in greater hedge fund concentration and volatility, which is not in the interest of our investors" (Loeb 2010, p. 5).

In this paper we examine overlap in hedge fund long equity portfolios and the potentially destabilizing role of hedge fund crowds. Our study has three primary goals. First, we investigate the premise that large groups of hedge funds follow correlated strategies resulting in greatly overlapping (i.e., "crowded") long equity portfolios. Second, we investigate how both the propensity for individual hedge funds to crowd into the same stocks and the size of hedge fund crowds change over time. Third, we test for evidence of negative externalities due to hedge fund crowds both in general and during crisis periods.

Our primary conclusion is that hedge fund long equity portfolios are remarkably independent. On average, 350 hedge fund companies file 13(f) reports each quarter during our sample period (1998–2011). Although these are very large hedge funds that hold at least \$100 million in 13(f) securities at some point during the year, the median pair of hedge funds holds approximately one stock in common amounting to portfolio overlap of less than one-third of 1% (based on the Bray and Curtis 1957 independence measure). Even at the tails of the distribution, there is little evidence that large groups of hedge funds follow highly correlated strategies—the 95th percentile of hedge fund pairs with greatest commonality average less than 10% overlap in their long equity holdings.

We do find, however, that the size of hedge fund crowds in individual securities increases substantially over our sample period. This increase results from the substantial growth in the number of hedge funds rather than an increase in the average propensity of individual hedge fund pairs to engage in crowded trades. In fact, the time trend in the average hedge fund portfolio overlap is negative.

Last, we find no evidence of a negative relation between aggregate hedge fund demand shocks and subsequent returns as would be expected if hedge fund crowds systematically drive prices from value. In contrast, we find a statistically significant positive relation between hedge fund demand shocks and returns over the next few quarters. We continue to find a positive relation between hedge fund demand shocks and subsequent returns when we partition the analysis into crisis and noncrisis periods—although the relation tends be weaker in crisis periods. For nonhedge fund institutions, subsequent returns are negatively related to demand shocks in both crisis and noncrisis periods.

The positive relation between aggregate hedge fund demand shocks and subsequent returns is consistent with the hypothesis that hedge funds tend to be better informed than other investors. Hedge fund informational advantages may result from a better understanding of fundamental value (and thus, their trades push prices toward fundamental values) or, as pointed out by Brunnermeier and Nagel (2004) and others, from a better understanding of how mispricing evolves (e.g., buying an overvalued stock prior to an increase in its *mispricing*). In the latter case, one would expect an eventual return reversal that we do not observe in the data. Of course, it is possible that such reversals are too gradual or in the midst of enough noise that our tests fail to capture the impact.

2. Data

Because hedge funds are typically exempt from the Investment Company Act of 1940, they are not required to disclose their holdings (or net asset values) in the same manner as other investment companies. Following several recent studies, we overcome this limitation by examining hedge funds' quarterly 13(f) filings.[2] These 13(f) reports are usually filed at the manager level. For example, Tudor Investment Corporation files a single 13(f) report that provides aggregate holdings of all Tudor funds.[3]

We combine the quarterly 13(f) institutional ownership filings with proprietary institutional type classifications provided by Thomson Reuters that identify all hedge fund managers providing 13(f) reports each quarter between 1998 and 2011.[4] Thomson Reuters began providing the data to us in 2001 for a sample period beginning in 1998. Between 2001 and 2005, Thomson Reuters provided five classification updates. From September 2006 through December 2011, Thomson Reuters provided investor type updates every

[2] See, for example, Brunnermeier and Nagel (2004), Griffin and Xu (2009), Blume and Keim (2011), Boyson et al. (2011), Ben-David et al. (2012), and Agarwal et al. (2013a, b).

[3] From the perspective of examining crowded portfolios, this is a positive attribute because we are interested in whether different managers make the same decisions, rather than whether a given manager makes the same decision for multiple funds they control (e.g., an offshore fund and its twin onshore fund).

[4] As noted by Ben-David et al. (2012), Thomson Reuters has a long-lasting relation with the U.S. Securities and Exchange Commission with respect to institutional filings (dating back to pre-Internet times) and extensive information about these institutions and their staff. To the best of our knowledge, Thomson Reuters has not provided this data set to other academics. Several recent studies use other interesting Thomson Reuters' lists or data. Discussions with these authors reveal that each of these data sets or lists is unique (see, for comparison, Ben-David et al. 2012, Cici et al. 2013).

quarter.[5] Our final sample consists of 4,873 unique 13(f) managers including 1,006 hedge funds and 4,021 non-hedge fund institutions. Because our time series of Thomson Reuters' manager types allows managers to change classifications as their business changes, the sum of the number of unique hedge funds and non-hedge fund institutions is greater than the number of unique managers.

The 13(f) data have two primary limitations when measuring crowded equity portfolios. First, the data do not capture all hedge funds or all hedge fund positions. Only institutions (including hedge funds) with more than $100 million in U.S. equities are required to file 13(f) reports, and filing institutions are not required to report positions less than 10,000 shares and $200,000. In addition, the U.S. Securities and Exchange Commission sometimes allows managers to have confidential filings that generally do not show up in the Wharton Research Data Services (WRDS) 13(f) data. These confidential positions can be large—for hedge funds that report confidential positions, these securities account for, on average, one-third of fund's long equity portfolio (see Agarwal et al. 2013b). Nonetheless, we do not view this limitation as severe for two reasons. First, recent work suggests that public 13(f) filings capture more than 96% of hedge fund stock positions and 89% of hedge funds never file a confidential report.[6] Second, our sample includes over 1,000 hedge fund companies and over 1.6 million hedge fund quarter positions—presumably adequate to detect evidence of hedge fund equity crowds.

The second limitation is potentially more challenging. We only capture hedge fund long positions in U.S. equities with no information about equity derivatives or short positions of hedge funds.[7] In addition, as we discuss later, our results remain robust when we incorporate short interest data into our analysis. Moreover, most hedge funds appear to be net long (e.g., Griffin and Xu 2009). Nonetheless, our inability to capture the complete set of hedge fund trades may reduce the power of our tests and could bias our results if the disclosed positions differ in a systematic manner from all positions.

[5] One potential concern is that the manager types could be backfilled prior to 2001. As a robustness test, we repeated our primary tests using only post-2000 data. Our results remain effectively unchanged.

[6] These figures are inferred from Table I in Agarwal et al. (2013b).

[7] There are, no doubt, a significant number of hedge funds that extensively employ equity derivatives that we do not capture in our 13(f) data. Recent work suggests, however, that U.S. equity derivatives make up a relatively small portion of the typical hedge fund's portfolio. Specifically, based on a sample of 250 hedge fund companies over the 1999–2006 period, Aragon and Martin (2012) report that the dollar value of assets underlying all option positions (i.e., the holdings if the options were exercised) averages approximately 4.5% of the value of direct common stock holdings.

To be included in the sample, a security must have returns for each month in quarter $t = 0$, Center for Research in Security Prices (CRSP) share code of 10 or 11, and price, shares outstanding, and capitalization data at the beginning and end of the quarter. Managers (both hedge funds and non-hedge fund institutions) must have nonzero *portfolio* holdings at both the beginning and end of the quarter to be included in the sample. We are careful to adjust holdings for stock splits and stock dividends, and for delays in reporting stocks splits. We also correct the data for known errors.[8] For our analysis of subsequent quarter returns ($t > 0$) we only require CRSP return data and use CRSP delisting returns for stocks that delist.

3. The Role of Hedge Funds in U.S. Equity Markets

Panel A in Table 1 reports that, on average, there are 350 hedge funds (ranging from 114 to 610) and 1,854 non-hedge fund institutions (ranging from 1,353 to 2,413) each quarter in our sample between June 1998 and December 2011. Figure 1 plots the number (right scale) and fraction (left scale) of 13(f) institutions classified as hedge funds over time. The results reveal a dramatic increase in the number of hedge funds filing 13(f) reports between June 1998 and March 2008 (from 114 to 610). The fraction of 13(f) filers classified as hedge funds also experiences dramatic growth—rising from 7% in 1998 to more than 21% in March 2008 before dropping back to 16% in 2011.

Panel B in Table 1 reports the time-series average of the cross-sectional mean and median long equity portfolio characteristics (number of securities held and portfolio size) for hedge funds and non-hedge fund institutions. Portfolio size is the total dollar value of 13(f) manager holdings. Because portfolio overlap is related to size (i.e., large managers are more likely to have overlapping portfolios than small managers), we form a matched sample of similar size non-hedge fund institutions. Specifically, for each hedge fund quarter we select (without replacement) the non-hedge fund institution closest in total portfolio size (based on the dollar value of their 13(f) holdings). The mean and median values for the sample of size matched non-hedge fund institutions are also reported in panel B. In addition, we report the time-series average of the

[8] See Blume and Keim (2011) and Gutierrez and Kelley (2009) for discussion of issues associated with the Thomson Reuters/WRDS 13(f) data. In addition, we find that the change in holdings files downloaded from WRDS are corrupt from June 2006-March 2007. Specifically, in more than 90% of the observations, changes in holdings are the negative of the end of quarter holdings for these four quarters. Following Yan and Zhang (2009) we exclude observations where reported institutional ownership exceeds 100% of shares outstanding.

Table 1 Descriptive Statistics

Panel A: Time-series descriptive statistics of 13(f) institutional investors

	Mean	Median	Minimum	Maximum
Number of hedge funds	350	400	114	610
Number of non-hedge funds	1,854	1,794	1,353	2,413
Number of institutions	2,203	2,194	1,479	2,893
Hedge funds (%)	15.11	16.46	7.40	21.43

Panel B: Time-series average of cross-sectional means and medians

	Mean				Median			
	Hedge funds	Non-hedge funds	Matched non-hedge funds	Difference (hedge fund-matched)	Hedge funds	Non-hedge funds	Matched non-hedge funds	Difference (hedge fund-matched)
No. securities	84	230	129	−45	37	88	71	−34
				(−22.88)***				(35.77)***
Portfolio size (M)	$681	$4,259	$681	−$0.098	$202	$321	$202	−$0.110
				(−1.03)				(−2.59)**

Panel C: The distribution of hedge fund positions

	Mean	95th percentile	Median	5th percentile
Observed entries and exits/holdings	0.356	0.739	0.336	0.041
Observed adjustments/holdings	0.472	0.233	0.500	0.566
No trade/holdings	0.172	0.027	0.163	0.393

Notes. Panel A reports the time-series descriptive statistics for the number of hedge funds and non-hedge fund institutions filing 13(f) reports between June 1998 and December 2011 ($n = 55$ quarters). Panel B reports the time series average of the cross-sectional mean and median portfolio characteristics of hedge funds, non-hedge fund institutions, and a size-matched sample of non-hedge fund institutions. The t-statistics (reported in parentheses) are based on the time-series of the 55 means or medians and Newey and West (1987) standard errors. Panel C reports the time-series average of the cross-sectional descriptive statistics of the fraction hedge fund positions accounted for by (1) observable entries and exits, (2) adjustments to existing positions, and (3) securities held but not traded over the quarter. Each column in panel C sums to one.

***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

mean (fourth column) and median (last column) difference between hedge funds and the matched sample of non-hedge fund institutions.

