Crowded Trades and Tail Risk

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Abstract

A growing body of research examines the implications of common holdings for asset price determination; however, far less is known about the impact of hedge fund ownership concentration on risk and return. Yet, hedge fund positions are an important component of the degree of *crowdedness* because these investment vehicles tend to be particularly active in their pursuit of outperformance, they often take highly concentrated positions, and they utilize leverage and short sales. Using a large database of U.S. equity position-level holdings for hedge funds, we measure the degree of security-level crowdedness. We construct a new factor by taking the difference between returns of high and low crowdedness portfolios. The average return on the crowdedness factor is sizable, and its variation is distinct from other traditional risk factors for U.S. equities. When hedge fund returns are regressed onto other risk factors and the crowdedness factor, the exposures to the latter are statistically and economically significant in explaining hedge fund return variation. Most important, the crowdedness factor is related to downside "tail risk" as stocks with higher exposure to crowdedness experience relatively larger drawdowns during periods of market distress. This tail risk extends to hedge fund portfolio returns as the crowdedness factor explains why some funds experience relatively large drawdowns.

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1 Introduction

Concentrated positions in investment assets, often referred to as "crowded trades", are increasingly a topic of interest to investors, regulators, and researchers. The concern centers, in part, around self-reinforcing downward price pressure resulting from liquidation of concentrated positions by vulnerable asset owners.[1] Substantial evidence suggests that illiquid markets such as real estate and corporate assets suffer from fire sales (see, Ellul et al. (2011) and Merrill et al. (2012) for examples in the corporate bond market). Evidence from the financial crisis suggests that more liquid assets could also be subject to non-fundamental price pressures from coincident forced selling during times of broad financial dislocation (see Duffie (2010)'s AFA Presidential Address for a broad survey on the literature). In a related fashion, even though public equities are considered liquid assets with generally diffuse investor bases, a growing body of academic research examines the implications of common holdings among investment managers for asset price determination (see, for example, Greenwood and Thesmar (2011), Lou (2012), Jotikasthira et al. (2012), and Antón and Polk (2014)). While the evidence suggests that stocks also may be subject to price pressure from involuntary liquidations, far less is known about the impact of hedge fund ownership on equity downside risk (see Khandani and Lo (2011) as an exception that focuses on the 'quant crisis' of 2007). Despite this growing body of research, the question regarding whether concentrated positions cause their own risk remains as the sources of these risks are debated and may derive from exogenous factors such as regulatory capital requirements. Across these avenues of research, it remains difficult to empirically differentiate between exogenous shocks and "endogenous risk" driven by crowded trades.

[1] Elements of this mechanism have been described in work by Allen and Gale (2007), Brunnermeier and Pedersen (2009), Kyle and Xiong (2001), Gromb and Vayanos (2002), Morris and Shin (2004), and Shleifer and Vishny (1992, 1997), among many others.

This paper seeks to shed new light on the importance of crowded trades, fire sales, and downside risk by utilizing a large dataset of equity holdings by hedge funds. Over the last 20 years the hedge fund industry has grown from a few hundred funds with an estimated $400 billion in assets under management (AUM) to several thousand funds with an estimated $3.5 trillion in AUM.[2] Hedge funds are fairly unique investors because they tend to be particularly active in their pursuit of outperformance, they often take highly concentrated positions, and they utilize leverage and short sales. Also worth noting is that over the last 20 years the number of publicly listed companies in the U.S. has declined by about 50% from nearly 8,000 in 1997 to under 4,000 in 2017 so that the universe of opportunities for hedge fund trades has shrunk significantly even as the number of funds and size of assets has grown. These facts all make the study of hedge fund positions a good laboratory for understanding the role of active traders in creating risks associated with crowded trades.

So, what constitutes a crowded trade? Conceptually, it is a collection of similar positions in a particular asset by investors who share a common investment thesis and may therefore want to trade in the same direction at about the same time. In practice, there is no single accepted definition, but commercial research services report statistics tracking concentration of equity ownership in terms of the number of hedge funds owning a stock and the aggregate size of positions. Furthermore, evidence suggests that the growth of hedge funds has evolved to include fund families who were trained on similar investment styles and therefore tend to seek similar investments Spilker (2017). Theoretically, risk associated with crowded trades has foundations in the banking literature on endogenous risk in the financial system (see Brunnermeier and Oehmke (2013) for an overview). Broadly speaking, fire sales happen when large investor(s) want to sell significant amounts of an

[2]See, for example, HFR 2017 Global Hedge Fund Industry Report.

asset and there are insufficient buys near the current market price. In this paper we seek to understand the more granular aspects of how endogenous risks are generated as well as their effects on asset and portfolio returns. Equity market data is well-suited for this because holdings for many investors in many assets can be observed at regular intervals. Because the equity market is relatively transparent and liquid, finding important effects would suggest that similar effects exist in less transparent markets with lower liquidity and more concentrated ownership.

We focus specifically on long positions in U.S. equities held by hedge funds from 2004 through 2016. Our data comes from several sources. First, we collect holdings data from 13F filings. This lets us identify on a quarterly basis which funds hold each stock.[3] We also collect data on monthly hedge fund returns from commercial data providers. These data cover thousands of funds with many strategies, including, but not limited to U.S. equity strategies. These data allow us to see how risks associated with crowded trades may propagate to portfolio returns. The hedge fund universe appears to be large when looking at the number of funds in commercial databases. However, the number of reported funds greatly exaggerates the number of important distinct entities in the hedge fund space. Many funds are small, and many more are slight variations on a common investment strategy with differences in liquidity terms, fees, leverage, or net positions. Our aggregation of positions utilizes a proprietary database of about 1,500 U.S. equity hedge fund firms tracked by Novus that we believe provides a nearly comprehensive set of "institutional quality" fund holdings. Novus is a leading portfolio intelligence platform that specializes in performance analytics of active managers.

Crowdedness does not have a single widely accepted definition and so we measure

[3]These data are aggregated at the firm (vs. individual fund) level and do not include short positions. Another drawback is that we will include some holdings from other types of strategies (like traditional 1940 Act mutual funds) for some asset managers that offer these types of products. These limitations should work against us identifying significant effects.

crowdedness in several ways. In all cases we find that our crowdedness measures are of magnitudes that appear economically significant and are increasing over our sample period. A very simple measure is the value of holdings by hedge funds. For the average stock in our sample, hedge fund holdings have grown more than three-fold from about $160MM in 2004 to over $500MM in 2016. Another simple measure is the number of hedge funds invested in each stock. We find that the typical stock has experienced roughly a doubling in the number of funds holding it from 15 in 2004 to 28 in 2016. A better measure of crowdedness is the percent of shares outstanding (PSO) held by hedge funds because it accounts for the relative size of hedge fund positions. Average PSO increased from about 8% in 2004 to 12% in 2016. Finally, we measure crowdedness by calculating hedge fund holdings as a percentage of average daily trading volume (days-ADV). For this measure we observe an increase from about 18 days in 2004 to 26 days in 2016. We believe that days-ADV is likely the best measure of the ones we consider because it measures crowdedness both in terms of the size of hedge fund holdings as well as the underlying liquidity of the stock. Days-ADV is also a commonly used measure by practitioners for gauging the liquidity of their individual and portfolio positions, and will be the main measure of crowdedness we employ throughout the paper. Specifically, this two-dimensional focus on ownership and (il)liquidity reinforces the idea that the time required to evacuate a building depends on the number of people in the room **and** the size of the door.

While each of the crowdedness measures increased over our sample period, most of the variation is cross-sectional. We examine the importance of this variation by sorting firms into 5 portfolios based on the cross-sectional variation of each measure. We then examine the average returns of these portfolios over the sample period and find that in each measure, the most crowded portfolios have the highest returns and the least crowded portfolios have the lowest returns. For example, when we examine value-weighted returns for portfolios sorted on days-ADV, we find that the low crowdedness portfolio (Q1) average return is 8.5% per annum versus 11.3% for the high crowdedness portfolio (Q5). We next construct crowdedness factors by taking the differences in monthly returns between the high and low crowdedness portfolios (Q5 less Q1). We observe that this factor typically generates statistically significant α's even after controlling for other traditional risk factors, including the relative illiquidity of the more crowded positions, on average. Taken together, the evidence suggests that our crowdedness measures capture a unique factor with a positive average return (and interesting state-dependent risk properties).

Accordingly, we next turn to examining how crowded positions perform relative to uncrowded positions during times of market stress. We examine the extent to which returns are disproportionately affected by crowdedness during the financial crisis by calculating cumulative abnormal returns for the crowded and uncrowded portfolios. We document significantly negative CARs for the crowded portfolios during 2008 which then largely reverse in 2009. CARs for uncrowded positions are closer to zero (or positive in some cases). These results suggest that during the financial crisis, firms with both significant hedge fund ownership and relatively low levels of daily liquidity can be characterized by exit frictions that exhibit significant, temporary price dislocations (i.e., fire sales).

While the results described above suggest that returns of individual stocks are subject to crowdedness risk, this does not mean that funds would necessarily have significant exposure to crowdedness. Funds may only hold a small part of their portfolio in crowded trades or may undertake other types of risk mitigation with short positions or derivatives unobserved in 13F filings. Consequently, we also examine monthly hedge fund returns to see if crowdedness is an important risk factor. We aggregate hedge funds returns to the parent firm level and regress these on our crowdedness measure and other traditional risk factors. We find that the days-ADV risk factor is statistically significant for about 26% of the hedge fund universe (and certain subsets of hedge fund strategies are highly exposed to crowdedness). These results indicate that crowdedness risk is important at the hedge fund portfolio level as well as the individual security holding level.

