Sentiment Metrics and Investor Demand

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ABSTRACT

Recent work suggests that sentiment traders shift from safer to more speculative stocks when sentiment increases. Exploiting these cross-sectional patterns and changes in share ownership, we find that sentiment metrics capture institutional rather than individual investors' demand shocks. We investigate the underlying economic mechanisms and find that common institutional investment styles (e.g., risk management, momentum trading) explain a significant portion of the relation between institutions and sentiment.

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Sentiment Metrics and Investor Demand

The investor sentiment literature typically assumes that irrational individual investors are the source of sentiment-based demand shocks that drive prices from value. For instance, the earliest academic article focusing on this issue uses odd-lot trading to identify demand shocks attributed to "public psychology" relative to the more rational views of "New York Stock Exchange members" (Drew et al. (1950)). The assumption that individual investors are responsible for sentiment-induced mispricing has been explicitly repeated in the nearly 70 years that have followed.[1] In fact, many of the traditional proxies for investor sentiment (e.g., closed-end fund discounts, mutual fund flows, odd-lot transactions) have been selected precisely because they are designed to capture the behavior of individual investors.

Contrary to this widely held assumption, we demonstrate that sentiment metrics capture the demand shocks of institutional, rather than individual, investors. Thus, if these metrics capture investor sentiment, then the traders driving the sentiment-induced mispricing are institutional, rather than individual, investors (in aggregate). We further show that our results make sense intuitively and economically as previously documented common institutional investment styles contribute to the relations between investor sentiment metrics, institutional demand shocks, and returns. These behaviors include institutions' risk management, reputational concerns, momentum trading, herding, bubble riding, and a small, but not dominant, amount attributable to underlying investor flows. Beyond these explanations, a substantial portion of the relation between institutional demand and sentiment metrics remains unexplained, leading to the possibility that omitted variables play a role in driving the relations between institutional demand shocks, investor sentiment, and equity returns.

[1] A small sample of the many studies that express this view include Zweig (1973), Shleifer and Summers (1990), Lee, Shleifer, and Thaler (1991), Neal and Wheatley (1998), Nagel (2005), Baker and Wurgler (2006, 2007), Lemmon and Portniaguina (2006), Barberis and Xiong (2012), Stambaugh (2014), and Da, Engelberg, and Gao (2015).

Prior to Baker and Wurgler (henceforth BW) (2006, 2007), empirical support for the investor sentiment hypothesis was, at best, mixed (see Internet Appendix for a review of this literature). BW's innovative approach to examining the relations between sentiment and asset prices led to a renewed focus on investor sentiment and the wide adoption of their sentiment metric (the two BW studies have been cited more than 4,900 times). Specifically, BW propose that sentiment traders shift from safe to speculative securities when sentiment increases and from speculative to safe securities when sentiment declines and these sentiment-induced demand shocks drive mispricing in financial markets. Consistent with their hypothesis, BW find positive sentiment betas for speculative stocks and negative sentiment betas for safe stocks and that speculative stocks average lower returns than safe stocks following periods of high sentiment levels. The authors conclude that these return patterns serve as "…a powerful confirmation of the sentiment-driven mispricing view" (2007, p. 135).

The sentiment hypothesis requires that sentiment-induced demand shocks (i.e., net buying by sentiment traders) impact prices. However, because every buyer requires a seller, sentiment traders' net demand shocks must be offset by supply from traders who are less susceptible to changes in sentiment. By recognizing this market clearing condition, we can identify whether the traders captured by sentiment metrics are, in aggregate, individual or institutional investors as *changes* in sentiment will be positively related to *changes* in sentiment traders' demand (i.e., demand shocks) for speculative stocks and inversely related to their demand shocks for safe stocks. Thus our initial test examines correlation, and not causation, as sentiment metrics capturing individual investors' demand shocks is a necessary, but insufficient, condition of the traditional interpretation of the investor sentiment hypothesis.