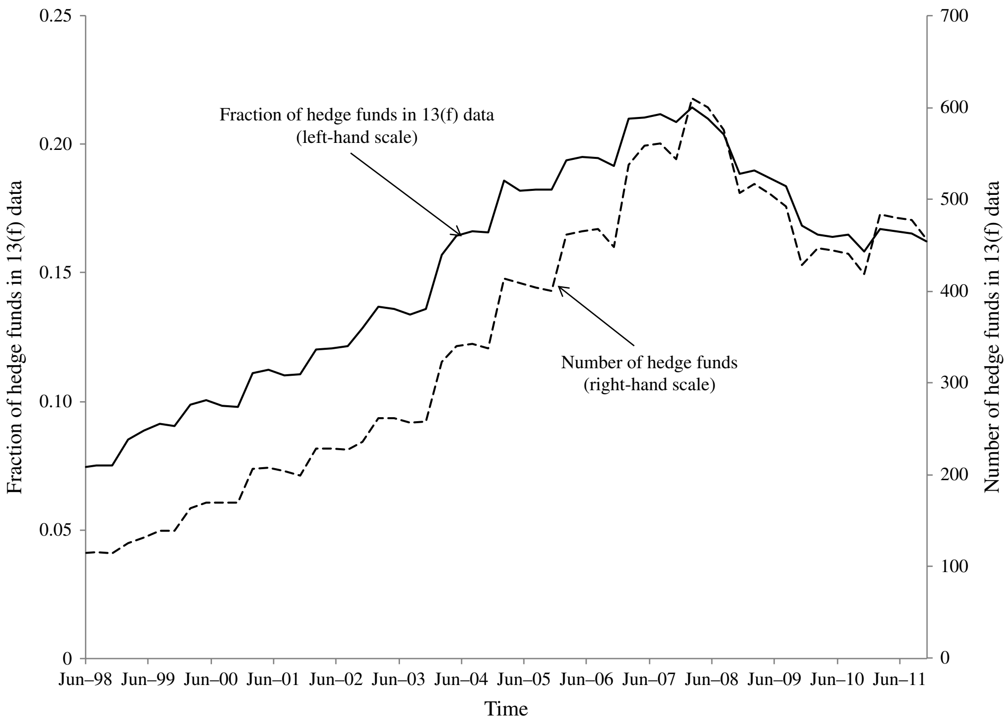
The results in panel B show that the typical (median) hedge fund manager in our sample holds 37 stocks worth $202 million versus 88 stocks worth $321 million for the median non-hedge fund institution. The results in panel B also reveal that our matching algorithm works well—the average hedge fund portfolio size does not significantly differ from the average matched non-hedge fund institution. The median hedge fund is about 0.05% smaller than the median matched non-hedge fund institution. Holding long equity portfolio value approximately constant, we find that hedge fund portfolios are much more concentrated—the median hedge fund holds 37 stocks versus 71 stocks for the median size matched non-hedge fund institution.

One limitation of the 13(f) data when examining hedge fund demand shocks and subsequent returns is the inability to observe intraquarter hedge fund trades. Recent work suggests hedge funds (and other institutions) play an important role in short-term returns—both as liquidity providers and incorporating information. For instance, Franzoni and Plazzi (2013) provide evidence that the price impact of hedge fund trades increases when funding liquidity tightens and Puckett and Yan (2011) find evidence that intraquarter institutional trades are informed. (See Aragon and Strahan 2012 and Anand et al. 2012, 2013 for additional evidence of the relation between hedge funds or other institutions and liquidity). Our use of quarterly data limits our ability to capture this behavior.

To provide some guidance regarding the potential importance of intraquarter trading, we measure how often hedge funds tend to exit and enter securities relative to making adjustments to, or not trading, securities in their portfolio (based on observable interquarter entries and exits). Our intuition is straightforward—if hedge funds typically follow short-term strategies that play out within a quarter, then most of the securities they hold at the end of the quarter will differ from the ones they hold at the beginning. Specifically, we partition the securities held by each hedge fund quarter into three groups—the fraction that are observable entries and exits over the quarter, the fraction that are adjustments to existing positions, and the fraction that are stocks held but not traded over the quarter (thus, the fractions sum to one).[9]

[9] Specifically, we use the average number of securities held by the manager at the beginning and end of the quarter as the denominator. The numerators are (1) the sum of the number of observed

Figure 1 **Hedge Funds in the 13(f) Data Over Time (1998–2011)**



Notes. The solid line depicts the fraction of 13(f) institutions identified as hedge fund companies (left-hand scale). The broken line depicts the number of 13(f) institutions identified as hedge fund companies (right-hand scale).

Panel C in Table 1 reports the time-series average of the cross-sectional descriptive statistics of each term based on the ratio of entries and exits to holdings. The results suggest that the typical (median) hedge fund does not appear to primarily engage in short-term intraquarter trades—approximately two-thirds of the stocks in the manager's portfolio at the end of the quarter were also held at the beginning of the quarter (i.e., the sum of the second and third rows). However, some hedge funds exhibit much higher turnover rates. For instance, nearly 74% (top row) of the stocks held at the end of the quarter differ from the stocks held at the beginning of the quarter for a hedge fund in the 95th percentile of observable entries and exits.

4. Overlap in Hedge Fund Equity Portfolios

We measure the extent to which hedge funds crowd into the same stocks by examining overlap in their long equity portfolios. This research design has five advantages. First, the 13(f) data provide 55 quarters that allow direct measurement of overlap in hedge fund U.S. long equity holdings. Second, we are not required to identify or hypothesize a specific strategy that hedge funds or subsets of hedge funds follow (e.g., if they crowd into value stocks). Third, our method allows the realistic possibility that "common" strategies may change over time. Fourth, the portfolio overlap tests are based on a complete sample of large (i.e., 13(f)) hedge fund ownership *levels* at 55 points in time, and are not impacted by the inability to observe intraquarter hedge fund trades. Fifth, our approach is not developed from measures of synchronization in trades.[10] In short, the approach provides a powerful and broad test of crowding across hedge funds.

We use four different measures of portfolio overlap for every pair of hedge funds—the number of securities held by both funds, the Bray and Curtis (1957) independence measure (henceforth, the portfolio independence metric), cosine similarity, and cosine similarity in positive active weights.[11] Unless every security was held uniquely by a single hedge fund,

entries and exits divided by two, (2) the number of adjustments (e.g., purchasing additional shares of a security owned at the beginning of the quarter), and (3) the number of securities held but not traded (i.e., same number of shares held at the beginning and end of the quarter).

[10] For example, if two hedge funds each hold 30% of their portfolio in Apple, but during the quarter one fund sells 0.01% of their shares and the other purchases 0.01% in additional shares, their trades do not overlap, yet both funds are clearly attracted to the same stock.

[11] See Cha (2007) for a discussion of similarity measures. The portfolio independence measure is also known as Sørensen (1948) distance. Cremers and Petajisto (2009) use this metric to measure individual mutual funds' independence from benchmark portfolios (denoted "active share").

there will be some overlap in hedge fund portfolios. Thus, "no portfolio overlap" is not the null hypothesis. Furthermore, as Griffin and Xu (2009) demonstrate, hedge fund ownership levels are related to a number of security characteristics; for example, hedge funds exhibit a preference for securities with higher share prices. Thus, we predict, and untabulated tests confirm, overlap in hedge fund portfolios is greater than overlap in purely random portfolios.[12]

Thus, as noted in the introduction, we use portfolio overlap of similar size non-hedge fund institutions to objectively benchmark the size of hedge fund crowds. Specifically, our null hypothesis is that hedge fund portfolio overlap is no greater than the portfolio overlap in comparable non-hedge fund institutions as the views implicit in the literature and financial press (see introduction) suggest that hedge funds are more likely to crowd into the same stocks (due to their correlated strategies) than other institutional investors.

Because we compute each measure for every pair of hedge funds and every pair of similar size non-hedge fund institutions each quarter, the number of observations for each measure ranges from 6,441 (when there are 114 hedge funds, i.e., $H_t * (H_t - 1)/2$) to 185,745 (when there are 610 hedge funds) for a total of just under four million hedge fund pair quarter observations and four million matched non-hedge fund institution pair quarter observations.

4.1. Number of Securities in Common

We begin with an intuitive, albeit crude, measure of portfolio overlap—the number of securities that each pair of hedge funds hold in common. The first row of panel A in Table 2 reports the time-series average of the cross-sectional 95th percentile, median, 5th percentile, and mean number of securities held in common by all hedge fund pairs. To provide scale, we also report (parenthetically) the time-series mean number of securities held by funds that make up the 95th, median, and 5th percentiles. The results reveal little evidence of excessive portfolio crowding for the typical hedge fund pair—the time-series average of the median fund pair holds less than one security in common (0.8 securities). In contrast, the median size-matched non-hedge fund institutional pair holds nine securities in common.

The fourth column reports the time-series average of the quarterly cross-sectional mean number of securities held in common for hedge fund pairs and the size-matched sample of non-hedge fund institution pairs. The last two rows in the final column report the number of quarters where the difference in means (hedge funds less non-hedge fund institutions) is positive or negative, respectively. We also report, in brackets, the number of quarters where the difference is statistically significant at the 5% level (based on a t-test for differences in means). In every quarter, we find that the average similar size non-hedge fund institution pair exhibits greater portfolio overlap (as

Table 2 **Overlap in Hedge Fund Portfolios and Similar Size Non-Hedge Fund Institution Portfolios**

	95th percentile	Median	5th percentile	Average
Panel A: Number of common securities				
Hedge funds	16.000	0.800	0.000	4.131
(No. of securities held)	(278)	(51)	(36)	
Non-hedge funds	74.982	9.000	0.000	20.865
(No. of securities held)	(319)	(103)	(54)	
Number positive	0			0
[Number significant]	[0]			[0]
Number negative	55			55
[Number significant]	[55]			[55]
Panel B: Portfolio independence				
Hedge funds	1.000	0.997	0.904	0.978
Non-hedge funds	1.000	0.946	0.645	0.895
Number positive			55	55
[Number significant]			[55]	[55]
Number negative			0	0
[Number significant]			[0]	[0]
Panel C: Cosine similarity in portfolio weights				
Hedge funds	0.153	0.002	0.000	0.031
Non-hedge funds	0.509	0.061	0.000	0.139
Number positive	0			0
[Number significant]	[0]			[0]
Number negative	55			55
[Number significant]	[55]			[55]
Panel D: Cosine similarity in positive active weights				
Hedge funds	0.123	0.001	0.000	0.024
Non-hedge funds	0.271	0.022	0.000	0.066
Number positive	0			0
[Number significant]	[0]			[0]
Number negative	55			55
[Number significant]	[55]			[55]

Notes. Each quarter between June 1998 and December 2011 ($n = 55$ quarters), we compute four measures of portfolio overall for every pair of hedge funds and every pair of a size-matched sample of non-hedge fund institutions—the number of securities in common (panel A), portfolio independence (panel B), cosine similarity in portfolio weights (panel C), and cosine similarity in positive active weights (panel D). The first two rows in each panel report the time-series average of the cross-sectional descriptive statistics for each metric. Panel A also reports parenthetically the mean number of securities held by each pair. The third row of the last column reports the number of quarters the difference in means is positive and the number of quarters the difference is statistically significant at the 5% level (based on a t-test for difference in means). The fourth row reports analogous statistics for negative differences. The first column in panels A, C, and D (and third column in panel B) reports analogous tests for differences when the sample is limited to hedge fund pairs that exhibit the 5% greatest overlap versus non-hedge fund pairs that exhibit the 5% greatest overlap.

[12] For instance, given hedge fund preferences for higher priced securities, overlap in actual hedge fund portfolios is greater than overlap in purely random portfolios because hedge fund portfolios tend to invest in higher priced stocks, relative to lower priced stocks, in greater proportion than a random draw.

measured by number of securities held in common) than the average hedge fund pair (statistically significant at the 5% level in every quarter).

Although we find little evidence that the typical hedge fund pair exhibits high levels of portfolio overlap, it is arguably more likely that there are large subsets of hedge funds that have substantial overlap. For instance, a group of hedge funds focusing on short-term reversals may hold one common set of stocks, whereas another group of hedge funds focusing on a value strategy may hold another set of common stocks. To evaluate this possibility, we examine the 95th overlap percentiles. Note that this is a very robust test—we do not need to identify which hedge funds exhibit similar strategies—we simply examine the overlap for pairs of hedge funds with greatest commonality in their holdings.

Even at this extreme, there is relatively little overlap in long equity holdings—hedge fund companies in the 95th overlap percentile only hold 16 stocks in common even though individual hedge fund companies in this group average a total of 278 securities in their portfolio (reported parenthetically). By comparison, the 95th percentile of similar sized non-hedge fund institution pairs hold 75 stocks in common out of an average portfolio of 319 securities. We next repeat the tests for differences in means, when limiting the sample (each quarter) to the 5% of hedge fund pairs that exhibit the greatest overlap versus the 5% of non-hedge fund pairs that exhibit the greatest overlap. Inconsistent with the hypothesis that there are large groups of hedge funds that closely follow the same strategies (resulting in greatly overlapping equity portfolios), we find the overlap in the top 5% of size-matched non-hedge fund pairs is greater (statistically significant at the 5% level) than the portfolio overlap in the top 5% of hedge fund pairs in all 55 quarters. In short, without exception, the evidence reveals that hedge funds, both in general and in the extremes, have lower levels of portfolio overlap than similar size non-hedge fund institutions.