Finally, we examine the relation between crowdedness and fund downside risk. We do this by measuring the correlations of fund drawdowns during the financial crisis with fund holdings of crowded positions. We find that funds with a higher average investment weight in the least crowded days-ADV portfolio experienced less severe drawdowns during the financial crisis, while funds with a higher allocation to the most crowded days-ADV portfolio experienced more severe drawdowns. This indicates that crowded trades are associated with relatively worse fund performance in particularly bad states of the world.

Our analysis makes contributions to four areas of hedge fund research. First, in the spirit of Fung and Hsieh (2001), Bollen and Whaley (2009), Bali et al. (2011), Bali et al. (2012), Avramov et al. (2013), Patton and Ramadorai (2013), Bali et al. (2014), Cao et al. (2016) we extend the literature related to risk factors that explain cross-sectional hedge fund returns. Second, our measure extends work by Agarwal and Naik (2004), Boyson et al. (2010), Agarwal et al. (2013), and Buraschi et al. (2014) on the importance of portfolio networks. Third, we also extend the results of Sadka (2010), Teo (2011), Cao et al. (2013), Gibson and Wang (2013) which document the role liquidity plays in hedge fund portfolios and returns. Finally, we connect our measure to downside risk, related to Jiang and Kelly (2012) and Agarwal et al. (2017).

The remainder of the paper proceeds as follows: Section 2 provides details of data sources and sample construction. Section 3 describes how we create our measures of crowded trades and the performance of stock portfolios created using the crowdedness measures. Section 4 and Section 5 examine the relations between crowdedness and hedge fund performance and risk. Section 6 concludes.

2 Data on Hedge Fund Holdings and Crowdedness

Our analysis centers on examining the implications of elevated hedge fund ownership concentration, so-called "crowdedness", for both security price dynamics as well as individual hedge fund risk exposures. Our interest focuses on the degree to which hedge fund ownership both evolves over time and varies in the cross-section of stocks. To attempt to gauge the extent of crowdedness, we collect long public equity positions for hedge funds from regulatory SEC 13F quarterly filings, cleaned and matched to the parent investment firms by Novus. This effort yields 6,238,988 long positions held by 1,466 hedge fund firms. While many more hedge funds exist than hedge fund firms, we believe that aggregation to the fund-firm level is appropriate in most instances and should work against us if we are mixing in other types of funds (e.g., traditional 1940 Act mutual funds). To limit the contaminating effects of difficult to trade micro-capitalization stocks, the smallest 20% of securities over the sample period are removed from the sample.[4] The sample is further filtered to include only CRSP common shares (share codes 10 and 11), thereby removing ADRs, units, ETFs, REITs, and securities incorporated outside the U.S. To enter our analysis, securities are also required to have at least 6 monthly observations over the sample period. This leaves us with 5,974 equities, with data spanning the first quarter of 2004 through the fourth quarter of 2016. For these stocks, we collect monthly returns, average daily trading volume (hereafter, ADV), and market capitalization for each stock from CRSP.

To characterize the time-series and cross-sectional nature of crowdedness, we con-

[4] Removing the smallest stocks by capitalization follows Hou et al. (2017)

struct three related (but distinct) point-in-time measures based upon collective hedge fund presence: (1) the number of total hedge fund firms invested in an individual security at a point in time, (2) the security's percentage of shares outstanding (PSO) owned by the measurable hedge fund universe (total value invested by hedge funds divided by the market capitalization), and (3) the hedge fund universe's total value invested in a security relative to the security's average daily volume (days-ADV). The latter, upon which we base most of the analyses in this paper, provides an estimate of how long (*in days*) it would take the hedge fund universe to collectively divest itself of a position in an individual security, supposing the industry could sell 100% of ADV per day.[5]

To highlight the evolving nature of hedge fund ownership, we first turn to an illustrative example of Delta Airlines. After Delta emerged from bankruptcy in 2007, we observe 41 hedge fund firms to be invested, their collective ownership represented 13% of the shares outstanding, with 3 days-ADV. In sharp contrast, by the end of our sample in 2016 there were 120 hedge fund firms that owned Delta collectively representing 22% of shares outstanding with 17 days-ADV. While the sharp change in hedge fund presence among the owners of Delta Airlines over time is compelling, this experience is quite representative of a broad trend observed across the U.S. equity market over this period. The relevant question is then whether this matters in any way for security prices, fund performance, and downside risk.

Figure 1 plots the patterns in crowdedness from 2004 through 2016. Panel A provides a measure of the average value (in US$ terms) invested by the entire hedge fund universe in an individual stock through time. Aside from an obvious disruption associated with the financial crisis, this figure highlights a remarkable increase from $160 million in 2004 to about $500 million in 2016. Panel B shows the number of hedge funds invested

[5]A common rule of thumb used by traders, is that it is unwise to trade more than 20% of volume in a given security, so practitioners often multiply this metric by 5 to measure position liquidity.

in the average security, Panel C shows the percentage of shares outstanding collectively held, and Panel D shows days-ADV. Each panel shows the average security's crowdedness has increased from 2004 through 2016, though the specific patterns are distinct. Over this time period, the average number of funds invested in a security has risen from 15 to 28, the percent of shares outstanding owned by the hedge fund universe has risen from 8% to 12%, and days-ADV has risen from 18 to 25. The focus of this paper is on the extent to which the degree of crowdedness is linked to different risk-return profiles for individual securities, and on the performance of the hedge funds themselves in certain bad states of the world, depending upon the magnitudes of their exposure to crowded positions.

We next turn to Table 1 which provides a comparison of the time-series (in Panel A) and cross-sectional (in Panel B) variation in crowdedness for individual U.S. equity positions. Specifically, Panel A measures the time-series variation in the *per-period* cross-sectional average of our three measures of crowdedness. The pure time-series dimension exhibits a modest degree of variability, whether measured by the number of invested funds, share ownership, or required liquidity. However, the variation is driven, in part, by the general upward trend in crowdedness across our sample period. Panel B measures the time-series average of the variation *across* stocks for each period. In contrast to the temporal dimension, cross-sectional variation in crowdedness is significant. For example, the average inter-quartile range in the number of funds holding a U.S. equity position at a point in time is 7 to 24 funds. Comparable inter-quartile ranges for share ownership and liquidity are 5 to 16 percent and 9 to 33 days-ADV, respectively.

From this characterization of the nature of hedge fund crowdedness, we uncover two important features of the data. First, hedge funds are, on average, increasingly exposed to relatively crowded positions. The time-series averages we observe are both large and generally growing. Second, there is substantial variation in fund crowdedness across equity positions. Thus, at a particular point in time, some hedge funds (and other institutional investors with common ownership) are disproportionately invested in relatively crowded positions whereas others are not.[6]

3 Building Crowdedness Portfolios

We next examine whether there is important cross-sectional variation in price dynamics related to hedge fund crowdedness. Specifically, we form portfolios based on crowdedness and evaluate the variation across portfolios in average returns, realized volatility, and downside risk. We focus on portfolio sorts based on PSO and days-ADV rather than the number of invested funds, as the latter treats large and small exposures as equivalent. Focusing on the days-ADV measure, a security can become more crowded if the security's illiquidity increases or if the hedge fund universe increases their position. To better understand the contribution of these two components, we measure a security's illiquidity (ILLIQ) as the security's market capitalization relative to the security's average daily volume. Separating the effects of illiquidity is particularly important as there is a long literature on the link between average returns and illiquid assets (see, for example, Amihud and Mendelson (1986), among many others).

Given our candidate measures of position crowdedness, we sort firms into quintile portfolios given breakpoints that characterize the point-in-time cross-sectional variation in each measure. For instance, Figure 2 presents the quantile breakpoints associated with

[6]While this is not the focus of this paper, it is important to note that there may be significant implications for other parts of the investment management landscape (both active and passive funds) that share significant ownership overlap with the hedge funds identified in this paper. First, given the sizable reduction in the number of listed firms in the U.S., this means that a more general notion of crowdedness may be appropriate (where we might also include managed equity funds of other types). Second, it may be the case that the catalyst for downside risk realization associated with position crowdedness could originate elsewhere. For instance, sizable passive portfolio outflows (and any associated fund liquidations) could trigger challenges for levered hedge funds with significant portfolio overlap.

days-ADV. The lowest days-ADV portfolio (henceforth Q1) is generally characterized by 5 or fewer days-ADV, indicating that these are not particularly crowded positions. In contrast, the highest portfolio (Q5) is generally around 30-35 days-ADV.

Table 2 provides the average returns across the quintile portfolios for the days-ADV and PSO crowdedness measures, as well as the security illiquidity measure ILLIQ. For each portfolio, we both equally-weight (Panel A) and value-weight (Panel B) the constituent firms. Recall that equal weighting will not be contaminated by very small (and presumably harder to trade) firms given that we screen out the smallest 20% of firms by capitalization. We provide the average annualized returns for each portfolio, along with associated annualized standard deviations in parentheses. We also provide results for HML (high-minus-low) crowdedness portfolios based on the difference between the returns of the high and low quintile portfolios (Q5 minus Q1). First, we observe that firms associated with relatively crowded positions, as measured by both days-ADV and PSO, exhibit larger average returns than firms associated with less crowded positions. This is true for both equal-weighted and value-weighted portfolios. For example, the low crowdedness portfolio average returns vary from 6.5% per annum (for the equal-weighted days-ADV) to 10.0% (for the equal-weighted PSO). In contrast, the high crowdedness portfolio average returns vary from 11.3% per annum (for value-weighted days-ADV) to as high as 15.6% (for equal-weighted days-ADV). In each of the four separate cases, the average return on the high crowdedness portfolio is well in excess of the average return on the low crowdedness portfolio and the differences are statistically significant at the 10% level or better. To separate out the presence of hedge funds from the illiquidity of the positions in which they invest, we also examine portfolio returns delineated by a security's illiquidity (ILLIQ). Consistent with earlier research, we observe that the difference between high and low illiquidity portfolios is positive and significant for the equal-weighted portfolio (despite the removal of the small firms); however, the difference is not significant for the value-weighted portfolio. Clearly, illiquidity is relevant, and we will control for this risk source later. However, we should emphasize that we find that it is the interplay between the magnitude of hedge fund ownership with the illiquidity of the positions that is collectively important (as opposed to illiquidity in isolation). That said, while these potentially large return differences are interesting, they may be related to other established risk factors. We examine this issue next.