Inconsistent with this traditional interpretation, we find that commonly used measures of investor sentiment capture the demand shocks of institutional, rather than individual, investors. That is, an increase in sentiment is associated with an increase in institutional investors' demand for risky stocks and, by definition, an associated decline in individual investors' demand for speculative stocks. Further supporting the hypothesis that the BW sentiment metric captures institutional, rather than individual, investors' demand, institutional investors' ownership *levels* of speculative stocks, relative to their ownership levels of safe stocks, are higher when sentiment *levels* are higher. Moreover, *none* of the 17 investor sentiment metrics we examine—the BW metric, the six individual components of the BW metric, three measures of mutual fund flows, two consumer sentiment measures, one survey-based measure of individual investors' sentiment, two measures of venture capital flows as proxies for sophisticated investors' sentiment, and two measures of aggregate economic activity or stress—capture individual investors' demand shocks. In contrast, 10 of the 17 measures are meaningfully related to institutional investors' demand shocks. Further, the ability of sentiment metrics to predict cross-sectional return patterns is limited *only* to those metrics that capture institutional investors' demand shocks. In short, the relations between sentiment metrics, returns, and institutional demand shocks are pervasive.

The balance of our study focuses on understanding why sentiment metrics surprisingly capture institutional, rather than individual, investors' behavior. (For ease of exposition, we henceforth denote the relation between institutions and sentiment as "institutional sentiment trading.") We first consider the possibility that retail investors actually drive our findings either because the complement of 13(f) demand shocks does not capture retail investors' demand shocks or because retail investor flows drive aggregate institutional investor demand. Inconsistent with the first possibility, individual investors' demand shocks—as captured by the Odean (1998) retail broker data—are strongly related to the inverse of 13(f)-inferred institutional demand shocks. With respect to the second possibility that underlying retail investor flows drive institutional investors' trades, we conduct four separate tests. First, we decompose 13(f) institutional demand shocks into flow-induced or managers' decisions. While we find that underlying investors' flows impact which securities 13(f) institutions buy and sell, there is no evidence that these flows drive the relation between aggregate 13(f) institutional demand shocks and changes in sentiment. Similarly, in a second test we examine mutual fund holdings data, which allows us to measure flows within a fund family. In this test we find some evidence that flows between funds in the same family contribute to institutional sentiment trading. Nonetheless, managers' decisions (whether at the 13(f) level or the mutual fund level) play the dominant role in driving the relation between institutional trading and the change in sentiment metrics. Third, following Edelen, Ince, and Kadlec (2016), we examine the relation between changes in sentiment and institutional demand shocks computed from only entry and exit trades—that is, trades that, by definition, cannot be fully explained by underlying investor flows. These results continue to support the hypothesis that sentiment metrics capture professional investors' active trading decisions. Finally, in a fourth test, we employ survey data from *Pensions & Investments* (*P&I*) for a subset of 13(f) institutions that identify the fraction of their assets attributed to retail versus institutional clients. Further inconsistent with retail investors' flows serving as the primary mechanism driving our results, institutions with a focus on institutional clients contribute disproportionally more to aggregate institutional sentiment trading than institutions with a retail client focus.

We begin to investigate the economic motivations driving the relation between sentiment and institutional investors by examining whether their investment styles can help explain the relation. Consistent with this explanation, we first demonstrate that three common and well-documented institutional trading behaviors account for 25%-41% of the institutional sentiment trading: (i) Risk management and reputation concerns in which institutional investors are reluctant to deviate from their benchmarks and tend to reduce risk exposure in volatile markets (risk budgeting); (ii) Institutional momentum trading in which institutions are attracted to stocks that have recently outperformed; and (iii) Institutional herding in which institutional investors tend to buy stocks that other institutions previously purchased.