4.2. Portfolio Independence

Our portfolio independence metric is one-half the sum (across stocks) of the absolute differences in two managers' portfolio weights. This measure has a possible range from zero to one. One minus the portfolio independence metric essentially captures the extent of overlap between two managers' portfolios. For example, if manager A has perfect overlap with manager B, the pair's portfolio independence is zero. If manager A holds only half the stocks held by manager B (that account for half of manager B's portfolio value), but at double manager B's weight, then the pair's portfolio independence is 50%. And if manager A holds none of the same stocks as manager B, the pair's portfolio independence is one. We use portfolio independence to provide an improved estimate of portfolio overlap for hedge fund pairs. Specifically, we compute one-half the sum of the absolute difference in portfolio weights between every pair of hedge funds each quarter:

$$PI(h_t, j_t) = \tfrac{1}{2}\sum_{k=1}^{K} |w_{h,k,t} - w_{j,k,t}|, \tag{1}$$

where K is the total number of securities in the market in quarter t, $w_{h,k,t}$ is hedge fund h's quarter t portfolio weight in security k, and $w_{j,k,t}$ is hedge fund j's quarter t portfolio weight in security k. We analogously compute portfolio independence for every pair of the size-matched non-hedge fund institutions.

Panel B in Table 2 reports the time-series average of the cross-sectional descriptive statistics for the portfolio independence measure for hedge fund pairs and the size matched sample of non-hedge fund institution pairs. Consistent with panel A, hedge fund portfolios exhibit greater independence from one another than do similar size non-hedge fund institution portfolios. In fact, the median hedge fund pair exhibits almost complete independence from one another—their portfolios overlap by less than one-third of 1% (i.e., $1 - 0.997$). The difference in mean values for the entire distribution of hedge fund pairs and non-hedge fund institution pairs is positive and statistically significant at the 5% level in all 55 quarters (last column, final two rows). Even at the extremes, there is relatively little overlap in hedge fund portfolios compared to overlap in non-hedge fund institutional portfolios. The 95th percentile of hedge fund pairs with the greatest overlap (i.e., the fifth portfolio independence percentile) averages less than 10% (i.e., $1 - 0.904$) portfolio overlap versus 35% (i.e., $1 - 0.645$) portfolio overlap for similar size non-hedge fund institution pairs (and the difference is statistically significant in all 55 quarters).

4.3. Cosine Similarity

One limitation of the portfolio independence measure is that the overlap contribution from any stock is the minimum of the smaller portfolio weight. If, for example, managers A and B each hold 10% in Apple and the rest of their portfolios do not overlap, then their portfolio independence is 90% (i.e., overlap is 10%). If investor B moves 100% of his portfolio to Apple, the overlap, as measured by portfolio independence, does not change (i.e., they still overlap by 10%). Yet, intuitively, Apple is more crowded when B has an Apple portfolio weight of 100% than when it is 10%. Thus, as an alternative to portfolio independence, we consider cosine similarity, which focuses on the product of the overlapping portfolio weights rather than the minimum of the overlapping portfolio weights. Specifically, the cosine similarity between hedge fund h's portfolio weights and hedge fund j's portfolio weights is given by

$$s(h_t, j_t) = \sum_{k=1}^{K} w_{h,k,t} w_{j,k,t} \Bigg/ \left(\sqrt{\sum_{k=1}^{K} w_{h,k,t}^2} \sqrt{\sum_{k=1}^{K} w_{j,k,t}^2} \right). \tag{2}$$

Cosine similarity is bounded between zero and one. If two hedge funds hold the same portfolio, the cosine similarity will equal one; whereas, if two hedge funds hold none of the same securities, cosine similarity will equal zero. In contrast to portfolio independence, a higher value for cosine similarity indicates greater portfolio overlap.

Panel C in Table 2 reports the cosine similarity analysis. Once again, we continue to find strong evidence that hedge fund companies exhibit greater independence than non-hedge fund institutions. For instance, the average cosine similarity for comparable size non-hedge fund institutions is over four times that for hedge funds (0.139 versus 0.031; last column of panel C). Even at the extremes, hedge fund pairs continue to display substantially lower portfolio overlap than non-hedge fund institution pairs. The last two rows reveal that hedge funds exhibit less portfolio overlap than non-hedge fund institutions in all 55 quarters whether the sample considers all hedge fund pairs versus all non-hedge fund institutional pairs (last column), or the 5% hedge fund pairs with the greatest portfolio overlap versus the 5% of non-hedge fund institution pairs with the greatest overlap (first column).

One potential explanation for the greater overlap in non-hedge fund institution portfolios is that non-hedge fund institutions hold portfolios that more closely mimic the market portfolio. To examine this possibility, we compare the similarity in deviations from market weights for stocks overweighted by hedge funds versus stocks overweighted by non-hedge fund institutions. We examine overweighted securities because overlap in underweighted securities primarily focuses on commonality in what investors are not holding. Clearly, if no hedge funds hold Apple, then Apple is not crowded with long hedge fund trades.

Because positive active weights do not sum to one, we use cosine similarity rather than portfolio independence to measure overlap in overweighted stocks.[13] Specifically, we replace the portfolio weights in Equation (2) with the deviation from market weights (i.e., $w_{h,k,t} - w_{mkt,k,t}$) for those securities each institution overweights (i.e., $w_{h,k,t} > w_{mkt,k,t}$) and zero for those securities each institution does not overweight.

The results, reported in panel D of Table 2, reveal a substantial decline in the overlap for non-hedge fund institutions when moving from portfolio weights (panel C) to deviations from market weights for overweighted stocks (panel D) indicating that some of the commonality in non-hedge fund institution portfolios arises because these portfolios have substantial overlap with the market portfolio. However, hedge fund pairs also exhibit a decline in commonality; for example, the average hedge fund pair cosine similarity falls from 0.031 to 0.024 when moving from portfolio weights (panel C) to positive deviations from market weights (panel D). More important, however, the results in panel D reveal that hedge funds exhibit less overlap in their overweighted positions than do similar size non-hedge fund institutions both on average and in the tail of the distribution—the difference is statistically significant at the 5% level in all 55 quarters. Thus, non-hedge fund institutions more closely mimicking the market portfolio cannot fully explain differences in portfolio overlap.[14]

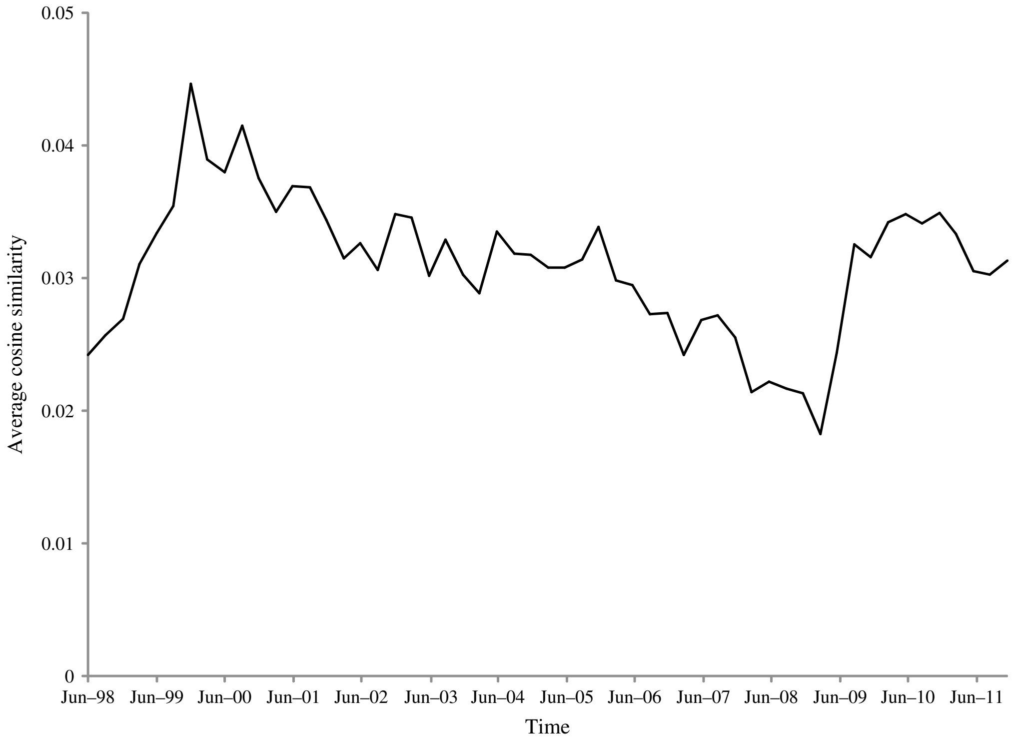
5. Crowded Stocks and Hedge Fund Crowding Over Time

Temporal changes in the size of hedge fund crowds are a function of both changes in the number of hedge funds and changes in the propensity of hedge funds to engage in crowding. As already shown in Figure 1, there is a dramatic increase in the number of hedge funds over time. Moreover, as noted in the introduction, some regulatory authorities have expressed concern that hedge funds' propensity to engage in crowding has also increased over time. Thus, we begin with an investigation of how hedge fund crowds change over time by examining whether hedge funds exhibit increasingly similar positioning in their equity portfolios. Specifically, we plot the cross-sectional mean cosine similarity for hedge fund pairs over time in Figure 2. The results reveal no evidence that portfolio

[13] It is straightforward to generate examples where portfolio independence based on positive active weights is less than one even when managers overweight none of the same stocks.

[14] One potential explanation for the low levels of hedge fund portfolio overlap is that some hedge funds may primarily focus on nonequities such as commodities, fixed income, or currencies. As a result, these funds may hold relatively few equities. To investigate this possibility, we use several methods to identify equity-oriented hedge funds (including multifactor style analysis and self-identified strategies in a sample of Hedge Fund Research and Center for International Securities and Derivative Markets (CISDM) hedge funds matched to our 13(f) hedge funds) and then examine portfolio overlap for these equity-oriented hedge funds versus the size matched sample of non-hedge fund institutions. Our results (untabulated) are robust across all samples. Specifically, we find absolute and relative levels of portfolio overlap for our restricted samples of equity-oriented hedge funds are very similar to the portfolio overlap for our broader sample.

Figure 2 **Average Cosine Similarity for Hedge Fund Pairs Over Time**



Notes. Each quarter we compute the cosine similarity (see Equation (2)) of portfolio weights between every pair of hedge funds. The graph depicts the evolution of average cosine similarity for hedge fund pairs over time.

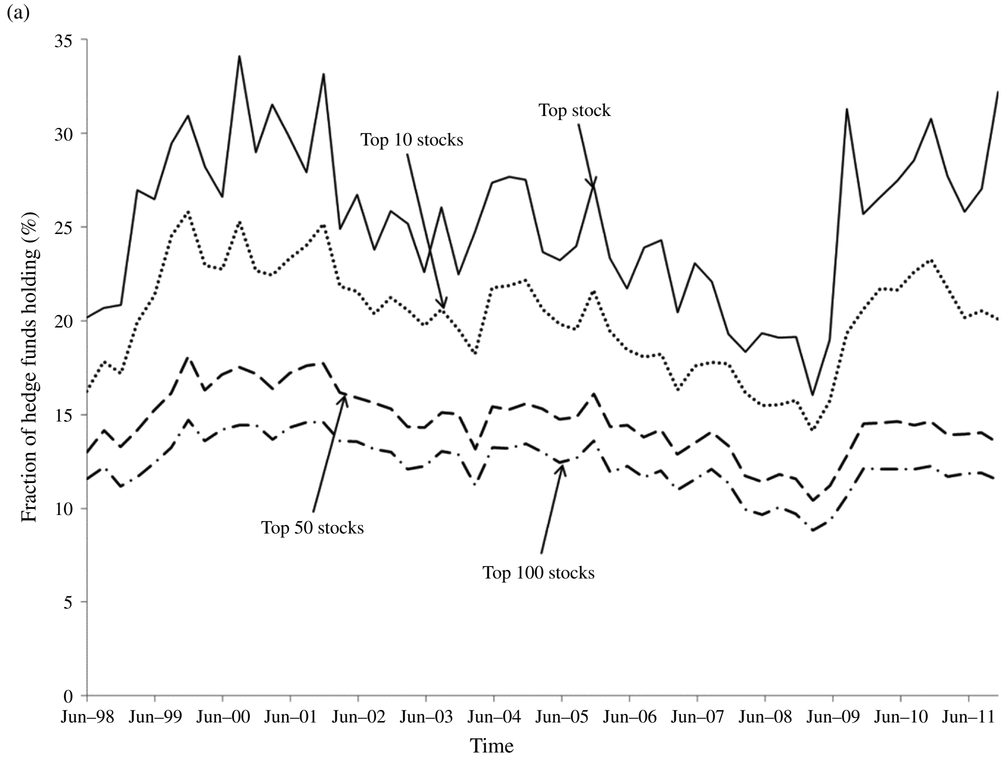
overlap in the average hedge fund pair has systematically increased over time. In fact, in untabulated tests, we document a statistically significant negative time trend for the cross-sectional mean, median, and 95th percentile of cosine similarity.[15]