First, we note that the constituent stocks in our portfolios are relatively sticky in the sense that the transition probabilities of firms across portfolios are reasonably low. Taking the equally-weighted days-ADV-based portfolios as an example, conditional on a firm being in portfolio Q1 (Q5), the empirical likelihood of remaining there next period is 77% (82%).[7] However, transition probabilities of the magnitudes we observe are also relatively common (see the Fama and French (1992) size and value quintile portfolios, for example). Despite these high values, there is still a reasonable likelihood of migrating to proximate portfolios and the less extreme portfolios are less sticky. These patterns are common across all four portfolios sorts that we consider.

Second, it is also important to note that the quintile portfolios exhibit significant variation along other important dimensions that have been shown to be relevant for risk pricing. For example, high PSO or days-ADV (Q5) firms are significantly smaller and less-liquid, on average, than firms in the low crowdedness portfolios (Q1). This is not surprising given that it is easier for the hedge fund universe to accumulate a sizable ownership fraction for relatively small firms (recalling again that we exclude the smallest 20% of firms by capitalization). At a minimum, this corroborates the concern raised above that it is important to control for these characteristics when interpreting the nature of any return

[7] The full portfolio transition matrix for the equal-weighted quintile portfolios is available as Appendix Table A.2.

differentials associated with our crowdedness portfolios. First, as we evaluate the significance of any portfolio return spreads, we will examine the degree to which these return spreads are spanned by other well known risk factors, including size and illiquidity.

We also consider separate three-by-three, two-way portfolio sorts. For example, we double sort firms into equally-weighted portfolios by days-ADV and market capitalization, and we do the same for a double sort by days-ADV and ADV or ILLIQ.[8] The two-way sorts confirm that the general patterns that we detect do not disappear. Holding market capitalization or illiquidity relatively constant, we continue to observe that high days-ADV stocks are characterized by larger average return than low days-ADV stocks.[9] However, the tercile-based portfolio spreads are smaller as might be expected given the lower spread in crowdedness. Nevertheless, as we next turn to an examination of the degree to which the univariate return spreads are spanned by traditional risk factors, we specifically include factors related to size and illiquidity.

3.1 A crowdedness factor

Given the average return differentials that we observe across portfolios sorted on crowdedness, we next create several candidate crowdedness "factors" by taking the return differences between the high and low univariate quintile crowdedness portfolios. Specifically, we consider two long-short portfolios: two based on quintile portfolios sorted on days-ADV (both equal-weighted and value-weighted). For completeness, we also create two equal-weighted and value-weighted portfolios based on PSO and ILLIQ directly.

In addition to the detail already discussed on the individual quintile portfolios, Pan-

[8]Unfortunately, some of these three-by-three portfolios have very few stocks (e.g., some corner portfolios have less than 5% of the sample). Five-by-five two-way sorted portfolios that would more closely resemble the quintile based nature of our main analyses unfortunately yield a few portfolios with less than 1% of all firms in the sample.

[9]Average returns for the portfolios associated with these two two-way sorts are presented in Appendix Table A.3.

els A (equal-weighted) and B (value-weighted) of Table 2 provide the average returns and standard deviations of these high-minus-low portfolios (labeled HML). Over our sample period, the average returns per annum for the HML crowdedness factors based on days-ADV are 9.1% and 2.8% across equal- and value-weighted, respectively. In both cases, these return spreads are statistically significant, suggesting that there may be an important link between the degree of hedge fund ownership concentration and equity returns. To provide some visual guidance, the two days-ADV factor returns are plotted in Panels A (equal-weighted) and B (value-weighted) of Figure 6 along with the market portfolio return.[10] Both days-ADV measures exhibit significant time variation; however, the factor volatilities are, as one might expect for a high-minus-low portfolio, significantly lower than the overall market volatility and the covariances between the factors and the market return are small. We next examine the degree to which the factor average returns are driven by other commonly examined risk factors.

To evaluate the uniqueness of these factors, we conduct a sequence of standard spanning tests (see e.g. Hou et al. (2018)). First, we evaluate whether the factor returns can be explained by (sequentially) the market risk factor (CAPM), the Fama and French three-factor model (the market factor plus size and book-to-market factors), or augmented versions of the Fama and French model that include momentum and reversal factors. The results along with the factors' average returns, standard deviations, Sharpe ratios, and CAPM market betas are provided in Table 3.[11]

Table 3 provides the results from the temporal regressions of each factor (one in each of the columns provided) onto the market portfolio, the three-factor model, and the augmented versions that include momentum and reversals. The sequential presentation

[10] The same plots for the factors based on PSO are available upon request.

[11] The market returns, plus the size, value, momentum, short and long-term reversal risk factors are obtained from Ken French's data library.

is additive in the sense that each row represents an excess return (α) derived from a time-series factor regression that includes the factors as explanatory variables from the preceding rows plus the listed variables. Hence, all spanning tests presented below the Fama and French three-factor model also include the size factor which is important given the overlap between crowdedness and size identified above. The results indicate that the α's associated with the days-ADV factor, regardless of whether we equal- or value-weight, are large and statistically different from zero for all cases that involve these traditional factors. This is particularly important given that the inclusion of the Fama and French size factor help to control for the differences in market capitalization across the constituent firms in these extreme quintile portfolios.[12]

Next, given the overlap between crowdedness and illiquidity identified above, we next include two factors related to the latter.[13] The first is the Pástor and Stambaugh (2003)'s traded liquidity risk factor from Lubos Pastor's webpage - this is designed to capture systematic variation in liquidity risk. Second, we include the *direct* ILLIQ high-minus-low factor that we construct based off of the same underlying equity securities (for the equal-weighted days-ADV portfolio, we use the equal-weighted ILLIQ, and vice versa for the value-weighted version). The latter allows us to control for the obvious fact that some of the cross-sectional return variation may be arising from relatively illiquid positions, rather than crowdedness per se. As mentioned, we are instead interested in the interplay between hedge fund presence and illiquidity, rather than illiquidity in isolation, so including this 'control' is important. We do not find that the Pástor and Stambaugh (2003)'s liquidity factor is significant. However, we do find that ILLIQ is statistically important (the days-ADV factor exposure to ILLIQ is statistically significant and the overall

[12] In the Appendix, we provide the full results from these regressions that include all the factor loadings as well as the alphas.

[13] Further, Sadka (2010) shows that the typical hedge fund loads on liquidity risk and that sensitivity to liquidity risk is priced in the cross section of hedge fund returns.

day-ADV α significantly declines). Hence, we interpret this evidence to suggest that when measuring hedge fund crowdedness, one needs to control for the direct illiquidity effect to isolate this joint exposure.

Finally, given the importance of hedge fund risk exposures for understanding hedge fund performance, we also include Fung Hsieh's bond, FX, commodity, interest rate and stock trend following risk factors, collected from David Hsieh's data library. We also include several recently identified AQR factors collected from AQR's data set. Specifically, we include Asness et al. (2013)'s "The Devil in HML's Details" DVL, Frazzini and Pedersen (2014)'s "Betting Against Beta" BAB, and Asness et al. (2017)'s "Quality Minus Junk" QMJ risk factors. Note that the BAB factor has also been identified as related to market and funding liquidity issues.

With these factors included, the α associated with the equal-weighted high-minus-low portfolio sorted on days-ADV continues to be both large and statistically different from zero regardless of what factors we include on the right-hand side. However, the α on the value-weighted version is borderline significant at the 10% level when the Fung and Hsieh hedge fund factors are included. Once we account for the AQR factors for the value-weighted portfolio, we again observe a statistical significant α. For the latter case, while the loading on the BAB factor is positive as one might expect given its link to illiquidity, that version of our crowdedness factor also exhibits a sizable, negative loading on AQR's “quality" factor. This is in the opposite direction from what might be expected, in that the larger average return (Q5) crowdedness portfolio has a much smaller quality loading than the Q1 portfolio.

Finally, we also let the data speak to the best risk model by conducting a step-wise regression approach. We search for the best linear regression model that explains the days-ADV factor. To operationalize this, the days-ADV factor is initially regressed onto a constant and the excess market return. In addition to the market factor, the set of possible explanatory variables includes size, value, and momentum factors; short and long-term reversal factors; Pastor Stambaugh and ILLIQ illiquidity factors; Fung Hsieh's bond, FX, commodity, interest rate and stock trend following factors; and betting-against-beta, devil-in-the-details, and quality-minus-junk factors. Using nested F-tests, the initial specification is compared against every specification containing the market and a second factor. Amongst the models with a p-value less that 5%, the second factor from the model with the smallest p-value is included in the regression model. Again using nested F-tests and comparing the two factor model against every specification with a single factor removed, it is then determined if any of the regressors in the current specification can be removed if their F-test results in a p-value greater than 5% and that regressor had the highest p-value amongst all tests. This process is repeated, adding a single factor and then testing if any existing factors can be removed, until the process stops and no new factors can be added to the model and no existing factors can be removed. As above, for the equal weighted ADV factor, we only include the equal weighted ILLIQ factor as a candidate explanatory variable, and vice versa for the value-weighted. Using the equal-weighted case as an example, we retain risk factors related to size, value, long-term reversals, illiquidity, interest rate movements, BAB and quality. Despite this statistically optimal specification, the α is 4.62% and highly significant. We observe similar retained factors and magnitudes for value-weighted version (see the last row of Table 3).