We further find that differences in investment styles across types of institutional investors help explain institutional sentiment trading. In particular, institutions' risk preferences and their management of risk influences their equity trading. For example, the tendency of some types of institutions (banks, insurance companies, pensions, and unclassified institutions) to avoid holding and trading risky stocks suggests that they will contribute little to the aggregate institutional sentiment trading. In contrast, the other types of institutions (mutual funds, independent advisors, and hedge funds) are not only more willing to hold such stocks but are also more sensitive to lag performance, suggesting that risk management and reputational concerns could influence their sentiment trading. Last, because hedge funds have been most strongly associated with bubble riding, we hypothesize that if some institutions (both hedge funds and other institutions) attempting to ride bubbles contribute to institutional sentiment trading, then hedge funds will disproportionally contribute to aggregate institutional sentiment trading. Consistent with investment styles contributing to the relation between institutions and sentiment, we find that mutual funds, independent advisors, and hedge funds account for 50% of the institutional ownership but a disproportionate 89% of aggregate institutional sentiment trading. Further consistent with the hypothesis that investment style influences sentiment trading, we also find that transient institutions (those with high turnover and small stakes in individual companies) strongly engage in sentiment trading.

Our results have important implications for understanding investor behavior and the large body of work that uses sentiment metrics as explanatory variables in other tests. First, our most fundamental finding is that contrary to the traditional view of investor sentiment, sentiment metrics capture the demand shocks of institutional, rather than individual, investors. This fact helps explain the inconsistency of results across studies of investor sentiment (see Internet Appendix for a review of this literature). For example, metrics that are more likely to capture institutional demand shocks (e.g., the dividend premium) are more likely to generate the return patterns documented by BW. Our results also suggest that at least part of the demand shocks captured by sentiment metrics are not necessarily associated with "sentiment" (i.e., irrational beliefs), but rather reflect common institutional investment styles including rational (e.g., risk management) decisions. Regardless, the relation between sentiment, institutions, and individual investors is more complicated than previously recognized.

Second, if individual investors are the noise traders whose demand shocks drive mispricing, then as pointed out in the AFA Presidential Addresses of French (2008) and Stambaugh (2014), one should expect markets to become more efficient over time as individual investors' equity ownership shifted from self-managed (i.e., directly owned and traded) to professionally managed. Our results suggest that there is no reason to believe the secular decline in direct retail share ownership should necessarily result in less mispricing. Rather, based on these authors' arguments, the opposite may be true.

Finally, and perhaps most importantly, our work has implications for the interpretation of a large literature that examines the role of investor sentiment in both asset pricing and corporate finance. For instance, studies use the BW metric to examine whether investor sentiment can help explain a number of different phenomena and behaviors including the value premium, momentum, the idiosyncratic volatility puzzle, financial stress, equity issuance, accruals, operating assets, profitability, asset growth, return on assets, investment, post-earnings drift, analyst forecast errors, hedge fund returns, responses to earnings announcements, the forward premium puzzle, time-series variation in the slope of the security market line, managers' corporate investment decisions, earnings management, cash holdings, earnings disclosures, and the CEO's view of firm valuation.[2] Given that this literature widely assumes sentiment metrics capture individual investors' demand shocks, these studies are commonly interpreted to reflect how individual investors' direct trading behaviors impact markets and corporations. Given the BW sentiment metric captures institutional investors' demand shocks, one must re-consider how to interpret these earlier findings.

In short, although our results are largely consistent with most previous work, they are inconsistent with traditional *interpretations* of earlier work that assumes sentiment metrics capture individual investors' aggregate sentiment-induced demand shocks. As far as we are aware, ours is the only study that finds evidence that: (i) investor sentiment metrics capture (in aggregate) institutional investors' demand shocks and (ii) individual investors' demand shocks move *opposite* the direction hypothesized in the literature. Moreover, we also demonstrate that only those sentiment metrics that capture institutional demand shocks are meaningfully related to subsequent returns.