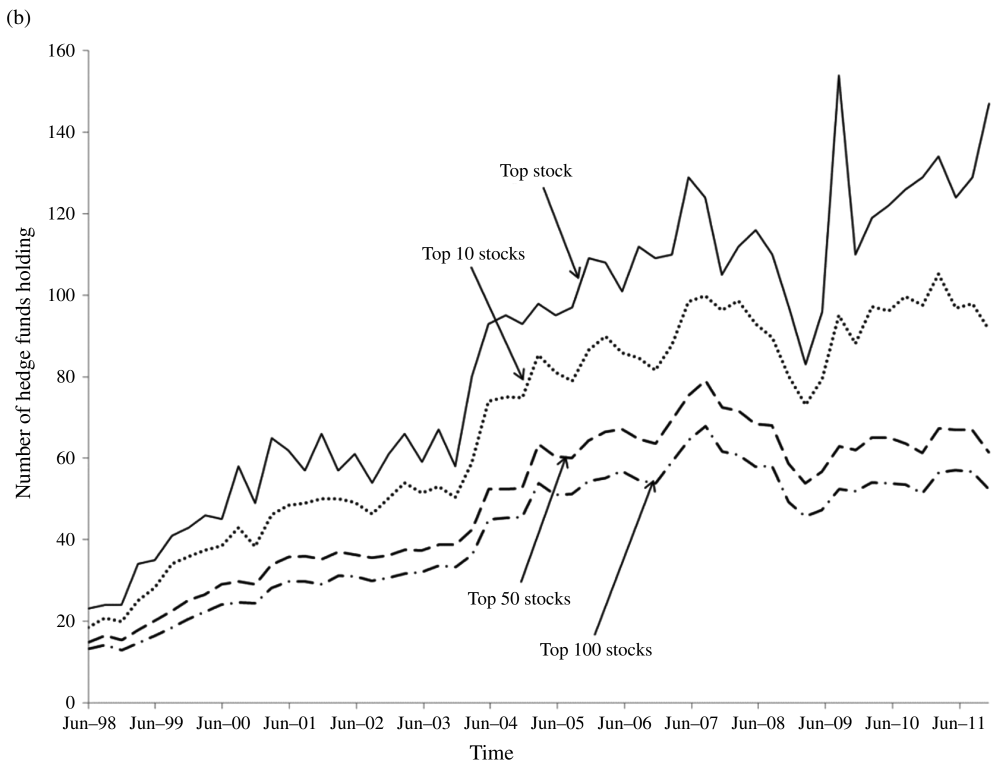
Although the results in Figure 2 reveal no evidence that hedge funds' propensity to hold the same securities has systematically increased over time, the results in Figure 1 show that the number of hedge funds has increased dramatically over time. In addition, although hedge fund portfolios exhibit relatively little overlap, some individual securities may still become crowded with hedge fund positions if the few securities that are common to hedge fund pairs are often the same securities. That is, although little overlap in hedge fund *portfolios* suggests that large groups of hedge funds do not appear to follow highly correlated strategies, this does not necessarily imply *all* stocks have little crowding. For instance, Apple was held by nearly one-third of hedge funds at the end of 2011 (Apple was the most popular hedge fund stock at the end of our sample period) even though the mean number of total securities held in common across all hedge fund pairs was only 3.80. Thus, we now shift our focus from an examination of overlap in hedge fund *portfolios* to aggregate hedge fund holdings at the individual security level. We begin by calculating the number of hedge funds holding the "most crowded" stocks. Specifically, each quarter, we identify the 1, 10, 50, and 100 stocks with the greatest number of hedge fund shareholders. Thus, this analysis focuses on the extreme tails of the distribution across securities; for example, the 10 (100) most crowded securities represent, typically, only 0.25% (2.5%) of all securities. Figure 3(a) plots the *fraction* of hedge funds holding these stocks over time. For instance, the far right-hand side of the top line in Figure 3(a) reveals that nearly 32% of hedge funds held a position in Apple (the most crowded stock at that point) at the end of our sample period.

Figure 3(a) reveals two interesting patterns. First, consistent with Figure 2, there is no evidence that the propensity of hedge funds to hold the same stocks has increased over time. In fact, in untabulated tests, we find that the lower three lines (the 10, 50, and 100 most crowded stocks) exhibit a statistically significant negative time trend (at the 5% level). Second, concentration drops off relatively quickly. For example, although 32% of hedge funds held Apple, the top

[15] Figure 2 also reveals a spike between the second and third quarter of 2009. Further investigation finds that this is largely driven by many hedge funds purchasing a few financial stocks in the second quarter of 2009. For instance, the number of hedge funds holding a position in Bank of America more than doubled in the second quarter of 2009 from 73 at the beginning of the quarter to 154 at the end of the quarter. (Bank of America was the number one hedge fund stock at the end of the second quarter of 2009.)

Figure 3 Fraction and Number of Hedge Funds Invested in the "Most Crowded" Stocks





Notes. Each quarter, we use 13(f) reports to compute the average fraction of hedge funds holding (panel (a)) and the average number of hedge funds holding (panel (b)) the most crowded stocks for the 1, 10, 50, and 100 stocks with the greatest number of hedge fund shareholders. For instance, at the end of 2011, the 100 most crowded hedge fund stocks were held by 11.5% of hedge funds filing 13(f) reports (bottom line, far right observation in panel (a)) and averaged 52 hedge fund shareholders (bottom line, far right observation in panel (b)).

stock, at the end of 2011, the top 100 most crowded stocks (at the same point in time) averaged ownership by only 11% of hedge fund companies (bottom line in Figure 3(a), extreme right-hand observation).

Although hedge fund portfolio overlap does not increase over time (see Figures 2 and 3(a)), the growth in the number of hedge funds (see Figure 1) means that hedge fund crowd size in individual securities may increase substantially. To investigate this possibility, Figure 3(b) reports the number of hedge funds holding the top 1, 10, 50, and 100 stocks with the greatest number of hedge fund owners. For instance, in the fourth quarter of 2011, 147 hedge funds held a position in Apple (Figure 3(b) top line, extreme right most observation). Figure 3(b) shows that hedge fund crowds have increased over time. For instance, the 100 most crowded stocks averaged 13 hedge fund shareholders in 1998 versus 52 hedge fund shareholders in 2011. In untabulated tests, we find that the time trend for each line in Figure 3(b) is significantly positive. In sum, hedge fund crowds in individual securities have grown over time as a result of the growth in the number of hedge funds and not because individual hedge funds increasingly focus on the same securities.

6. The Impact of Hedge Fund Demand Shocks on Contemporaneous and Future Returns

Although there is little evidence that large groups of hedge funds follow the same strategies resulting in greatly overlapping portfolios, our analysis shows that some stocks are crowded with hedge fund positions. Moreover, there are a number of reasons that even small hedge fund crowds may cause large price effects including (1) equilibrium can be fragile (e.g., Brunnermeier and Pedersen 2009), (2) hedge fund positions can be relatively large, (3) hedge funds have higher turnover than other institutions, (4) hedge funds use greater leverage, and (5) network effects.[16]

Although portfolio overlap is the appropriate metric for assessing whether hedge funds follow similar strategies, hedge fund demand shocks are the appropriate metric for capturing the negative externalities associated with the impact of crowded portfolios on prices. In particular, synchronized *changes* in hedge fund ownership, especially in times of market stress, are the source of price destabilization that underlies theory and concerns market participants and regulators.

[16] For example, if funds A and B overlap by a few securities and funds B and C overlap by a few different securities, a shock to fund A could impact both funds B and C (even though C holds no securities in common with A) if B is forced to sell off securities it holds in common with fund C.

We use changes in reported 13(f) holdings to infer hedge fund transactions over each calendar quarter. Specifically, we define a hedge fund as a buyer of a security if they hold more split-adjusted shares at the end of the quarter than the beginning of the quarter, and a seller if they hold fewer. As noted in the data section, the limitation of 13(f) data is that we cannot view intraquarter hedge fund trades (i.e., stock entered and exited within the same quarter). The turnover analysis discussed in the §3 (Table 1, panel C), however, suggests that most hedge funds have a low turnover component to their long equity portfolios. Consistent with this view, Jame (2012) estimates (based on *ANcerno* transaction data) that unobservable intraquarter hedge fund trading accounts for only 3% of the typical (median) hedge fund's trades. Even at the extremes, Jame's results suggest the 13(f) data capture most hedge fund trades, e.g., at the 95th percentile of intraquarter trading, the 13(f) data capture 63% of hedge funds' trades.

Moreover, although we are unable to infer intraquarter trading from 13(f) data, the data do allow us to identify a set of securities heavily purchased by hedge funds and set of securities heavily sold by hedge funds each quarter (including crisis quarters). As a result, we can examine return patterns for a sample of stocks that experiences large hedge fund demand shocks.

6.1. Hedge Fund Demand Shocks and Returns—Sorts

If hedge fund demand shocks impact prices, then hedge fund demand shocks will be positively related to contemporaneous returns. If hedge funds tend to be better informed than other investors—either about deviations from fundamental values or about how mispricing evolves over time—then their demand shocks will tend to be positively related to subsequent returns.[17] In the latter case (e.g., hedge funds riding bubbles), however, one should eventually see an inverse relation between hedge fund demand shocks and subsequent returns.

To begin to evaluate these relations, we form hedge fund demand shock portfolios each quarter,

[17] Recent work (e.g., Anand et al. 2013, Franzoni and Plazzi 2013) suggests that at least some hedge funds provide liquidity to the market and the withdrawal of their liquidity materially impacts trading costs consistent with the Brunnermeier and Pedersen (2009) model. As a result, a decrease in hedge funds' liquidity providing role will allow prices to deviate from fundamentals if demand shocks by liquidity consuming traders are unrelated to fundamentals. Nonetheless, a large body of work also suggests informed traders' actions consume liquidity and push prices toward fundamentals (e.g., Easley et al. 2002). Thus, we follow previous work (e.g., Coval and Stafford 2007) and assume that the impact of liquidity consuming traders may push prices either toward equilibrium (if the demand shock is based on information) or away from equilibrium (if the demand shock is not based on information).

and examine the subsequent raw and risk-adjusted returns of those portfolios. Because large stocks exhibit greater absolute changes in the number of hedge funds buying or selling the stock (e.g., if a small stock is only held by two hedge funds, the maximum number of hedge fund sellers is two), we sort all stocks in our sample into capitalization quintiles at the beginning of each quarter. We then sort stocks, within each capitalization quintile, into five groups each quarter based on "hedge fund demand," defined as the difference between the number of hedge funds buying the stock and the number selling the stock. Stocks that experience negative hedge fund demand are split into two equal-size groups (within each capitalization quintile) based on hedge fund demand (heavy selling and light selling). Analogously, stocks that experience more hedge funds buying than selling are also partitioned into two groups by hedge fund demand. The final group consists of stocks that have an equal number of hedge funds buying and selling (most of these stocks have no hedge fund ownership). We then reaggregate the stocks across capitalization quintiles to form five capitalization-stratified hedge fund demand shock portfolios.

Note that for the smallest of stocks, we cannot always form hedge fund demand quintiles because few small stocks, especially in the early part of our sample, have any hedge fund ownership. For example, in the first quarter of our sample (June 1998), 88% of stocks in the smallest capitalization quintile had zero hedge fund ownership. Moreover, the maximum number of hedge fund sellers was one. Thus, to be included in the analysis, we require each hedge fund demand group within a quarter-capitalization quintile to contain at least 10 stocks. For each portfolio, we compute the equal-weighted return for three periods—the same quarter that we measure hedge fund demand shocks, the following quarter, and the average quarterly return for the following year. We use the Jegadeesh and Titman (1993) calendar aggregation method to calculate returns for the following year. We also compute benchmark adjusted returns as the intercept from a time-series regression of quarterly excess portfolio returns on quarterly excess market returns, size, value, and momentum factors (data from Ken French's website).[18]

The first two columns in Table 3 report the time-series mean number of securities in each portfolio and the time-series mean of the cross-sectional average hedge fund demand shock (number of hedge funds buying less the number selling) for stocks within each of the size-stratified hedge fund demand shock portfolios. The mean number of hedge funds buying and selling is reported in brackets underneath the hedge fund demand shock. The next six columns report mean quarterly raw and benchmark adjusted returns (in percent). The first row reveals that, on average, there were 637 stocks in the size-stratified portfolio of stocks heavily sold by hedge funds. These stocks experienced 5.16 more hedge funds selling than buying (i.e., on average, 4.36 and 9.52 hedge funds were buying and selling, respectively, as shown in brackets) and earned 1.87% in the quarter hedge funds net sold the stock, 1.67% the following quarter, and averaged 2.47% per quarter over the following year. Corresponding quarterly benchmark adjusted returns were 0.11%, −0.39%, and 0.45%. The last row in Table 3 reports the difference between stocks heavily purchased by hedge funds and those heavily sold. All *t*-statistics (reported parenthetically) are based on Newey and West (1987) standard errors.