While the evidence on the uniqueness of the HML crowdedness factors is not categorical, it does appear that the average returns associated with firms sorted along hedge fund crowdedness exhibit important differences that are not fully explained by extant risk-based factors (even when we employ a rather comprehensive factor-based model). Furthermore, the portfolios sorted on the *interaction* between ownership and liquidity (i.e., days-ADV) are, in part, unique. These results reinforce the importance of a two-dimensional perspective on position crowdedness for gauging the implications of hedge fund ownership. While α's associated with days-ADV-based required liquidity are largely significant, an important complementary discussion surrounds the economic source of this outperformance. Is the average return difference that we document due to risk compensation separate from that embodied in the other common risk factors that we examine? Or, is this an indication that hedge funds are, on average, picking the right securities and delivering bona fide outperformance for their clients? In support of the latter, by showing that the highest conviction positions within active mutual fund managers portfolios strongly forecast subsequent average returns, Polk et al. (2018) provide evidence that active managers' positions reflect informative views. Nevertheless, despite the possibility that skill is indeed central, the relevant next question is whether crowded positions also exhibit problems during certain states of the world. As a reminder, our two-dimensional focus on ownership and (il)liquidity reinforces the idea that the time required to evacuate a building depends on the number of people in the room and the size of the door.

4 Crowdedness & Fund Performance

We next examine how the days-ADV crowdedness factor is associated with fund performance. We use hedge fund returns from the Morningstar CISDM hedge fund performance database and merge these with our hedge fund holdings data. We aggregate hedge funds in Morningstar to the parent firm level by equally weighting hedge fund returns because AUM data are missing for a large portion of hedge funds in Morningstar. In total, 363 hedge fund firms are matched, consisting of 1,555 hedge funds. This subsample is used when comparing hedge fund holdings to performance. The full Morningstar database of 14,053 hedge funds is used for analysis when holdings are not needed. Finally, since our holdings are long-only positions in U.S. equities, we primarily focus our performance analysis on funds with strategies related to U.S. equities.

We regress each hedge fund i's excess return R^e_{it} onto the market excess return R^e_{Mt} and the days-ADV crowdedness factor R_{ADVt}:[14]

$$R^e_{it} = \alpha_i + \beta_{iM} \times R^e_{Mt} + \beta_{iC} \times R_{ADVt} + \varepsilon_{it}$$

As shown in Table 4, the days-ADV factor is statistically significant at the 10% level for 26% of the full Morningstar hedge fund universe. The 25% percentile, average and 75% percentile days-ADV coefficients are -0.16, 0.03 and 0.28, respectively. We see that even after controlling for traditional risk factors, some funds disproportionately load on our crowdedness factor, whereas others less so. For example, 58% of "Fund of Funds - Equity" funds have significant exposures to crowdedness while only 18% of "Global Macro" funds have significant exposures. Given that some funds appear to load significantly on crowdedness, we next explore if crowdedness matters specifically for fund-level risk.

5 Crowdedness & Fund Risk

We next ask if hedge funds with exposures to crowded risk also appear to be riskier relative to their peers. From Bloomberg, we identify 3,305 hedge funds that report both daily and monthly returns.[15]. With these data in hand, we regress excess monthly hedge

[14]For our analysis involving crowdedness exposures, we also replicate our analysis using our full factor model specification (including Fama French factors, Fung Hsieh factors, and AQR factors). See Table A.5. Results from the full specification are consistent with results from our reduced factor model with the market and crowdedness factor. For brevity, we report the results of the latter.

[15]Bloomberg data are a relatively novel addition to the hedge fund research landscape - particularly given that a significant number of funds report daily returns. Bloomberg sources these data directly from fund

fund returns onto the excess market return and the days-ADV factor. Using the days-ADV exposures, we sort hedge funds into 5 quantiles. Using daily realized hedge fund returns, we calculate *realized* volatilities and correlations at the monthly frequency within each quantile. Defining "Low" as the quantile for the smallest days-ADV exposures and "High" as the quantile for the largest days-ADV exposures, in Figure 3 and Figure 4 are plotted the average realized volatility and correlation for both the Low and High quantiles. We see that firms with relatively higher exposures to crowdedness exhibit greater realized volatilities during the financial crisis. At the same time, these firms become relatively more correlated with peers holding similar investment positions. In bad states of the world, funds holding crowded securities, on average, appear to become riskier.

5.1 Crowdedness & Fund Downside Risk

To further examine the state-dependent relationship between crowded trades and hedge fund downside risk, we measure the correlations of drawdowns with fund holdings of crowded positions. Table 5 documents that funds with a higher investment weight in the most crowded days-ADV portfolio experienced more severe drawdowns during the financial crisis. The correlation is statistically significant at the 5% level. These results indicate that crowded trades are associated with relatively poorer fund performance in bad states of the world.

Table 6 further documents an association between risk exposures and crowded trades by showing that funds with higher allocations to the most crowded days-ADV portfolios are positively correlated with higher days-ADV risk exposures. To explore if the risk

managers. Further, we confirm that reported monthly returns from Bloomberg are either identical or very similar to the returns reported by the same funds identified in alternative commercial hedge fund performance databases. Finally, we conduct a data quality check by confirming that the daily returns compounded to monthly returns also match the monthly return series. Given this, we use the reported daily Bloomberg hedge fund returns to examine the dynamics of realized risk measures for these funds.

factors have cross-sectional explanatory power, we regress hedge fund drawdowns onto the market and crowdedness factor coefficients. Table 7 shows that funds with higher exposures to crowded risk experienced larger drawdowns during the financial crisis. When conditioning on strategies, we see crowded risk exposures have significant explanatory power for HF Long/Short US Equity, HF Long/Short US Small Cap, and Fund of Funds - Equity strategies. The key takeaway is that hedge funds with crowded exposures suffer greater declines during the financial crisis, a period characterized by widespread hedge fund distress.

5.2 Crowdedness & Fund Drawdowns

Finally, we measure the cumulative average returns of the individual stocks in the extreme crowdedness portfolios around the largest observed hedge fund drawdown period in our sample - the global financial crisis of 2008. Given the importance of the two-dimensional perspective on crowdedness highlighted above, we focus here on the portfolio differences sorted by days-ADV.

Specifically, we examine the extent to which equity prices are disproportionately affected during the financial crisis if they are associated with higher levels of hedge fund crowdedness. We attempt to answer the question, does investor crowdedness exacerbate downside risk? Figure 5 presents cumulative abnormal returns (CARs) for the Q1 and Q5 portfolios sorted by days-ADV in the periods before, during, and after the sizable hedge fund industry drawdown around the financial crisis. The CARs are constructed by cumulating residual days-ADV portfolio returns starting 12 months prior to the start of an identified drawdown period and continuing 12 months after the completion of the drawdown period. The drawdown period is determined by an equal-weighted hedge fund portfolio holding all hedge funds in our sample. Residual days-ADV portfolio returns are calculated by differencing days-ADV portfolio returns and predicted days-ADV portfolio returns using either the CAPM or Fama-French three factor model. Models are estimated using data prior to the start of the drawdown period. All days-ADV CARs are statistically significant at the 1% level. Each panel presents stock prices dynamics for constituent firms for the Q1 and Q5 portfolios as measured by the CARs over the entire evolution of the financial crisis. For our equal-weighted and value-weighted portfolios, we trace the price patterns for the constituent firms in each portfolio to ascertain whether the price effects of the hedge fund industry drawdown are disproportionately larger for crowded stocks (Q5 versus Q1). For each return series, we compute abnormal returns relative to the CAPM or to the Fama and French 3-factor model.

The four panels in Figure 5 present CARs from equal-weighting or value-weighting from the CAPM or Fama-French 3-factor model. All of the panels exhibit two interesting features. First, crowded stocks suffer significantly larger price declines (negative CARs) as the financial crisis unfolds. By controlling for standard pricing factors, the residual price dynamics suggest that hedge fund distress may transmit to the prices of the securities in which they disproportionately invest. CARs for less crowded positions are much closer to zero (or positive). Second, the price declines associated with crowded positions fully reverse in the quarters after the resolution of hedge fund industry distress. The latter observation (and generally any price decline followed by a reversal) suggests that relevant market participants were engaged in distressed selling (fire sales) where more liquidity was required than was available at the longer-term equilibrium market price. During the financial crisis, firms with both significant hedge fund ownership and relatively low levels of daily liquidity can be characterized by exit frictions that exhibit significant, temporary price dislocations.

6 Conclusion

We show that the crowdedness of an equity position is an important ingredient for characterizing risk. Using position-level holdings for hedge funds, we measure the degree of crowdedness for each U.S. equity share held by the hedge fund universe. While crowdedness has significantly increased over time, we also document that it exhibits significant cross-sectional variation. Correspondingly, portfolios sorted on crowdedness are associated with sizable variation in average returns, conditional volatility, and hedge fund risk exposures, even after controlling for common risk factors and position illiquidity. Finally, we also document that hedge funds with high exposure to crowdedness risk experience relatively larger drawdowns and crowded positions exhibit price dislocations during periods characterized by correlated hedge fund distress.

Nevertheless, more refined measures of crowdedness can possibly be created. Importantly, we are, at present, only measuring the degree to which a single security is crowded. One could also consider whether a related group of securities (or broad factor exposures) may be crowded, even if it appears individual securities are not. That is, factor or portfolio dynamics may be more interesting as they pertain to crowdedness. We also believe this line of research can be further extended using hedge fund holdings that contain short positions. The correlations between hedge fund and market returns are traditionally relatively low due to short positions taken on by hedge funds. Understanding how short positions either mitigate or potentially amplify crowdedness risk, and its interaction with fund leverage or compensation incentives, is extremely important. Finally, a broader use of daily hedge fund holdings would allow us to better understand the relationship between crowdedness, liquidity, and the potential liquidity risk premium earned by hedge funds. These data do exist, but have not yet been made broadly available to academic researchers.