The balance of the paper is organized as follows: We discuss the data in the next section. Section

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[2] Examples of asset pricing phenomena that have been examined with the BW metric include the value premium (Piotroski and So (2012)), momentum (Antoniou, Doukas, and Subrahmanyam (2013)), the idiosyncratic volatility puzzle (Stambaugh, Yu, and Yuan (2015)), 11 asset pricing anomalies associated with financial stress, equity issuance, accruals, operating assets, momentum, profitability, asset growth, ROA, and investment (Stambaugh, Yu, and Yuan (2012)), post earnings drift and accruals (Livnat and Petrovits (2009)), analyst forecast errors (Hribar and McInnis (2012)), hedge fund returns (Chen, Han, and Pan (2016)), responses to earnings announcements (Mian and Sankaraguruswamy (2012)), the accruals anomaly (Ali and Gurun (2009)), the forward premium puzzle (Yu (2013)), and time-series variation in the slope of the security market line (Antoniou, Doukas, and Subrahmanyam (2015)). Analogously, in the corporate finance arena, papers use the BW metric to examine if investor sentiment impacts managers' corporate investment decisions (Arif and Lee (2014)), firms' financing costs (McLean and Zhao (2014)), earnings management (Simpson (2013)), cash holdings (Li and Lou (2016)), managers' earnings disclosures (Brown et al. (2012)), the qualitative tone of managers' earnings disclosures (Bochkay and Dimitrov (2014)), and the CEO's view of firm valuation (Hribar and Quinn (2013)).

II examines whether the BW metric captures institutional or individual investors' demand shocks. Section III extends the analysis to alternative measures of investor sentiment. Section IV focuses on understanding the mechanisms linking sentiment measures and institutional investors' demand. The final section provides conclusions.

I. Data

BW measure investor sentiment as the first principal component of six investor sentiment proxies: closed-end fund discounts, NYSE share turnover, the number of IPOs, average first day IPO return, the share of equity issues in total debt and equity issues, and the dividend premium (the difference between the average market-to-book ratios for dividend payers versus nonpayers). BW also compute "orthogonalized sentiment" as the first principal component of the residuals from regressions of each of the six proxies on a set of business cycle variables. Analogously, the authors measure the change (both raw and orthogonalized) in investor sentiment as the first principal component of changes in the six proxies.[3] Because our demand metrics are based on quarterly holdings, we compute the quarterly change in investor sentiment as the sum of the monthly BW change in sentiment metric over the quarter.

We limit the sample to ordinary securities (CRSP share code 10 or 11) and, as suggested by BW (2007), use monthly return volatility (over the previous 12 months for stocks with at least nine monthly returns in the prior year) as the measure of a stock's speculative nature.[4] We use quarterly

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[3] Because the BW change in sentiment is the first principal component of changes in the proxies rather than the change in the first principal component of the proxies, the BW change-in-sentiment measure is not equal to the changes in their sentiment levels index (see BW (2007) footnote 6 for additional detail).

[4] In the Internet Appendix, we repeat our primary tests using four alternative definitions of a stock's speculative nature (size, age, whether the stock pays a dividend, and whether the company has positive earnings). Our conclusions remain unchanged.

13(f) reports to measure fractional institutional ownership levels and institutional demand shocks (the change in the number of shares held by institutions over the quarter divided by the number of shares outstanding) for each stock-quarter between 1980 and 2010.[5] We assume that the negative of institutional demand shocks proxies for individual investors' demand shocks (we later examine the reasonableness of this proxy).[6] We merge (using WRDs MFlinks) Thomson Financial N-30D and CRSP mutual fund data to form the mutual fund sample (see Internet Appendix for details).

We use two sources for the 13(f) manager classifications. First, we use a proprietary Thomson Financial dataset to identify insurance companies, pensions and endowments (henceforth denoted "pensions"), banks, and hedge funds filing 13(f) reports. Second, we use the "Type" classifications maintained by Brian Bushee to identify mutual funds (Type=3) and independent investment advisors (Type=4). All remaining institutions are denoted "unclassified." The Internet Appendix provides details regarding the institutional classifications.

We require securities to have at least five 13(f) institutional owners at the beginning or end of

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[5] Many firms have changes in the number of shares outstanding with no change in the CRSP share adjustment factor (e.g., as a result of an employee exercising an option). To ensure such events do not drive our results, we measure the institutional demand shock as the (split-adjusted) change in the number of shares held by institutions divided by end of quarter shares outstanding (rather than the change in the fraction of shares held by institutions at the beginning and end of the quarter). We find nearly identical results when measuring institutional demand shocks as the difference between the fraction of outstanding shares held by institutions at the end of the quarter and the beginning of the quarter. We exclude observations where reported institutional ownership exceeds 100% of shares outstanding (about 1% of observations) following Yan and Zhang (2009).