The results in Table 3 reveal that hedge fund demand shocks are positively correlated with contemporaneous returns consistent with the possibility that their demand shocks impact prices. The coarseness of the quarterly data, however, limits our ability to infer whether hedge fund demand shocks actually drive prices.[19] Table 3 also shows that hedge fund demand shocks tend to be positively related to both raw and benchmark-adjusted subsequent returns—securities heavily purchased by hedge fund crowds outperform those heavily sold by hedge funds over the next quarter and year (statistically significant at the 1% level in all cases).[20] The results also suggest

[18] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (last accessed May 28, 2015).

[19] That is, a positive relation between hedge fund demand and same quarter returns could reflect intraquarter hedge fund momentum trading, hedge fund demand shocks driving prices, or hedge fund demand shocks forecasting intraquarter price changes.

[20] Our tests add to a large literature that examines whether hedge funds garner abnormal returns (see Stulz 2007 for a review). However, unlike nearly all previous studies of hedge fund performance, we do not examine the returns earned by hedge funds, but rather the returns garnered by a portfolio that is long, or short, in the stocks hedge funds crowd into, or out of, respectively. As far as we know, the only other study that takes a similar approach is by Griffin and Xu (2009). Specifically, they regress quarterly returns (for quarters +1 to +4) on changes in the fraction of shares held by hedge funds. The authors report evidence of a positive relation between hedge fund demand and returns over the following year (see their Table 3), but find the relation is no longer significantly different from zero once accounting for lag returns. We attempt to reconcile the studies using their exact tests and demand metrics. However, their sample period includes six years (1992–1997) prior to our sample period. Limiting the analysis to the overlapping period (1998–2005), we continue to find a statistically significant positive relation between hedge fund demand shocks and subsequent returns even when controlling for lag returns (untabulated). Their Table 5 provides guidance as to why our results likely differ as it demonstrates that the security selection component for hedge fund performance averages 0.20% for the 1992–1997 nonoverlapping sample period versus 3.797% for the 1998–2004 overlapping sample period.

Table 3 **The Relation Between Hedge Fund Demand Shocks and Contemporaneous and Subsequent Raw Returns**

			Mean quarterly return (%)			Benchmark adjusted returns (%)			Earnings surprises (%)	
Portfolio	No. of stocks	Hedge fund demand$_{t=0}$ [# buy: # sell]	Return$_{t=0}$	Return$_{t=1}$	Return$_{t=1\text{ to }4}$	Adjusted return$_{t=0}$	Adjusted return$_{t=1}$	Adjusted return$_{t=1\text{ to }4}$	CAR$_{t=1}$	I/B/E/S$_{t=1}$
Heavy sell	637	−5.158	1.873	1.672	2.473	0.114	−0.391	0.449	−0.202	0.046
		[4.359: 9.517]	(0.92)	(0.93)	(1.46)	(0.26)	(−0.80)	(1.21)	(−3.68)***	(8.00)***
Sell	768	−1.500	1.118	2.094	2.613	−0.813	−0.279	0.434	−0.138	0.045
		[3.729: 5.229]	(0.65)	(1.28)	(1.70)*	(−2.31)**	(−0.91)	(1.50)	(−2.61)**	(8.29)***
No change	1,404	0.000	1.040	2.673	2.626	−0.746	0.407	0.436	−0.181	0.043
		[1.306: 1.306]	(0.61)	(1.63)	(1.77)*	(−1.33)	(0.80)	(0.93)	(−3.22)***	(5.67)***
Buy	820	1.510	3.347	3.442	3.060	1.241	1.085	0.818	−0.009	0.048
		[5.127: 3.617]	(1.84)*	(2.09)**	(2.01)**	(2.24)**	(2.59)**	(2.56)**	(−0.12)	(8.12)***
Heavy buy	713	5.372	8.125	4.510	3.133	5.721	2.232	0.990	0.042	0.057
		[9.528: 4.156]	(3.32)***	(2.58)**	(1.99)*	(3.77)***	(4.03)***	(2.56)**	(0.69)	(8.35)***
Heavy buy − Heavy sell			6.252	2.838	0.660	5.607	2.623	0.542	0.245	0.011
			(3.15)***	(5.14)***	(2.80)***	(3.22)***	(5.28)***	(3.13)***	(5.15)***	(3.63)***

Notes. At the beginning of each stock quarter we compute hedge fund demand as the number of hedge funds buying the stock less the number selling the stock. We then sort stocks into capitalization quintiles, and form five portfolios—stocks with more hedge fund buyers than sellers are partitioned into two groups by hedge fund demand, stocks with more sellers than buyers are partitioned into two groups by hedge fund demand, and the final group consists of stocks with an equal number of hedge fund buyers and sellers (usually zero of both). We then reaggregate over capitalization quintiles to form capitalization-stratified portfolios of hedge fund demand. We then compute the cross-sectional average return for securities within each portfolio and the intercept from a time-series regression of the portfolio return on market, size, value, and momentum factors. We use the Jegadeesh and Titman (1993) calendar aggregation method to compute quarterly returns from overlapping observations in the four quarter holding period. The first and second columns report the time-series mean ($n = 55$ quarters) of the number of stocks within each portfolio and time-series mean of the cross-sectional average hedge fund demand for stocks within that portfolio. Below hedge fund demand for each portfolio, we report the average number of hedge funds buying and selling constituent securities in quarter $t = 0$. Mean and benchmark adjusted quarterly returns are reported for the same quarter as institutional demand shock ($t = 0$), the following quarter ($t = 1$), and the following year ($t = 1$ to 4) in the next six columns. The final two columns report the time-series means ($n = 55$ quarters) for two measures of earnings surprises in the following quarter for each portfolio. CAR$_{t=1}$ is the cross-sectional median three-day market adjusted return $[-1, +1]$ around the next quarter's earnings announcement. The final column reports analogous statistics for earnings surprises defined as actual earnings less analysts' consensus estimate from I/B/E/S divided by beginning of quarter stock price. The last row reports differences in mean returns (or benchmark adjusted returns, or earnings surprises) for stocks heavily purchased by hedge funds and those heavily sold by hedge funds. All t-statistics (reported in parentheses) are computed with Newey and West (1987) standard errors.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

that the informational content of hedge fund trades is primarily limited to their purchases.[21]

Although Table 3 reveals no evidence that hedge fund demand shocks, in general, drive prices from value, it is possible that hedge fund demand shocks are more likely to result in subsequent reversals in smaller, less liquid, stocks. To examine this possibility, we repeat the analysis (untabulated to conserve space) by both capitalization quintile and liquidity quintile (based on the Amihud 2002 metric). We find no evidence of a subsequent return reversals associated with hedge fund demand shocks in small or illiquid stocks.

As a test of whether the positive relation between hedge fund demand shocks and subsequent returns results, at least in part, from superior hedge fund information regarding fundamental values, we examine the relation between hedge fund demand shocks and subsequent earnings surprises. Specifically, we compute earnings surprises as either the earnings announcement abnormal return (computed as the three day market adjusted return around the announcement date reported by Compustat), or as actual earnings less the consensus analyst forecast (median estimate in the 90 days prior to announcement) divided by beginning of quarter stock price.

Following the method in Yan and Zhang (2009), the last two columns of Table 3 report the time-series mean of the cross-sectional median of the two earnings surprise estimates in the quarter immediately following the hedge fund demand shock. Consistent with the hypothesis that hedge fund demand shocks are related to future returns, at least partly due to superior hedge fund information about companies' fundamentals, stocks heavily purchased by hedge funds have larger earnings surprises than stocks heavily sold by hedge funds (significantly at the 1% level for both measures).[22]

[21] Consistent with the hypothesis that hedge funds push prices toward fundamentals, Giannetti and Kahraman (2014) report that hedge funds purchase the "fire-sold" stocks of mutual funds.

[22] Consistent with Burgstahler and Eames (2006), the median analyst forecast error is positive.

6.2. Hedge Fund Demand Shocks and Returns—Panel Regressions

In this section, we examine the relation between hedge fund demand shocks and both contemporaneous and subsequent returns in a panel regression framework that admits other controls including demand shocks by non-hedge fund institutions, lag returns, and the variables suggested by Dennis and Strickland (2002) including firm size, turnover, idiosyncratic variance, and beta:

$$\begin{aligned} Return_{k,t+j} &= \sum_{t=1}^{55} \gamma_{0,t} + \gamma_1 \ln(Capitalization)_{k,t} \\ &\quad + \gamma_2 Turnover_{k,t} + \gamma_3 Idiosyncratic\ \sigma^2_{k,t} + \gamma_4 Beta_{k,t} \\ &\quad + \gamma_5 Return_{k,t=\{0,-1\}} + \gamma_6 NHF\ demand_{k,t} \\ &\quad + \gamma_7 HF\ demand_{k,t} + \varepsilon_{k,t}. \end{aligned} \tag{3}$$

Here, $Return_{k,t+j}$ is the raw return (in percent) for stock k in quarter $t+j$. We measure the natural logarithm of capitalization at the beginning of the quarter and turnover as the mean monthly turnover in a quarter (number of shares traded/shares outstanding). Following Dennis and Strickland (2002), we compute idiosyncratic variance and beta from a market model estimated over 200 days beginning 50 days prior to the quarter. The cumulative return (in percent) for stock k in quarters 0 and -1 is denoted by $Return_{k,t=(0,-1)}$; $HF\ demand_{k,t}$ is the number of hedge funds buying security k in quarter t less the number selling; and $NHF\ demand_{k,t}$ is analogously defined for non-hedge fund institutions. For ease of interpretation, all independent variables (except lag returns) are standardized over the entire panel. We cluster standard errors at the firm level and admit fixed time effects.

Table 4 reports our results for five return periods—the same quarter as the demand shock, and each of the subsequent four quarters. The initial five columns present results for raw returns and the final five columns present analogous results for the characteristic based benchmark adjusted returns of Daniels, Grinblatt, Titman, and Wermers (DGTW 1997). Specifically, $Return_{k,t+j}$ in Equation (3) becomes the DGTW-adjusted returns (in percent) for stock k in quarter $t+j$.

The results in column (1) of Table 4 are consistent with the possibility that hedge fund demand shocks impact prices, i.e., a strong positive relation between hedge fund demand shocks and same quarter returns (significant at the 1% level). We also find a strong positive relation between demand by non-hedge fund institutions and same quarter returns. As before, the coarseness of the quarterly data, however, do not allow us to disentangle the price impact of their trades from intraquarter feedback trading or intraquarter price forecasting.

The results in columns (2)–(4) reveal a positive relation between hedge fund demand shocks and returns over the three following quarters (significant at the 5% level). Because hedge fund demand shocks are standardized over the entire panel, the coefficients represent the return associated with a one-standard-deviation increase in hedge fund demand. For instance, the results in column (2) reveal that a one-standard-deviation increase in hedge fund demand is associated with a 55 basis point higher return the following quarter. In contrast, non-hedge fund institutional demand shocks are inversely related (statistically significant at the 1% level) to returns in the subsequent four quarters.[23]

To examine the possibility that the subsequent higher returns associated with hedge fund demand shocks arise from hedge funds exploiting known characteristics related to returns (e.g., value, size, and momentum effects), we repeat the panel regression analysis but replace raw returns with the DGTW adjusted returns. The results, reported in columns (6)–(10), are qualitatively similar to the raw return results reported in the initial five columns. non-hedge fund demand shocks are positively related to contemporaneous abnormal returns (significant at the 1% level). In contrast, we find no evidence of a significant relation between hedge fund demand shocks and same quarter DGTW-adjusted returns. The point estimates reveal that the relation between hedge fund demand shocks and subsequent returns is slightly weaker for the DGTW-adjusted returns (columns (6)–(10)) relative to raw returns (columns (1)–(5)) consistent with the hypothesis that some hedge funds exploit the relations between security characteristics and subsequent returns. For instance, a one-standard-deviation higher hedge fund demand shock is associated with a 55 basis point higher raw return the following quarter (column (2)) versus a 49 basis point higher DGTW-adjusted return the following quarter (column (7)).