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7 Tables

Table 1: Crowdedness Statistics

Panel A: Time-Series Crowdedness Statistics

	NHF	ADV	PSO
Average	22.1	24.9	11.8%
Standard Deviation	3.5	3.0	1.5%
25% Percentile	19.6	23.2	10.7%
75% Percentile	25.2	26.8	12.9%

Panel B: Cross-Sectional Crowdedness Statistics

	NHF	ADV	PSO
Average	18.9	28.0	12.7%
Standard Deviation	18.4	34.6	10.0%
25% Percentile	7.2	8.9	5.7%
75% Percentile	24.0	31.5	17.1%

NHF is the number of hedge funds. ADV is HFU value invested in a security relative to the security's ADV. PSO is the percent of shares outstanding.

Table 2: Portfolio Return Statistics

Panel A: Equal Weighted Portfolios

	Low	**Q2**	**Q3**	**Q4**	**High**	**HML**
ADV	6.5%	11.0%	13.1%	14.4%	15.6%	9.1%
	(21.3%)	(19.6%)	(19.3%)	(19.4%)	(17.9%)	(8.0%)
PSO	10.0%	11.6%	11.7%	13.5%	13.9%	3.9%
	(17.1%)	(18.7%)	(19.3%)	(20.4%)	(21.5%)	(7.2%)
ILLIQ	8.7%	10.4%	12.9%	13.9%	14.8%	6.1%
	(25.5%)	(20.0%)	(18.4%)	(18.0%)	(15.9%)	(12.6%)

Panel B: Value Weighted Portfolios

	Low	**Q2**	**Q3**	**Q4**	**High**	**HML**
ADV	8.5%	10.1%	10.4%	12.1%	11.3%	2.8%
	(14.9%)	(13.4%)	(13.6%)	(14.0%)	(13.8%)	(6.2%)
PSO	7.8%	10.8%	9.5%	11.1%	13.3%	5.5%
	(12.1%)	(14.6%)	(15.7%)	(16.0%)	(18.1%)	(9.8%)
ILLIQ	9.8%	9.0%	9.6%	9.8%	7.5%	–2.3%
	(21.0%)	(16.6%)	(13.2%)	(10.7%)	(12.2%)	(14.6%)

All statistics annualized. Top row are average returns. Bottom row in parentheses are standard deviations. PSO is the percent of shares outstanding. ADV is the percent of ADV. The security universe is constructed as securities identified in SEC 13F filings and CRSP. The security universe is filtered to include only CRSP share codes 10 and 11. Share codes 10 and 11 include ordinary common shares. This removes ADRs, units, ETFs, REITs, and securities incorporated outside the US. Securities are required to have at least 6 monthly observations over the sample period. The smallest 20% of securities over the sample period are removed. The data is collected from the first quarter of 2004 through the fourth quarter of 2016. One, two and three stars represent significance at the 10%, 5%, and 1% levels.

Table 3: Days-ADV Factor Regressions

	Equal Weighted	**Value Weighted**
Average	9.08%	2.79%
Standard Deviation	8.04%	6.25%
Sharpe Ratio	0.98	0.26
Market β	−0.25	−0.13
CAPM	11.22%	3.87%
	(0.00)	(0.02)
FF3	10.97%	4.18%
	(0.00)	(0.01)
+Mom	10.62%	4.36%
	(0.00)	(0.01)
+Reversal	9.76%	4.04%
	(0.00)	(0.02)
+Pastor Stambaugh	9.78%	4.05%
	(0.00)	(0.02)
+ILLIQ	3.20%	3.33%
	(0.03)	(0.03)
+Fung Hsieh	3.03%	2.67%
	(0.04)	(0.11)
+BAB+DVL+QMJ	4.07%	3.71%
	(0.00)	(0.01)
Stepwise	4.62%	4.24%
	(0.00)	(0.00)

All statistics annualized. Market beta is the factor's loading when regressed onto the market return. Alphas from model regressions and P-values in parenthesis are shown. P-values calculated using HAC robust standard errors. CAPM includes the market return. FF3 adds size and value factors. +Mom adds momentum. +Reversal adds short and long-run reversal. +Pastor Stambaugh adds traded liquidity factor. +ILLIQ adds illiquidity turnover factor. +Fung Hsieh adds bond, FX, commodity, interest rate and stock trend following factors. BAB is betting-against-beta, DVL is devil-in-the-details, and QMJ is quality-minus-junk. Stepwise is the final specification from performing stepwise regression with all factors.

Table 4: Percent of Hedge Funds with Significant ADV Crowdedness Exposure

Strategy	**Funds**	**Coefficient**	**Significant**
Full - Average	14,154	0.03	26%
Full - 25% Percentile		−0.16	
Full - 75% Percentile		0.28	
HF Bear Market Equity	43	0.08	26%
HF Convertible Arbitrage	199	0.26	61%
HF Distressed Securities	208	0.26	54%
HF Diversified Arbitrage	68	0.01	40%
HF Equity Market Neutral	431	0.10	35%
HF Event Driven	329	0.23	52%
HF Fund of Funds - Equity	1,124	0.25	58%
HF Fund of Funds - Event	184	0.30	71%
HF Fund of Funds - Macro/Systematic	290	0.10	28%
HF Fund of Funds - Multistrategy	1,896	0.24	53%
HF Fund of Funds - Other	495	0.27	41%
HF Fund of Funds - Relative Value	156	0.30	62%
HF Global Long/Short Equity	681	0.17	36%
HF Global Macro	579	−0.01	18%
HF Long-Only Equity	146	−0.36	28%
HF Long-Only Other	73	−0.04	35%
HF Merger Arbitrage	34	0.04	27%
HF Multistrategy	776	0.09	39%
HF Systematic Futures	865	−0.04	13%
HF U.S. Long/Short Equity	1,146	0.08	35%
HF U.S. Small Cap Long/Short Equity	248	0.06	35%
HF Volatility	83	−0.20	26%

Percent of funds with significant crowdedness exposures from regressing fund returns onto market and crowdedness risk factor. Results from monthly time series regressions. Statistical significance at the 10% significance level. Unless otherwise noted, average coefficients are presented.

Table 5: Correlation of Fund Holdings with Fund Drawdowns

Portfolio	**ADV**	**PSO**	**ILLIQ**
Low	0.04	0.04	-0.03
	(0.53)	(0.48)	(0.64)
Q2	0.02	-0.04	-0.07
	(0.69)	(0.55)	(0.27)
Q3	-0.10	-0.08	-0.12
	(0.10)	(0.21)	(0.05)
Q4	-0.20	-0.11	-0.13
	(0.00)	(0.08)	(0.03)
High	-0.13	-0.17	-0.11
	(0.03)	(0.00)	(0.06)

Correlations of average percent of hedge fund holding of crowdedness portfolios with fund drawdowns. P-values in parenthesis are shown. PSO is the percent of shares outstanding. ADV is the percent of ADV. The drawdown period is 11/2007-02/2009.

Table 6: Correlation of Fund Holdings with Crowdedness Coefficients

Portfolio	**ADV**	**PSO**	**ILLIQ**
Low	-0.14	-0.17	-0.15
	(0.01)	(0.00)	(0.00)
Q2	-0.05	-0.09	0.01
	(0.36)	(0.08)	(0.77)
Q3	0.00	0.04	0.03
	(0.94)	(0.45)	(0.53)
Q4	0.02	0.16	0.08
	(0.68)	(0.00)	(0.14)
High	0.09	0.19	-0.01
	(0.09)	(0.00)	(0.85)

Correlations of average percent of hedge fund holding of crowdedness portfolio with crowdedness coefficient. P-values in parenthesis are shown. PSO is the percent of shares outstanding. ADV is the percent of ADV.

Table 7: Cross Sectional Drawdown Regressions

Strategy	**ADV**	**PSO**	**ILLIQ**
HF Bear Market Equity	0.85	-0.89	1.55
	(0.17)	(0.02)	(0.00)
HF Convertible Arbitrage	-0.48	-0.40	-0.67
	(0.00)	(0.00)	(0.00)
HF Distressed Securities	-0.46	-0.48	-0.05
	(0.01)	(0.00)	(0.83)
HF Diversified Arbitrage	-0.50	-0.38	-0.60
	(0.00)	(0.00)	(0.00)
HF Equity Market Neutral	-0.28	-0.34	-0.09
	(0.00)	(0.00)	(0.38)
HF Event Driven	-0.05	-0.31	0.05
	(0.58)	(0.00)	(0.56)
HF Fund of Funds - Equity	-0.35	-0.28	-0.32
	(0.00)	(0.00)	(0.00)
HF Fund of Funds - Event	-0.29	-0.11	-0.23
	(0.01)	(0.19)	(0.01)
HF Fund of Funds - Macro/Systematic	-0.61	-0.46	-0.58
	(0.00)	(0.00)	(0.00)
HF Fund of Funds - Multistrategy	-0.35	-0.28	-0.49
	(0.00)	(0.00)	(0.00)
HF Fund of Funds - Other	-0.51	-0.35	-0.46
	(0.00)	(0.00)	(0.00)
HF Fund of Funds - Relative Value	-0.26	-0.12	-0.60
	(0.09)	(0.40)	(0.00)
HF Global Long/Short Equity	-0.41	-0.36	0.19
	(0.00)	(0.00)	(0.25)
HF Global Macro	-0.61	-0.61	-0.26
	(0.00)	(0.00)	(0.22)
HF Long-Only Equity	-0.14	-0.15	-0.01
	(0.39)	(0.11)	(0.96)
HF Long-Only Other	-0.47	-0.17	-0.29
	(0.01)	(0.36)	(0.24)
HF Merger Arbitrage	-0.05	-0.50	0.28
	(0.89)	(0.11)	(0.60)
HF Multistrategy	-0.42	-0.39	-0.10
	(0.00)	(0.00)	(0.63)
HF Systematic Futures	-0.52	-0.33	-0.34
	(0.00)	(0.00)	(0.04)
HF U.S. Long/Short Equity	-0.27	-0.32	0.09
	(0.00)	(0.00)	(0.15)
HF U.S. Small Cap Long/Short Equity	-0.40	-0.37	-0.13
	(0.00)	(0.00)	(0.23)
HF Volatility	0.05	0.09	-0.21
	(0.80)	(0.61)	(0.22)

Drawdown exposures from regressing drawdown returns onto market and crowdedness exposures. Drawdown is 11/2007-02/2009. P-values calculated using HAC robust standard errors are shown in parenthesis.