[6] Small institutions (those with less than $100 million in 13(f) securities) and small positions (less than $200,000 and 10,000 shares) are excluded from the 13(f) data. In addition, institutions are sometimes able to file confidential reports. Figures from Agarwal et al. (2013) Table I show that confidential filings account for less than 1% of all institutional stock positions.

the quarter to ensure an adequate proxy for institutional/individual investor demand levels and shocks. Our sample averages 3,945 stocks each quarter between June 1980 and December 2010 (n=123 quarters). The Internet Appendix reports descriptive statistics for our sample. Because the average raw change in the fraction of shares held by institutions is positive (reflecting the growth in institutional ownership over time), for ease of interpretation, we henceforth define the "institutional demand shock" as the raw change in institutional ownership less the mean change in the fraction of shares held by institutions across all stocks in quarter t.[7]

II. Does the BW Metric Capture Institutions' or Individuals' Demand Shocks?

We first examine the relation between quarterly changes in sentiment and quarterly 13(f) demand shocks to determine whose demand shocks are captured by the sentiment metrics.[8] The first column in Table I reports the time-series correlations between orthogonalized changes in sentiment and the contemporaneous quarterly cross-sectional average institutional demand shocks (or, equivalently, individual investors' supply shocks) for securities within each volatility decile (formed on NYSE breakpoints following BW). The results reveal that the BW sentiment metric captures institutional, rather than individual, investors' aggregate demand shocks. When sentiment increases, institutions buy high volatility stocks from individual investors (i.e., the correlation between time-series variation in institutional demand shocks for high volatility stocks and changes in orthogonalized sentiment is 31.5%) and sell low volatility stocks to individual investors (e.g., the correlation in the top cell of the

[7] This also accounts for seasonality in the filing of 13(f) reports, e.g., once meeting a $100M hurdle at the end of any month, a manager is required to file the first report in December of that year (see Lemke and Lins (1987)).

[8] In the Internet Appendix, we show that the two major BW (2007) findings based on their monthly data from 1966 to 2005 also hold for our quarterly data from 1980 to 2010: (i) high volatility stocks exhibit larger sentiment betas than low volatility stocks, and (ii) high volatility stocks tend to underperform (outperform) low volatility stocks following high (low) sentiment levels.

first column is -28.7%). The correlations between the differences in institutional demand shocks for high and low volatility stocks and changes in sentiment (last row of first column) is statistically (at the 1% level) positive.

[Insert Table I about here]

If sentiment metrics capture institutional, rather than individual, investors' demand, then institutional ownership *levels* for high volatility stocks relative to their ownership *levels* for low volatility stocks should be higher when sentiment *levels* are higher. The second and third columns in Table I report the time-series mean of the cross-sectional average detrended institutional ownership levels for stocks within each volatility decile during high (above median) and low (below median) orthogonalized sentiment periods, respectively.[9] The test reported in the bottom row of the final column shows that detrended institutional ownership levels for high volatility stocks relative to their ownership levels for low volatility stocks are significantly greater in high orthogonalized sentiment periods. In sum, both the demand shocks (first column) and levels (last column) analyses demonstrate that the BW metric captures institutional, rather than individual, investors' demand.[10]

The above tests focus on time-series variation in cross-sectional averages in the extreme volatility deciles. To broaden our results, and to provide a framework for our subsequent tests, we construct an alternative two-step approach that uses the full sample of securities. In the first step, each quarter we measure the extent to which institutions buy risky stocks from (or sell risky stocks to) individual investors as the cross-sectional correlation between institutional demand shocks and securities' return volatility. Thus, positive values indicate that institutions net *buy* volatile stocks from

[9] Because institutional ownership grows substantially throughout this period, we detrend institutional ownership levels (by regressing mean institutional ownership levels for each volatility portfolio on time). In the Internet Appendix, we repeat these tests without detrending institutional ownership levels and find similar results.