[23] The non-hedge fund institutional demand shock results are consistent with Sias and Whidbee (2010) and San (2010) who demonstrate that the relation between aggregate institutional demand shocks and subsequent returns is negative for the post 1993 period. See Sias and Whidbee (2010) for a summary of the evidence of the relation between aggregate institutional demand shocks and subsequent returns. In untabulated analysis, we partition non-hedge fund institutional demand into the standard classifications—banks, insurance companies, investment companies/advisors, and others. Our results reveal evidence that all types of institutions play some role in driving the negative relation between non-hedge fund institutional demand shocks and subsequent returns—there is, however, some variation across investor types. The negative relation tends to be stronger for banks and insurance companies consistent with the hypothesis that these investors are exploited by better informed institutions (such as hedge funds).

Table 4 Panel Regressions of Returns on Hedge Fund and Non-Hedge Fund Demand Shocks

	(1) *Return*$_{t=0}$	(2) *Return*$_{t=1}$	(3) *Return*$_{t=2}$	(4) *Return*$_{t=3}$	(5) *Return*$_{t=4}$	(6) *DGTW-adjusted return*$_{t=0}$	(7) *DGTW-adjusted return*$_{t=1}$	(8) *DGTW-adjusted return*$_{t=2}$	(9) *DGTW-adjusted return*$_{t=3}$	(10) *DGTW-adjusted return*$_{t=4}$
ln(*Capitalization*)	−0.733	−0.689	−1.063	−1.056	−0.889	−0.249	−0.261	−0.320	−0.223	−0.131
	(−6.89)***	(−9.27)***	(−13.55)***	(−13.95)***	(−11.30)***	(−2.39)**	(−3.23)***	(−3.87)***	(−2.78)***	(−1.62)
Turnover	5.542	−0.577	−0.473	−0.523	−0.426	5.022	−0.468	−0.393	−0.489	−0.411
	(14.67)***	(−6.21)***	(−4.07)***	(−6.10)***	(−5.16)***	(12.99)***	(−4.78)***	(−3.11)***	(−5.54)***	(−4.99)***
Idiosyncratic σ^2	−0.340	−0.066	−0.041	−0.134	−0.456	−0.187	0.011	0.015	−0.085	−0.170
	(−1.76)*	(−0.92)	(−0.54)	(−1.70)*	(−2.47)**	(−1.70)*	(0.10)	(0.20)	(−1.50)	(−1.31)
Beta	−2.203	0.110	0.502	0.435	0.443	−1.592	0.597	0.661	0.637	0.747
	(−15.94)***	(1.20)	(5.38)***	(4.82)***	(4.82)***	(−11.31)***	(6.37)***	(6.96)***	(7.11)***	(8.19)***
Return$_{t=(0,-1)}$		0.013	0.007	−0.007	−0.017		0.005	0.005	−0.006	−0.016
		(6.74)***	(3.65)***	(−4.09)***	(−8.91)***		(2.77)***	(2.68)***	(−3.37)***	(−7.54)***
HF demand	0.253	0.547	0.192	0.134	0.033	0.048	0.494	0.169	0.047	0.004
	(3.81)***	(12.06)***	(4.19)***	(2.69)**	(0.66)	(0.75)	(10.78)***	(3.69)***	(0.91)	(0.08)
NHF demand	3.349	−0.539	−0.479	−0.620	−0.471	2.866	−0.323	−0.237	−0.369	−0.342
	(16.46)***	(−11.14)***	(−9.00)***	(−10.87)***	(−8.72)***	(15.52)***	(−6.86)***	(−4.93)***	(−6.99)***	(−6.43)***
Firms (clusters)	10,636	10,636	10,375	10,091	9,800	9,416	9,416	9,110	8,827	8,541
Observations	248,836	248,836	243,272	237,516	231,730	214,348	214,348	209,738	205,081	200,429
R^2 (%)	17.21	13.88	12.86	13.24	13.30	3.48	0.45	0.52	0.52	0.49

Notes. Panel regressions examine the relation between contemporaneous (column (1)) or subsequent (column (2) to column (5), respectively) quarter raw percentage returns and quarterly hedge fund and non-hedge fund demand shocks as specified in Equation (3). Analogous DGTW-adjusted returns are reported in columns (6)–(10). Independent variables include firm size measured by the beginning of quarter natural logarithm of market capitalization, mean monthly turnover in a quarter measured by the number of shares traded/shares outstanding, idiosyncratic σ^2, beta, cumulative returns over quarters 0 and −1, hedge fund demand shocks in quarter $t = 0$, and non-hedge fund institutions' demand shocks in quarter $t = 0$. Hedge fund demand is defined as the number of hedge fund buyers less number of hedge fund sellers. All independent variables (except lag returns) are standardized to have zero mean and unit variance over the entire panel. We cluster standard errors at the firm level, and admit fixed time effects.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

The negative relation between non-hedge fund institutional demand shocks and subsequent adjusted returns remains statistically significant (1% level in all cases).

Although our results thus far reveal no evidence that large groups of hedge funds hold greatly overlapping portfolios or that, in general, hedge fund demand shocks result in subsequent return reversals, the negative externalities of hedge fund crowds may be primarily limited to periods of extreme market stress. Thus, we next examine these relations in crisis versus noncrisis periods.

6.3. Identifying Crisis Periods

We objectively identify crises periods by examining five measures of hedge fund stress: (1) the percent change in the dollar value of aggregate hedge fund equity positions over the quarter, (2) the fraction of hedge funds reducing their equity portfolio during the quarter, (3) the fraction of hedge funds reducing their equity portfolio by more than 20% during the quarter, (4) the quarterly return on the Hedge Fund Research Composite Index, and (5) the lowest monthly average percentile rank within each quarter for eight HFRI index returns.[24] The first three measures are motivated by Ben-David et al. (2012) and attempt to capture whether there is evidence hedge funds are being forced to liquidate positions, as well as the breadth of the hedge fund exodus. To ensure our results are driven by hedge fund trades rather than stock returns, the first three measures use both beginning and end of quarter values based on beginning of quarter prices. The final two measures, motivated by Boyson et al. (2010), capture whether hedge funds suffer large losses, and the breadth of such losses across different types of hedge funds. Note that the last measure—the lowest monthly average performance percentile rank for eight HFRI indices—is analogous to the Boyson et al. (2010) "COUNT8" variable.[25]

We generate a composite ranking of hedge fund stress based on the average percentile rank across the five stress measures to objectively rank quarters on hedge fund stress levels. Table 5 reports the five stress measures and the related composite rank. For instance, the top row indicates that in the second quarter of 1998, hedge funds increased their aggregate equity holdings by 3.2%, 32.5% of hedge funds

[24] Specifically, the eight Hedge Fund Research (HFRI) indices are equity market neutral, quantitative directional, technology/healthcare, distressed, merger arbitrage, macro, convertible arbitrage, and fixed income corporate.

[25] For instance, if in June of 1998, four of the HFRI indices experienced a 20th percentile return and the other four indices experienced a 10th percentile return, then our variable would take a value of 0.15 for the second quarter of 1998 (assuming April and May returns were higher). We focus on the "worst" month in a quarter for consistency with Boyson et al. (2010).

Table 5 Identifying Hedge Fund Stress Periods

Quarter	*% chg. in aggregate HF equity*	*%HF selling equities*	*%HF selling >20%*	*Eight HFRI avg. return p-tile*	*Aggregate HF return index*	*Aggregate HF stress ranking*	*%chg. gross HF leverage*
Jun-98	0.032	0.325	0.140	0.303	−0.013	33	
Sep-98	−**0.043**	0.474	0.233	**0.013**	−**0.088**	**3.5**	
Dec-98	0.057	0.435	0.183	0.414	0.079	38	
Mar-99	0.091	0.317	0.135	0.210	0.041	43.5	
Jun-99	0.050	0.439	0.136	0.530	0.091	47.5	
Sep-99	0.020	0.432	0.151	0.444	0.007	32	
Dec-99	0.050	0.432	0.130	0.463	0.149	50	
Mar-00	−0.002	0.417	0.166	0.419	0.078	35.5	
Jun-00	−**0.112**	0.456	0.207	0.317	−0.012	11	
Sep-00	0.092	0.359	0.100	0.376	0.019	47.5	
Dec-00	0.002	0.485	**0.302**	0.218	−0.033	7	
Mar-01	0.154	0.359	0.160	0.375	−0.005	37	
Jun-01	0.062	0.409	0.144	0.406	0.035	40.5	
Sep-01	0.030	0.456	**0.235**	0.278	−**0.040**	10	
Dec-01	−0.017	0.472	0.181	0.529	0.059	26.5	
Mar-02	−0.030	0.371	0.127	0.215	0.016	24	
Jun-02	0.110	0.430	0.175	0.285	−0.016	26.5	
Sep-02	0.100	0.432	0.189	0.128	−**0.039**	16	
Dec-02	0.008	0.466	0.216	0.401	0.025	18	
Mar-03	0.117	0.321	0.118	0.388	0.008	49	
Jun-03	−0.028	0.441	0.134	0.595	0.077	39	
Sep-03	0.025	0.436	0.160	0.517	0.044	35.5	
Dec-03	−0.035	0.461	0.178	0.536	0.055	29	
Mar-04	0.134	0.365	0.090	0.430	0.037	52	
Jun-04	0.054	0.412	0.135	0.211	−0.010	28	
Sep-04	0.038	0.431	0.131	0.273	0.008	30	
Dec-04	0.045	0.441	0.145	0.540	0.054	42	
Mar-05	0.128	0.350	0.109	0.245	0.007	40.5	0.017
Jun-05	0.069	0.460	0.176	0.145	0.011	19	0.032
Sep-05	0.093	0.369	0.094	0.499	0.051	53.5	−0.017
Dec-05	−0.010	**0.548**	0.183	0.195	0.021	12	0.015
Mar-06	0.081	0.344	0.110	0.498	0.060	55	0.057
Jun-06	0.020	0.477	0.209	0.294	0.000	14	−0.083
Sep-06	0.034	0.472	0.160	0.386	0.010	22	0.008
Dec-06	0.039	0.502	0.150	0.665	0.054	34	−0.004
Mar-07	0.107	0.344	0.100	0.514	0.028	53.5	0.080
Jun-07	0.116	0.394	0.111	0.439	0.046	51	0.058
Sep-07	−**0.096**	0.487	0.207	0.176	0.012	9	−0.137
Dec-07	−0.016	0.489	0.224	**0.123**	0.011	8	−0.060
Mar-08	0.054	0.454	0.223	0.135	−0.034	13	−0.050
Jun-08	0.052	0.475	0.188	0.311	0.022	21	0.096
Sep-08	−**0.146**	**0.616**	**0.370**	**0.039**	−**0.096**	**1**	−**0.188**
Dec-08	−**0.108**	**0.633**	**0.440**	**0.127**	−**0.092**	**2**	−**0.217**
Mar-09	0.145	0.462	0.226	0.286	0.003	20	−0.004
Jun-09	0.075	0.437	0.198	0.615	0.092	46	0.058
Sep-09	0.079	0.461	0.175	0.695	0.067	43.5	0.010
Dec-09	0.030	0.470	0.159	0.442	0.026	31	
Mar-10	0.087	0.409	0.119	0.380	0.024	45	
Jun-10	−0.038	0.505	0.227	**0.109**	−0.027	**5**	
Sep-10	0.012	0.488	0.172	0.414	0.050	23	
Dec-10	−0.016	**0.551**	0.212	0.299	0.053	15	
Mar-11	0.011	0.443	0.147	0.397	0.017	25	
Jun-11	0.025	0.435	0.154	0.206	−0.009	17	
Sep-11	−0.013	**0.516**	**0.260**	**0.080**	−**0.068**	**3.5**	
Dec-11	−**0.080**	**0.680**	**0.311**	0.229	0.009	**6**	

Notes. For each quarter between June 1998 and December 2011 we compute five measures of hedge fund stress: (1) the percent change in the dollar value of aggregate hedge fund equity positions over the quarter, (2) the fraction of hedge funds reducing their equity portfolio during the quarter, (3) the fraction of hedge funds reducing their equity portfolio by more than 20% during the quarter, (4) the lowest monthly average performance percentile rank for eight HFRI indices, and (5) the quarterly return on the Hedge Fund Research Composite Index (an equal-weighted hedge fund return index, net of fees, comprised of over 2,000 hedge funds). The second to last column reports a composite ranking of hedge fund stress based on the average percentile rank across the five measures. The last column reports, for the March 2005-September 2009 subperiod, the percentage change in gross hedge fund leverage from Ang et al. (2011). Bold cells indicate the top 10th percentile of stress based on that measure (i.e., the six most extreme observations for the first five measures, and the two most extreme observations for the leverage measure).

were net sellers, 14% of hedge funds sold at least 20% of their long equity portfolio, the eight HFRI indexes averaged performance in the 31st percentile in the "worst" month of that quarter, the HFRI quarterly aggregate hedge fund index lost 1.3%, and overall, the quarter was the 33rd most stressful quarter for hedge funds (out of the 55 quarters in our sample). We also report, for the March 2005 through September 2009 subperiod, the percentage change in gross hedge fund leverage from Ang et al. (2011).[26] The bold cells in Table 5 indicate the decile of most stressful quarters based on that measure; for example, the 6 (of 55) quarters that experienced the greatest percentage decline in hedge fund equity holdings are shown in bold in the first column. Given the hedge fund leverage data are available for 19 quarters, we show in bold only the two extreme leverage change observations.