8 Figures

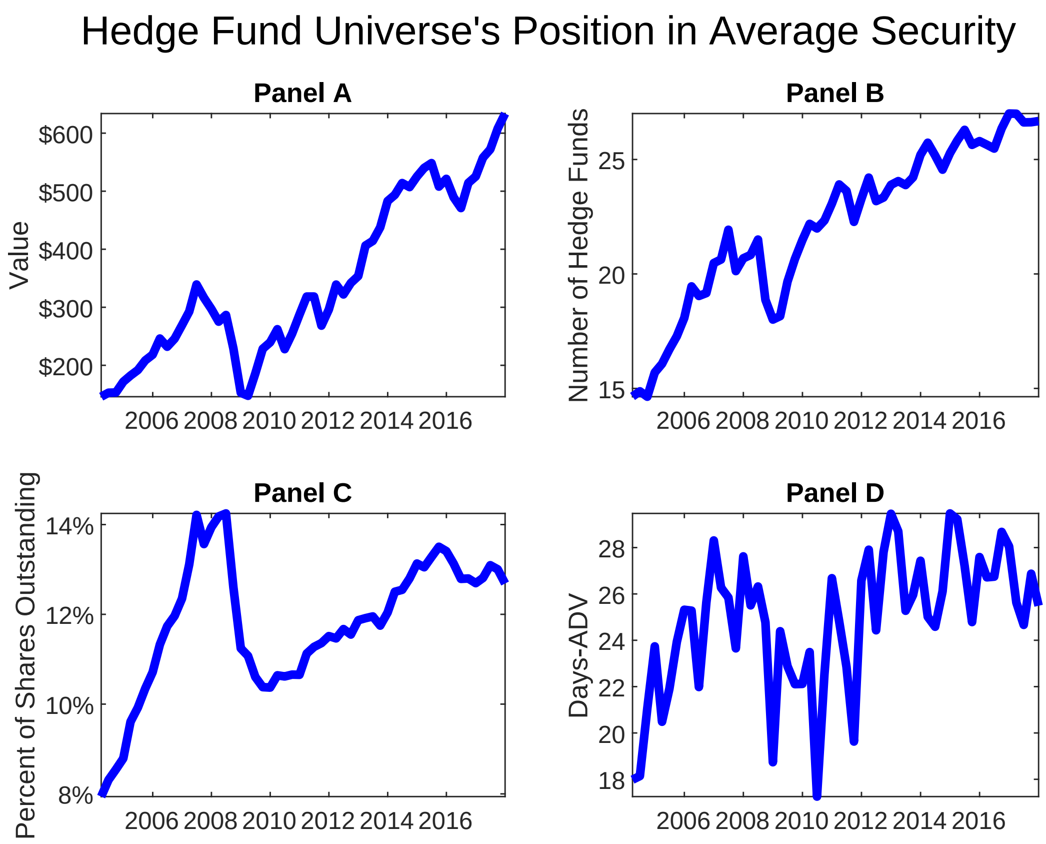

Figure 1: Value ($MM) is value held by the hedge fund industry. Days-ADV is shares outstanding held by hedge funds divided by average daily trading volume

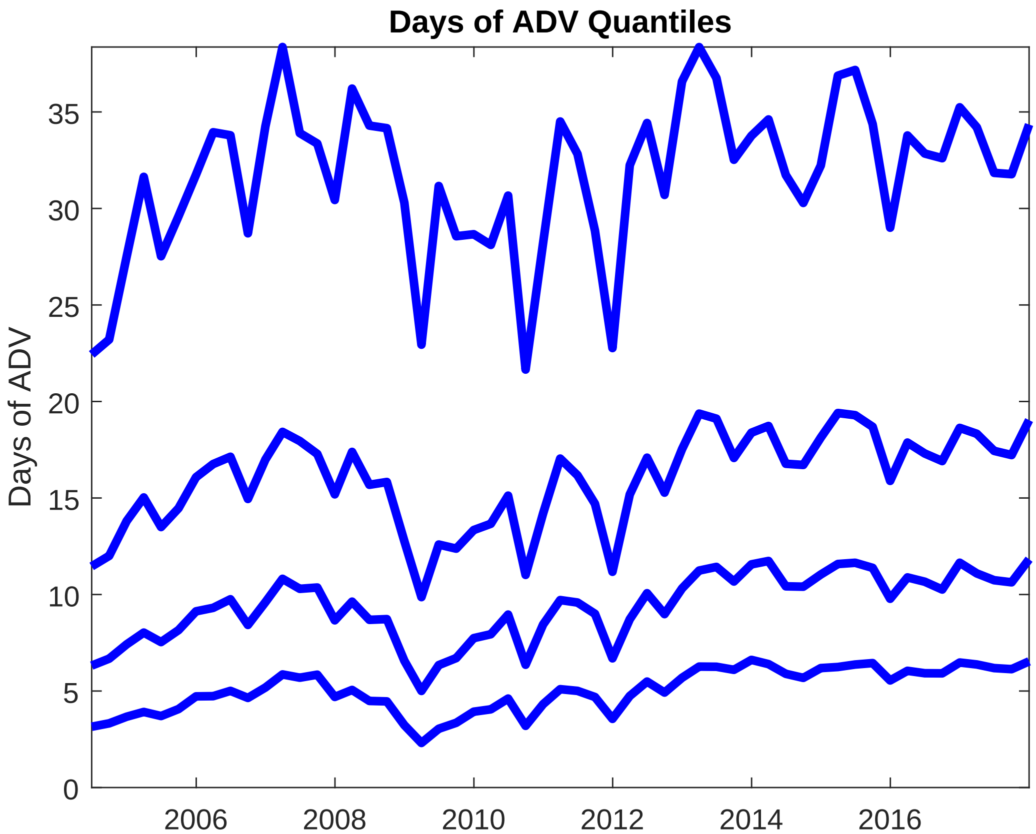

Figure 2: Breakpoints for 5 quantiles days-ADV portfolios.

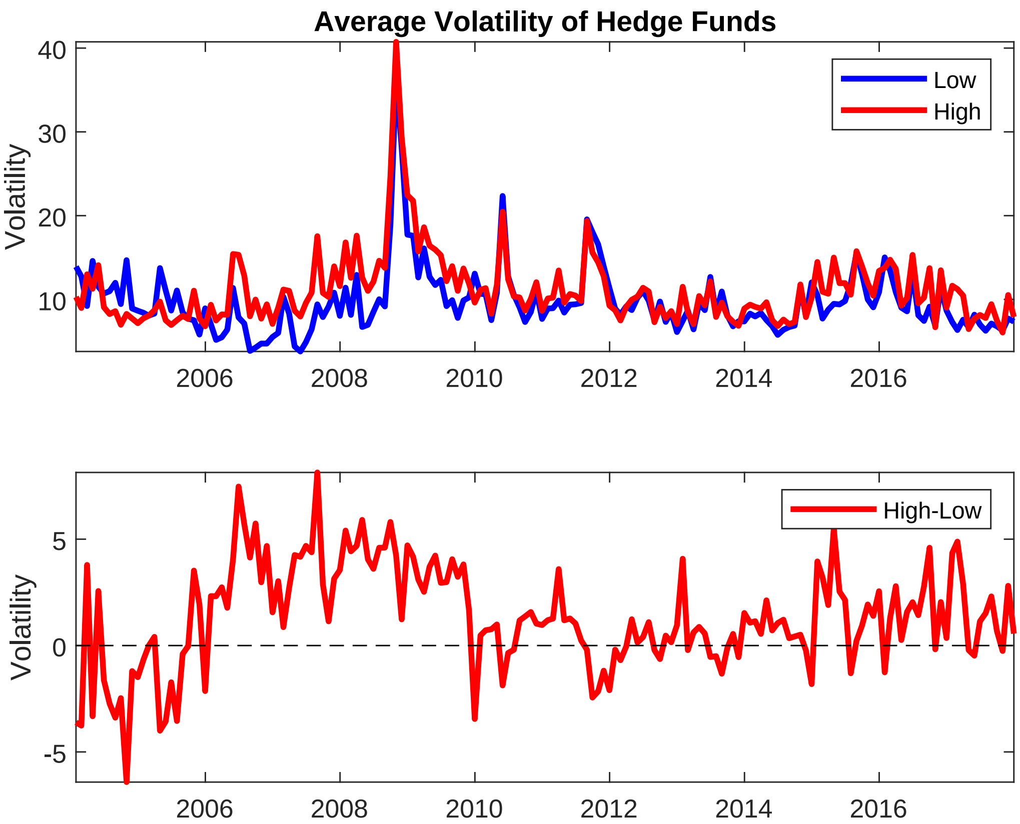

Figure 3: Average annualized realized volatility of hedge funds plotted. Using monthly returns, excess hedge fund returns are regressed onto the excess market return and ADV risk factor. Using the ADV exposures, hedge funds are sorted into 5 quantiles. "Low" is the quantile for the smallest ADV exposures and "High" is the quantile for the largest ADV exposures. Using daily hedge fund returns, realized volatility for each hedge fund is calculated at the monthly frequency. Plotted is the average realized volatility for both the Low and High quantiles.