6.4. Hedge Fund Demand Shocks, Returns, and Crises

We next repeat the analysis in Table 4, but estimate the impact of hedge fund and non-hedge fund demand shocks for crisis versus noncrisis periods:

$$\begin{aligned}
&\mathit{Return}_{k,\,t+j}\\
&\quad=\sum_{t=1}^{55}\gamma_{0,\,t}+\gamma_1\ln(\mathit{Capitalization})_{k,\,t}\\
&\qquad+\gamma_2\mathit{Turnover}_{k,\,t}+\gamma_3\mathit{Idiosyncratic}\ \sigma^2_{k,\,t}\\
&\qquad+\gamma_4\mathit{Beta}_{k,\,t}+\gamma_5\mathit{Return}_{k,\,t=\{0,\,-1\}}\\
&\qquad+\gamma_6\mathit{NHF\ demand}_{k,\,t}*\mathit{Noncrisis\ dummy}_t\\
&\qquad+\gamma_7\mathit{HF\ demand}_{k,\,t}*\mathit{Noncrisis\ dummy}_t\\
&\qquad+\gamma_8\mathit{NHF\ demand}_{k,\,t}*\mathit{Crisis\ dummy}_t\\
&\qquad+\gamma_9\mathit{HF\ demand}_{k,\,t}*\mathit{Crisis\ dummy}_t+\varepsilon_{k,\,t}.
\end{aligned}\tag{4}$$

Here, *Noncrisis dummy*$_t$ equals one if quarter t is not in the bottom decile (i.e., six worst) of stressful quarters identified in Table 5 and zero otherwise. Analogously, the variable *Crisis dummy*$_t$ equals one if quarter t is in the bottom decile of stressful quarters identified in Table 5 and zero otherwise. Hence, the coefficients γ_7 and γ_9 reflect the relation between hedge fund demand shocks and returns in noncrisis and crisis quarters, respectively. Analogously, the coefficients γ_6 and γ_8 reflect the relation between non-hedge fund institutional demand shocks and returns during noncrisis and crisis quarters, respectively. As before, our panel includes fixed time effects, standard errors clustered at the stock level, and all independent variables (except lag return) are standardized over the entire panel. Table 6 reports the coefficient estimates based on raw and DGTW-adjusted returns, respectively.

For noncrisis periods, the results in Table 6 are similar to those reported for the entire sample in Table 4—hedge fund demand shocks are associated with higher raw and DGTW-adjusted returns for both the contemporaneous quarter (columns (1) and (6)) and for subsequent quarters (statistically significant at the 5% level for the following three quarters when examining raw returns and the following two quarters when examining DGTW-adjusted returns). For noncrisis quarters, we continue to find a strong positive relation between non-hedge fund demand shocks and contemporaneous returns and a strong inverse relation between non-hedge fund demand shocks and returns over the next four quarters (statistically significant at the 1% level in all cases).

If hedge fund crowds exert negative externalities on each other and asset prices during crisis periods, then (i) the positive relation between hedge fund demand shocks and same quarter returns should be especially strong during crisis periods as hedge funds trample each other while rushing for the exits, and (ii) the relation between hedge fund demand shocks in crisis quarters and subsequent returns should eventually turn negative as prices ultimately rebound toward fundamental values. The results in columns (1) and (6) of Table 6 reveal no evidence that the relation between hedge fund demand shocks and contemporaneous raw or DGTW-adjusted returns is stronger in crisis periods. In fact, the coefficients associated with crisis-period hedge fund demand shocks is negative (and statistically significant at the 1% level) for both contemporaneous raw (column (1)) and DGTW-adjusted (column (6)) returns. Thus, the results do not support the hypothesis that hedge funds drive prices from value as they trample each other in a rush for the exits during crisis periods.

The results for subsequent quarters in Table 6 reveal no evidence that hedge fund demand shocks in crisis periods are inversely related to later returns. Rather, we continue to find evidence of a weak positive relation between hedge fund demand shocks and subsequent returns—crisis period hedge fund demand shocks are positively related to raw returns in quarter $t=2$ (column (3); statistically significant at the 5% level) and positively related to DGTW-adjusted return in quarters $t=1$ and $t=2$ (columns (7) and (8); statistically significant at the 5% and 1% levels, respectively). For instance, the coefficient estimate suggests that during a crisis period, a one-standard-deviation hedge fund demand shock is associated with a 31 basis point higher DGTW-adjusted return the following quarter (column (7)).

[26] We thank the authors for sharing this data. See Ang et al. (2011) for details regarding this measure.

Table 6 Panel Regressions of Returns on Hedge Fund and Non-Hedge Fund Demand Shocks During Crisis and Noncrisis Periods

	(1) $Return_{t=0}$	(2) $Return_{t=1}$	(3) $Return_{t=2}$	(4) $Return_{t=3}$	(5) $Return_{t=4}$	(6) DGTW-adjusted $return_{t=0}$	(7) DGTW-adjusted $return_{t=1}$	(8) DGTW-adjusted $return_{t=2}$	(9) DGTW-adjusted $return_{t=3}$	(10) DGTW-adjusted $return_{t=4}$
ln(*Capitalization*)	−0.792	−0.700	−1.060	−1.059	−0.898	−0.292	−0.265	−0.321	−0.233	−0.134
	(−7.40)***	(−9.38)***	(−13.46)***	(−13.91)***	(−11.39)***	(−2.80)***	(−3.27)***	(−3.87)***	(−2.90)***	(−1.65)*
Turnover	5.514	−0.583	−0.471	−0.525	−0.430	5.000	−0.471	−0.392	−0.494	−0.413
	(14.64)***	(−6.27)***	(−4.06)***	(−6.12)***	(−5.21)***	(12.96)***	(−4.80)***	(−3.10)***	(−5.60)***	(−5.00)***
Idiosyncratic σ^2	−0.342	−0.067	−0.041	−0.134	−0.457	−0.189	0.011	0.015	−0.086	−0.170
	(−1.76)*	(−0.93)	(−0.54)	(−1.70)*	(−2.47)**	(−1.70)*	(0.10)	(0.20)	(−1.51)	(−1.31)
Beta	−2.197	0.111	0.502	0.435	0.444	−1.587	0.597	0.661	0.638	0.748
	(−15.92)***	(1.20)	(5.38)***	(4.82)***	(4.83)***	(−11.29)***	(6.37)***	(6.96)***	(7.12)***	(8.19)***
$Return_{t=(0,-1)}$		0.013	0.007	−0.007	−0.017		0.005	0.005	−0.006	−0.016
		(6.73)***	(3.65)***	(−4.09)***	(−8.92)***		(2.76)***	(2.67)***	(−3.38)***	(−7.54)***
HF demand noncrises	0.378	0.618	0.167	0.163	0.068	0.162	0.523	0.112	0.097	0.028
	(5.24)***	(12.86)***	(3.56)***	(3.31)***	(1.27)	(2.32)**	(10.76)***	(2.36)**	(1.93)*	(0.53)
NHF demand noncrises	3.566	−0.541	−0.472	−0.628	−0.452	3.018	−0.326	−0.174	−0.357	−0.347
	(16.45)***	(−10.43)***	(−8.81)***	(−10.95)***	(−7.96)***	(15.29)***	(−6.55)***	(−3.59)***	(−6.57)***	(−6.07)***
HF demand crises	−0.405	0.073	0.364	−0.063	−0.177	−0.560	0.311	0.593	−0.260	−0.154
	(−2.88)***	(0.55)	(2.33)**	(−0.33)	(−1.31)	(−4.20)***	(2.24)**	(3.84)***	(−1.32)	(−1.11)
NHF demand crises	1.992	−0.477	−0.546	−0.541	−0.564	1.973	−0.284	−0.679	−0.405	−0.294
	(9.85)***	(−3.64)***	(−3.28)***	(−3.36)***	(−4.93)***	(10.81)***	(−2.11)**	(−4.04)***	(−2.67)**	(−2.61)***
R^2 (%)	17.25	13.88	12.86	13.24	13.30	3.50	0.45	0.53	0.53	0.49

Notes. Panel regressions examine the relation between contemporaneous (column (1)) or subsequent (column (2) to column (5), respectively) quarter raw returns and quarterly hedge fund and non-hedge fund demand shocks during crisis and noncrisis periods as identified in Equation (4). Analogous DGTW-adjusted returns are reported in columns (6)–(10). A quarter is defined as stressful if it is one of the bottom decile of observations as identified in the aggregate stress ranking of Table 5. Variable definitions, firms (clusters), and observations are as reported in Table 4.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In contrast to hedge fund demand shocks, we continue to find a strong negative relation between non-hedge fund institution demand shocks and subsequent return when focusing on crisis periods. For instance, a one-standard-deviation larger non-hedge fund institution demand shock in a crisis period is associated with a 48 basis point lower raw return (column (2)) and a 28 basis point lower DGTW-adjusted return (column (7)) the following quarter.

7. Discussion

Although the positive relation between hedge fund demand shocks and subsequent returns is consistent with the explanation that hedge funds are better informed than other investors, the "information" exploited by hedge funds may be a better understanding of fundamental value or a better understanding of how mispricing evolves. For instance, Brunnermeier and Nagel (2004) find evidence that some hedge funds rode the tech bubble—capturing much of the gains in individual securities and then selling before prices collapsed. Thus, our finding of a positive relation between hedge fund demand shocks and subsequent returns in the next few quarters is potentially also consistent with the Brunnermeier and Nagel (2004) finding of hedge fund trading of technology stocks during the bubble period.

Nonetheless, if hedge fund demand shocks, either in general or during crisis periods, systematically drive prices from values, one should find subsequent return reversal as prices eventually retreat toward fundamental values (e.g., Coval and Stafford 2007). As noted in the introduction, however, it is possible that the reversal may be very gradual or in the midst of enough noise that our tests fail to capture the impact.[27] Another possibility is that the price impact of hedge fund demand shocks are quickly reversed and our examination of quarterly returns misses such reversals. For instance, Khandani and Lo (2007, 2011) and Pedersen (2009) demonstrate that large abnormal factor returns over August 6–9, 2007 (i.e., the quant crisis) were quickly reversed over the next few days.[28]

The 13(f) data that underlies our tests miss small positions (that do not have to be reported in 13(f) fil-

[27] In untabulated analysis, we examine hedge fund (and non-hedge fund) demand shocks over quarters five through eight. We continue to find no evidence of a systematic negative relation between hedge fund demand shocks and subsequent returns.

[28] In untabulated analysis, we identify a set of large quantitative hedge funds by measuring their exposure to those securities that were most impacted by the quant crisis. We then examine the portfolio overlap in this restricted hedge fund sample. We continue to find low absolute and relative levels of portfolio overlap consistent with the results reported in Table 2.

ings), small hedge funds (that are not required to file 13(f) reports), and confidential holdings. Our data also miss all nonlong U.S. equity positions. Our results, therefore, do not suggest that hedge fund portfolios are largely independent in other areas (e.g., currency or fixed income trades) or that crowding in non-U.S. equities does not result in systematic market dislocations.

In addition, hedge fund long-equity portfolio overlap is only one of a number of potential contagion channels. There are likely other important linkages between individual hedge funds and other institutions. Aragon and Strahan (2012), for example, demonstrate linkages between hedge funds due to commonality in prime brokerage. Similarly, Billio et al. (2012, p. 536) discuss potential linkages between key players in the financial markets, e.g., the link between hedge funds and insurance companies through, "...insuring financial products, credit-default swaps, derivatives trading, and investment management..."