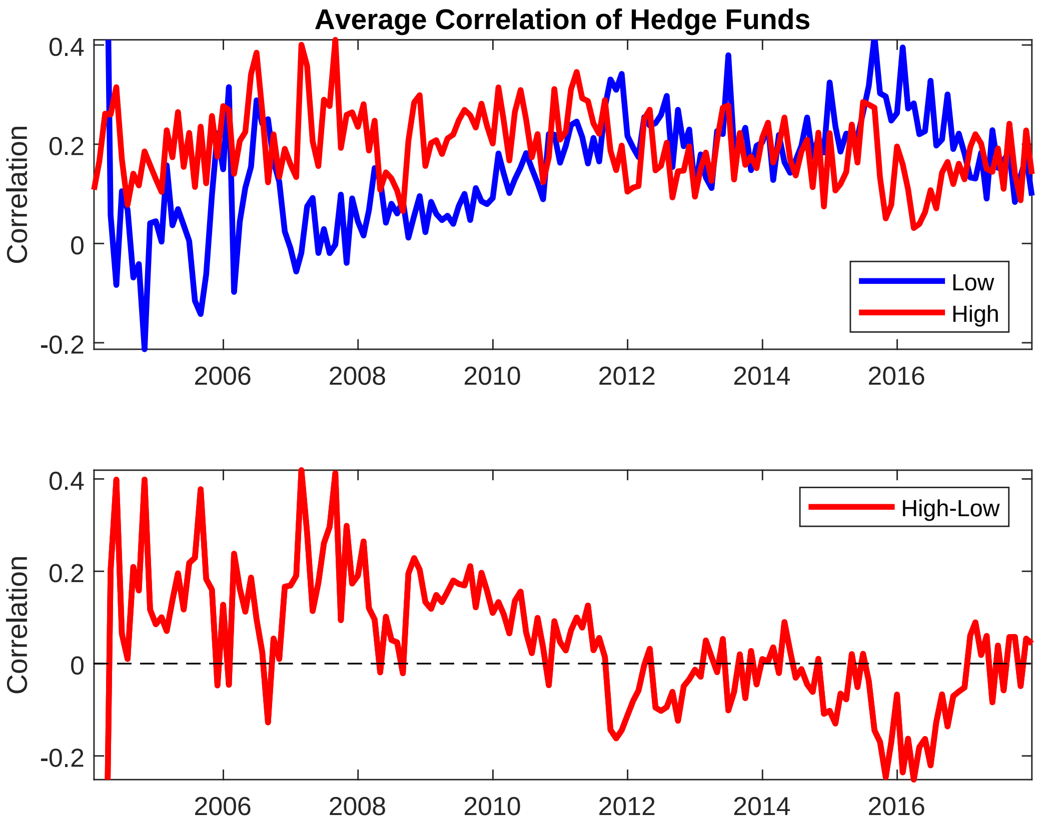

Figure 4: Average realized correlations of hedge funds plotted. Using monthly returns, excess hedge fund returns are regressed onto the excess market return and ADV risk factor. Using the ADV exposures, hedge funds are sorted into 5 quantiles. "Low" is the quantile for the smallest ADV exposures and "High" is the quantile for the largest ADV exposures. Using daily hedge fund returns, realized correlations is calculated at the monthly frequency within each quantile. Plotted is the average realized correlation for both the Low and High quantiles.

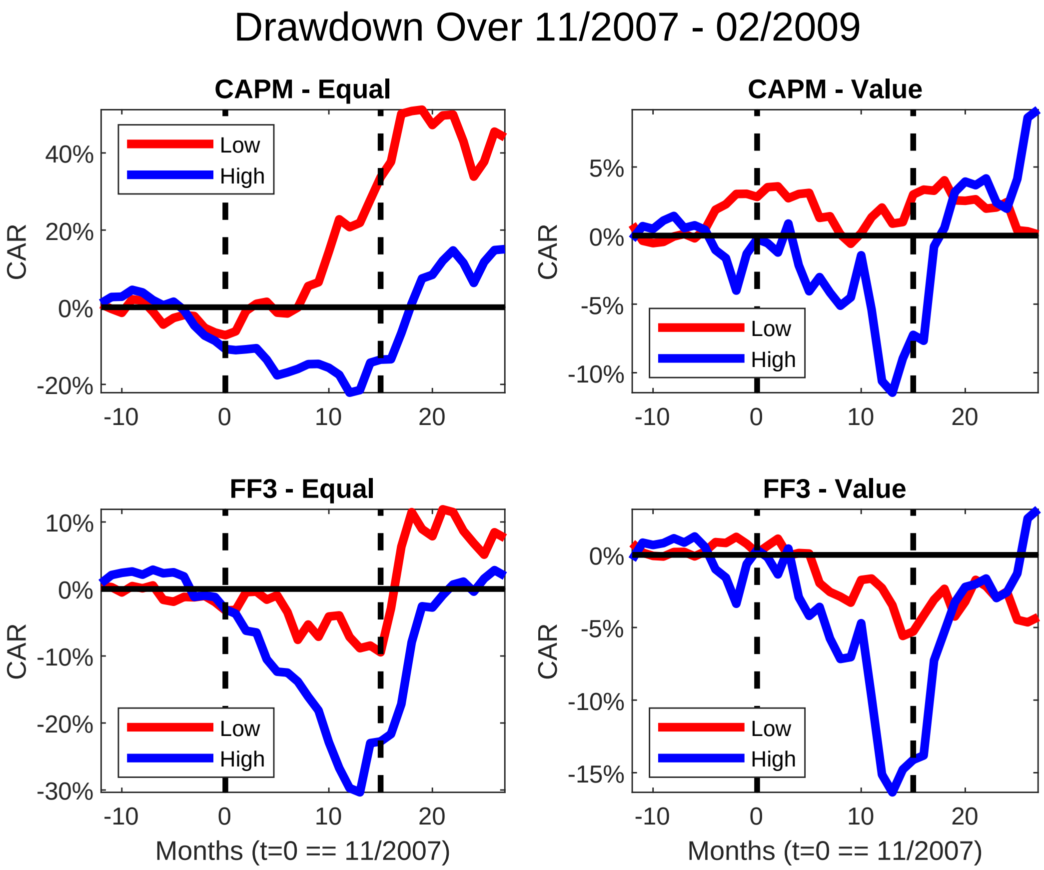

Figure 5: ADV cumulative abnormal returns during 11/2007 - 02/2009.