Our results are related to several other recent studies that examine hedge fund trading during crisis periods.[29] Ben-David et al. (2012), for example, find that hedge funds exited equity markets in the third and fourth quarters of 2007 and the last two quarters of 2008 (the "sell-off" quarters) and (based on a sample of Trading Advisor Selection System (TASS) hedge funds matched to a sample of the 13(f) hedge funds) that funds with investor outflows and leverage sold more equity during the sell-off quarters. The authors, however, do not investigate hedge fund crowding or the potential price effects associated with the sell-off.[30] Consistent with the authors, we find hedge funds exited equity markets in late 2007 and 2008 (see Table 5).

We also consider a number of robustness tests. For instance, recognizing that a few large hedge fund trades may have a larger effect than many small hedge fund trades, we consider alternative measures of hedge fund demand shocks including net hedge fund buying normalized by shares outstanding (i.e., change in fractional ownership) or volume, and adjusting hedge fund demand shocks for changes in aggregate short interest. We also consider the possibility that hedge fund demand shocks have a predictable component. Specifically, we model hedge fund demand shocks as a function of a number of variables including lag returns (we find evidence of both hedge fund and non-hedge fund momentum trading) and lag hedge fund demand shocks to examine the relation between unexpected hedge fund demand shocks (i.e., the residuals from these forecasting regressions) and returns.[31] Note that evidence of hedge fund momentum trading is consistent with the Stein (2009) model in the sense that it is possible some traders follow a mechanical momentum trading strategy without a fundamental anchor. Regardless of how we frame the tests, however, we consistently find a significant positive relation between aggregate hedge fund demand shocks and subsequent returns over the next few quarters and no evidence of subsequent return reversals associated with hedge fund demand shocks in crisis periods.

8. Conclusions

The role of hedge funds in U.S. equity markets has dramatically increased over the past 15 years. Contrary to the classical view that rational speculators move to correct mispricing, the popular press, regulators, theoretical models, and recent empirical studies suggest that hedge fund crowds may systematically drive equity prices from value. We contribute to this debate by examining overlap in hedge fund long equity portfolios. Contrary to apparent common beliefs, hedge funds hold long equity portfolios that are largely independent of one another—both in an absolute sense and relative to other non-hedge fund institutions. Even at the extremes, hedge funds hold much more independent long equity portfolios than other institutional investors—the 95th percentile of hedge fund pairs with greatest overlap average less than 10% in common long equity holdings versus 35% overlap for similar size non-hedge fund institutions. We also find that hedge fund crowds in individual securities have increased over time. This increase, however, results from the large growth in the number of hedge funds and not an increase in the commonality of hedge fund portfolios.

Consistent with the hypothesis that hedge funds tend to be better informed than other institutions, we find that hedge fund demand shocks are positively

[29] Our results may be surprising in light of the evidence of liquidity shock induced hedge fund contagion in Boyson et al. (2010). In a related paper (Sias et al. 2015), we demonstrate that after correcting for two problems in their study, and extending the analysis, there is little evidence of liquidity shock induced contagion.

[30] In untabulated analysis, we merge hedge fund data from the CISDM and Hedge Fund Research databases with the 13(f) data and examine the relation between returns and demand shocks from those funds that use leverage and experience outflows. We continue to find no evidence of a negative relation between hedge fund demand shocks and subsequent returns within this subsample. Note, however, that because we use Hedge Fund Research data we are forced to use a leverage dummy variable rather than average leverage (as in Ben-David et al. 2012). Thus, it is possible that cross-sectional variation in leverage (not captured by our dummy variable specification) may better capture stressed and leveraged hedge funds and yield a stronger test.

[31] The R^2s from these regressions average 3.5%, i.e., we estimate that more than 96% of the variation in hedge fund demand is unexpected.

related to subsequent returns over the next few quarters, and this relation holds even after adjusting for the standard asset pricing factors. The positive relation between hedge fund demand shocks and returns over the next few quarters could result from hedge funds trading against deviations from fundamental values (e.g., purchasing undervalued securities) or hedge funds exploiting their superior understanding regarding the evolution of mispricings. Consistent with the former, we find no evidence that hedge fund demand shocks, either in general, or during crisis periods, are inversely related to subsequent raw or abnormal returns.

Acknowledgments

The authors thank Vikas Agarwal, George Aragon, Phelim Boyle, Nicole Boyson, Gjergji Cici, Darrell Duffie, John Griffin, Wei Jiang (the department editor), Andrew Karolyi, Eric Kelley, Alexander Kurov, Mathias Kruttli, Jeff Nickel, Blake Phillips, Clemens Sialm (the associate editor), Laura Starks, and Sterling Yan, as well as seminar participants at Colorado State University, Cornell University, Indiana University, Texas Tech University, the University of Arizona, the University of Cincinnati, the University of Texas at San Antonio, the University of Waterloo, the 2013 Asian Financial Management Association meetings, the 2013 Western Finance Association meetings, the 2014 Finance Down Under meetings, and the 2014 European Finance Association meetings for their helpful comments. The authors thank Luke DeVault for excellent research assistance. Portions of this work were completed while H. J. Turtle was at West Virginia University. Turtle also acknowledges financial support from the Dean's Scholars Summer Research Grant and the Kennedy–Van Scoy Fund. The authors thank Andrew Ang, Ken French, David Hsieh, Russ Wermers, and Thomson Reuters for providing data.

References

Acharya VV, Philippon T, Richardson M, Roubini N (2009) Prologue: A bird's eye view. The financial crisis of 2007–2009: Causes and remedies. *Wiley Periodicals* 18:89–137.

Adrian T, Brunnermeier MK (2011) CoVaR. Working paper, Federal Reserve Bank of New York, New York.

Agarwal V, Fos V, Jiang W (2013a) Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings. *Management Sci.* 59:1271–1289.

Agarwal V, Jiang W, Tang Y, Yang B (2013b) Uncovering hedge fund skill from the portfolio holdings they hide. *J. Finance* 68:739–783.

Amihud Y (2002) Illiquidity and stock returns: Cross-section and time-series effects. *J. Financial Markets* 5:31–56.

Anand S, Irvine P, Puckett A, Venkataraman K (2012) Performance of institutional trading desks: An analysis of persistence in trading costs. *Rev. Financial Stud.* 25:557–598.

Anand S, Irvine P, Puckett A, Venkataraman K (2013) Institutional trading and stock resiliency: Evidence from the 2007–2009 Financial Crisis. *J. Financial Econom.* 108:773–797.

Ang A, Gorovyy S, Van Inwegen G (2011) Hedge fund leverage. *J. Financial Econom.* 102:102–126.

Aragon GO, Martin JS (2012) A unique view of hedge fund derivatives usage: Safeguard or speculation. *J. Financial Econom.* 105:436–456.

Aragon GO, Strahan PE (2012) Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. *J. Financial Econom.* 103:570–587.

Ben-David I, Franzoni FA, Moussawi R (2012) Hedge fund stock trading in the financial crisis of 2007-2008. *Rev. Financial Stud.* 25:1–54.

Billio M, Getmansky M, Lo AW, Pelizzon L (2012) Econometric measures of systemic risk in the finance and insurance sectors. *J. Financial Econom.* 104:535–559.

Blume ME, Keim DB (2011) Changing institutional preferences for stocks: Direct and indirect evidence. Working paper, University of Pennsylvania, Philadelphia.

Boyson NM, Helwege J, Jindra J (2011) Crises, liquidity shocks, and fire sales at financial institutions. Working paper, Northeastern University, Boston.

Boyson NM, Stahel CW, Stulz RM (2010) Hedge fund contagion and liquidity shocks. *J. Finance* 65:1789–1816.

Bray J, Curtis JT (1957) An ordination of the upland forest of the southern Wisconsin. *Ecological Monographs* 27:325–349.

Brunnermeier MK (2009) Deciphering the liquidity and credit crunch 2007–2008. *J. Econom. Perspect.* 23:77–100.

Brunnermeier MK, Nagel S (2004) Hedge funds and the technology bubble. *J. Finance* 59:2013–2040.

Brunnermeier MK, Pedersen LH (2009) Market liquidity and funding liquidity. *Rev. Financial Stud.* 22:2201–2238.

Burgstahler D, Eames M (2006) Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. *J. Bus., Finance, Accounting* 33:633–653.

Cha SH (2007) Comprehensive survey on distance/similarity measures between probability density functions. *Int. J. Math. Models and Methods Appl. Sci.* 4:300–307.

Cici G, Kempf A, Puetz A (2013) The valuation of hedge funds' equity position. Working paper, College of William and Mary, Williamsburg, VA.

Coval J, Stafford E (2007) Asset fire sales (and purchases) in equity markets. *J. Financial Econom.* 86:479–512.

Cremers M, Petajisto A (2009) How active is your fund manager? A new measure that predicts performance. *Rev. Financial Stud.* 22:3329–3365.

Daniel K, Grinblatt M, Titman S, Wermers R (1997) Measuring mutual fund performance with characteristic-based benchmarks. *J. Finance* 52:1035–1058.

Dennis PJ, Strickland D (2002) Who blinks in volatile markets, individuals or institutions? *J. Finance* 57:1923–1949.

Easley D, Hvidkjaer S, O'Hara M (2002) Is information risk a determinant of asset returns? *J. Finance* 57:2185–2221.

European Central Bank (2006) Financial Stability Review—June 2006. European Central Bank, Frankfurt, Germany. http://www.ecb.int/.

Franzoni F, Plazzi I (2013) Do hedge funds provide liquidity? Evidence from their trades. Working paper, University of Lugano, Lugano, Switzerland.

Giannetti M, Kahraman B (2014) Who trades against mispricing? Working paper, Stockholm School of Economics, Stockholm, Sweden.

Griffin JM, Xu J (2009) How smart are the smart guys? A unique view from hedge fund stock holdings. *Rev. Financial Stud.* 22:2531–2570.

Gromb D, Vayanos D (2002) Equilibrium and welfare in markets with financially constrained arbitrageurs. *J. Financial Econom.* 66:361–407.

Gutierrez RC Jr, Kelley EK (2009) Institutional herding and future stock returns. Working paper, University of Oregon, Eugene.

Jame RE (2012) How skilled are hedge funds? Evidence from their daily trades. Working paper, University of Kentucky, Lexington.

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

Khandani AE, Lo AW (2007) What happened to the quants in August 2007? *J. Investment Management* 5:5–54.

Khandani AE, Lo AW (2011) What happened to the quants in August 2007? Evidence from factors and transactions data. *J. Financial Markets* 14:1–46.

Kyle AS, Xiong W (2001) Contagion as a wealth effect. *J. Finance* 56:1401–1440.

Loeb DS (2010) First quarter 2010 investor letter, June 11. Third Point, New York. http://www.thirdpointpublic.com/wp-content/uploads/2011/10/first-quarter-2010-investor-letter.pdf.

Newey WK, West KD (1987) A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–708.

Pedersen LH (2009) When everyone runs for the exits. *J. Central Banking* 5:177–199.

Puckett A, Yan S (2011) The interim trading skill of institutional investors. *J. Finance* 66:601–633.

San G (2010) Who gains more by trading—Institutions or individuals? Working paper, Hebrew University of Jerusalem, Jerusalem.

Sias RW, Whidbee DA (2010) Insider trades and demand by institutional and individual investors. *Rev. Financial Stud.* 23:1544–1595.

Sias RW, Turtle HJ, Zykaj B (2015) Hedge fund return dependence: Model misspecification or liquidity spirals. Working paper, University of Arizona, Tucson, AZ.

Sørensen T (1948) A method of establishing groups of equal amplitude in plant sociology based on similarity of species and its application to analyses of the vegetation on Danish commons. *Biologiske Kongelige Danske Videnskabernes Selskab* 5:1–34.

Stein JC (2009) Sophisticated investors and market efficiency. *J. Finance* 64:1517–1548.

Strasburg J, Pulliam S (2011) Pack mentality grips hedge funds. *Wall Street Journal* (January 14), http://www.wsj.com/articles/SB10001424052748704361504575552462233274960.

Stulz R (2007) Hedge funds: Past, present, and future. *J. Econom. Perspect.* 21:175–194.

Yan X, Zhang Z (2009) Institutional investors and equity returns: Are short-term institutions better informed? *Rev. Financial Stud.* 22:893–924.