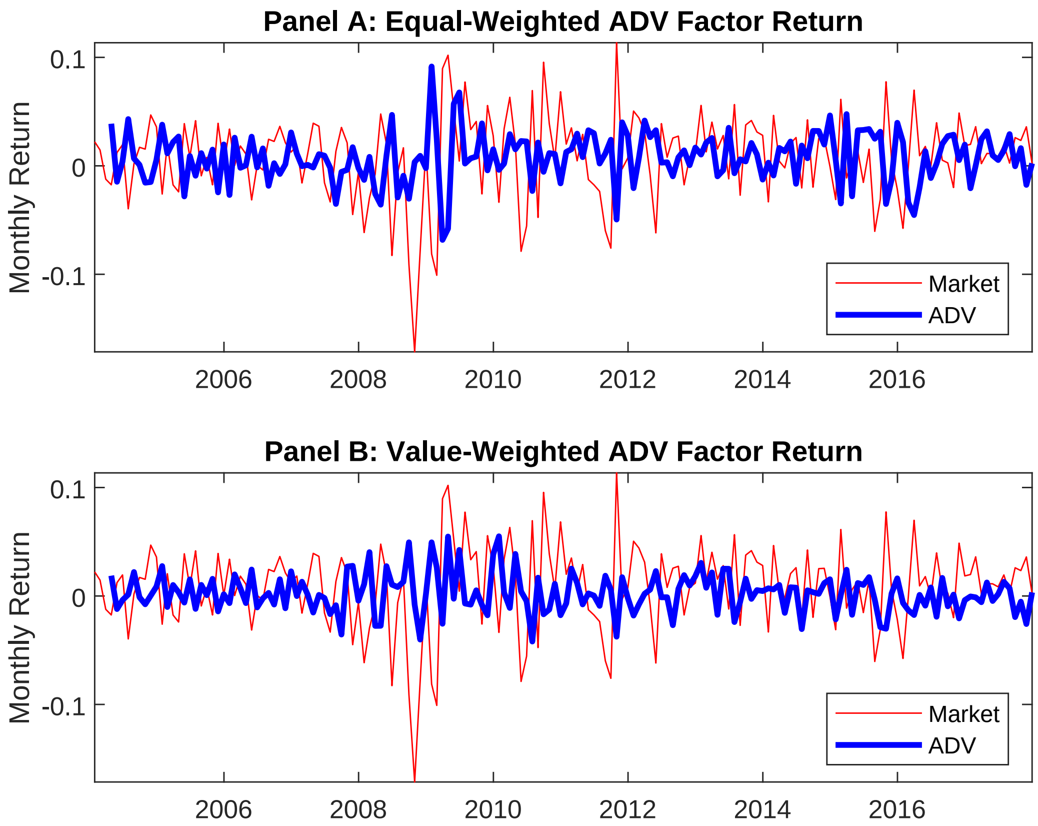

Figure 6: Monthly Days-ADV Factor Return

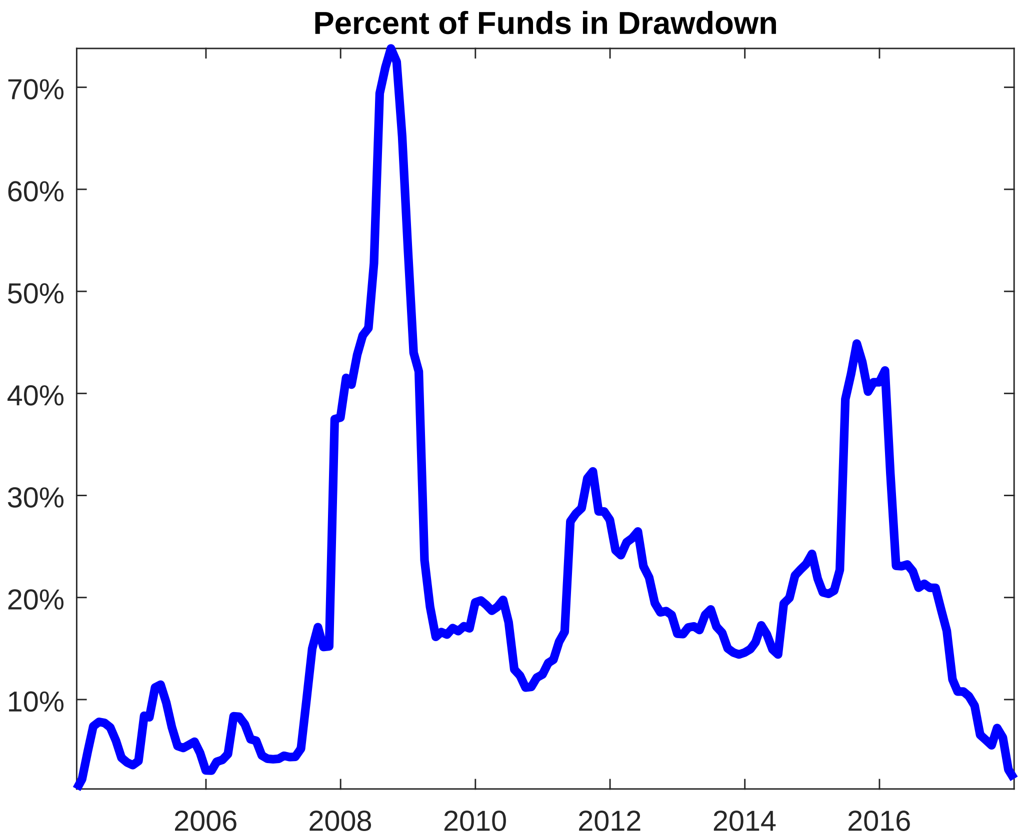

Figure 7: Percent of hedge funds experiencing a their largest drawdown between 2004 to 2017.

A Appendix

Table A.1: Portfolio Characteristics

Average Market Capitalization

	Low	**Q2**	**Q3**	**Q4**	**High**
NHF	$408,867	$584,249	$1,166,569	$2,833,937	$38,648,181
PSO	$57,390,394	$30,306,774	$12,375,126	$6,454,207	$3,521,541
ADV	$37,397,813	$26,998,071	$13,847,856	$8,519,318	$5,826,381
ILLIQ	$9,202,292	$14,318,283	$22,057,420	$39,711,900	$25,326,034

Average Monthly Volume

	Low	**Q2**	**Q3**	**Q4**	**High**
NHF	$2,438	$3,640	$9,345	$27,255	$286,278
PSO	$303,906	$260,593	$112,047	$67,232	$44,741
ADV	$341,769	$175,377	$92,968	$55,802	$24,641
ILLIQ	$178,012	$137,638	$146,105	$168,637	$64,501

Illiquidity

	Low	**Q2**	**Q3**	**Q4**	**High**
NHF	599	284	172	126	132
PSO	262	176	147	133	138
ADV	126	136	140	167	344
ILLIQ	60	107	156	240	644

Market capitalization and volume in $1,000's. NHF is the number of hedge funds. PSO is the percent of shares outstanding. ADV is the percent of ADV.

Table A.2: Average ADV Probability Transition Matrix

	Low	**Q2**	**Q3**	**Q4**	**High**
Low	77%	19%	3%	1%	0.3%
Q2	19%	55%	21%	3.4%	0.6%
Q3	3%	23%	52%	20%	2%
Q4	1%	3.6%	21%	59%	15%
High	0.3%	0.4%	2%	16%	82%

Time-series average of average probability transition matrix of ADV crowdedness portfolios. Row i column j represents the probability of moving from portfolio i in quarter t to portfolio j in quarter t+1. ADV is the percent of ADV.

Table A.3: Expected Return of Two-Way Portfolio Sorts

Panel A: Days-ADV x Market Capitalization

	Market Capitalization		
ADV	**Small**	**Q2**	**Big**
Low	11.9%	10.7%	11.6%
Q2	13.7%	12.1%	12.3%
High	13.6%	13.7%	12.7%

Panel B: Days-ADV x Volume

	Volume		
ADV	**Low**	**Q2**	**High**
Low	12.4%	11.0%	11.2%
Q2	13.1%	12.7%	12.0%
High	13.6%	13.3%	13.0%

Panel C: Days-ADV x Illiquidity

	Illiquidity		
ADV	**Low**	**Q2**	**High**
Low	11.0%	12.4%	11.2%
Q2	12.0%	13.2%	12.7%
High	12.7%	13.8%	13.0%

Annualized expected returns presented. Panel A reports two-way portfolio sorts with ADV on rows and market capitalization on columns. Panel B reports two-way portfolio sorts with ADV on rows and volume on columns. ADV is the percent of ADV. Equal weighted portfolio returns reported.

Table A.4: Equal Weighted Days-ADV Factor Regressions

	CAPM	**FF3**	**+MOM**	**+Rev**	**+PS**	**+ILLIQ**	**+FH**	**+Smart**	**Stepwise**
alpha	11.22	10.97	10.62	9.76	9.78	3.20	3.03	4.07	4.62
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)
Market	−0.25	−0.22	−0.18	−0.16	−0.16	0.09	0.09	0.01	
	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.12)	(0.12)	(0.81)	
SMB		−0.08	−0.09	−0.04	−0.05	0.20	0.20	0.18	0.18
		(0.31)	(0.21)	(0.57)	(0.48)	(0.00)	(0.00)	(0.00)	(0.00)
HML		−0.12	−0.05	0.10	0.10	−0.12	−0.12	−0.16	−0.11
		(0.23)	(0.65)	(0.29)	(0.29)	(0.11)	(0.11)	(0.08)	(0.02)
MOM			0.12	0.12	0.12	−0.05	−0.05	0.00	
			(0.01)	(0.00)	(0.01)	(0.36)	(0.36)	(0.94)	
STREV				−0.03	−0.03	0.02	0.02	0.00	
				(0.73)	(0.69)	(0.65)	(0.65)	(0.93)	
LTREV				−0.29	−0.27	−0.08	−0.08	−0.10	−0.11
				(0.01)	(0.00)	(0.21)	(0.21)	(0.11)	(0.03)
PS					0.03	0.06	0.06	0.02	
					(0.67)	(0.20)	(0.20)	(0.59)	
ILLIQ						0.64	0.64	0.62	0.60
						(0.00)	(0.00)	(0.00)	(0.00)
BD						0.00	0.00	0.01	
						(0.80)	(0.80)	(0.50)	
FX						−0.01	−0.01	−0.01	
						(0.29)	(0.29)	(0.39)	
COM						0.00	0.00	0.00	
						(0.84)	(0.84)	(0.94)	
IR						−0.01	−0.01	−0.01	−0.01
						(0.01)	(0.01)	(0.03)	(0.00)
STK							−0.01	−0.01	
							(0.50)	(0.50)	
BAB								0.12	0.12
								(0.09)	(0.02)
DVL								0.05	
								(0.56)	
QMJ								−0.21	−0.24
								(0.02)	(0.00)

Coefficent estimates and P-values in parenthesis are shown. P-values calculated using HAC robust standard errors. alpha is annualized. SMB, HML, MOM, STREV and LTREV are size, value, momentum, short and long-term reversal risk factors. PS is Pastor Stambaugh traded liquidity risk factor. ILLIQ is illiquidity turnover factor. BD, FX, COM, IR and STK are bond, FX, commodity, interest rate and stock trend following risk factors. BAB, DVL and QMJ are betting-against-beta, devil-in-the-details, and quality-minus-junk risk factors. Stepwise is the final specification from performing stepwise regression with all factors.

Table A.5: Percent of Hedge Funds with Significant Days-ADV Crowdedness Exposure

Strategy	**Funds**	**Coefficient**	**Significant**
Full - Average	14,154	0.02	17%
Full - 25% Percentile		−0.25	
Full - 75% Percentile		0.33	
HF Bear Market Equity	43	0.05	20%
HF Convertible Arbitrage	199	0.12	32%
HF Distressed Securities	208	0.10	29%
HF Diversified Arbitrage	68	−0.04	17%
HF Equity Market Neutral	431	−1.33	12%
HF Event Driven	329	0.11	25%
HF Fund of Funds - Equity	1,124	0.11	17%
HF Fund of Funds - Event	184	0.13	29%
HF Fund of Funds - Macro/Systematic	290	0.05	11%
HF Fund of Funds - Multistrategy	1,896	0.11	18%
HF Fund of Funds - Other	495	−0.07	25%
HF Fund of Funds - Relative Value	156	0.05	22%
HF Global Long/Short Equity	681	−0.03	18%
HF Global Macro	579	0.15	15%
HF Long-Only Equity	146	−0.08	15%
HF Long-Only Other	73	0.46	1%
HF Merger Arbitrage	34	0.09	18%
HF Multistrategy	776	−0.31	19%
HF Systematic Futures	865	0.32	13%
HF U.S. Long/Short Equity	1,146	0.04	16%
HF U.S. Small Cap Long/Short Equity	248	−0.03	22%
HF Volatility	83	−0.14	1%

Percent of funds with significant crowdedness exposures from regressing fund returns onto market, size, value, momentum, reversal, trend-following, betting-against-beta, devil-in-the-details, quality-minus-junk, liquidity, and crowdedness risk factor. Results from monthly time series regressions. Statistical significance at the 10% significance level.