[10] As shown in the Internet Appendix, we find similar results when we repeat these tests based on raw sentiment.

individual investors while negative values indicate that individual investors buy volatile stocks from institutional investors.[11] Panel A in Table II reveals that these cross-sectional correlations vary substantially over time—falling as low as -16.87% (i.e., a quarter when institutions strongly move away from volatile stocks) and rising as high as 17.65% (i.e., a quarter when institutions strongly move toward volatile stocks).

[Insert Table II about here]

In the second step we compute the correlation between quarterly changes in sentiment and time-series variation in the extent to which institutions buy risky stocks from individuals, i.e., the time-series of the 123 cross-sectional correlations estimated in the first step. That is, we test whether institutional investors *increase* their preference for risky stocks when sentiment *increases*. Consistent with our earlier tests indicating that changes in sentiment capture institutional investors' demand shocks, the correlation between time-series variation in changes in institutions' attraction to volatile stocks and changes in sentiment is 37.34% based on changes in raw sentiment and 37.27% based on changes in orthogonalized sentiment (both significant at the 1% level).[12,13]

These results are consistent with recent studies of institutional investor behavior. For example, Griffin et al. (2011) show that institutional investors were much bigger *buyers* of technology stocks

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[11] Following BW (2006), volatility is winsorized at the 0.5% and 99.5% levels each quarter. To account for skewness, we use the natural logarithm of 1 plus the return standard deviation (measured in percent).

[12] In the Internet Appendix, we decompose total volatility into market risk and idiosyncratic risk and find, not surprisingly (given market risk and idiosyncratic risk are strongly positively correlated in the cross-section), that institutions shift toward both high beta and high idiosyncratic risk stocks when sentiment increases.

[13] The dividend premium is unique from the other components of the BW sentiment metric in that it is computed from the cross-section of securities and therefore allows us to directly examine whose demand shocks are captured by changes in this sentiment metric. We do so in the Internet Appendix and find, consistent with our other tests, that the dividend premium shrinks when institutions buy dividend paying stocks from individual investors.

than individual investors (relative to non-technology stocks) during the January 1997 to March 2000 run-up in technology stock prices (which coincides with a large cumulative increase in the BW sentiment metric). Similarly, the authors show that institutions sold technology stocks to individual investors in the April 2000 to March 2001 period when sentiment declines sharply and technology prices plummet.[14]

A potential limitation of our tests is that we measure risk prior to the quarter of interest and the stock's risk could change during the quarter, thus, affecting our interpretation. For instance, it is possible that contemporaneous to institutions shifting toward (previously defined) high volatility stocks when sentiment increases, mean reversion in the stocks' volatilities could occur in which case the institutions' new holdings could have the same, or even lower, volatility levels at the end of the quarter. Because this possible alternate explanation for our results is based on changes in stock risk, we move from the BW volatility estimate to measures of risk based on non-overlapping data. Specifically, we generate non-overlapping risk estimates from daily returns for three different quarters: the natural logarithm of the estimated monthly return standard deviation computed from squared daily returns in quarter t-1 ($\sigma_{i,t-1}$), quarter t ($\sigma_{i,t}$), and quarter t+1 ($\sigma_{i,t+1}$).[15] This approach has the added advantage of testing whether our results are sensitive to the method used to estimate volatility.

We conduct four tests to examine whether changes in the risk of a firm's stock can resurrect the

[14] The patterns in demand shocks do not mean individual investors suffer the losses while institutions garnered the gains. Griffin et al. (2011), for example, show that institutions had much greater exposure than individual investors to technology stocks *throughout* the bubble bursting period, i.e., although institutions were selling to individuals, institutions still bore the brunt of the losses. For instance, the authors' Figure 1 shows that six months after the peak (November 2000), institutions held about 7% of their portfolio in technology versus slightly over 4% for individual investors.

[15] We require securities to have at least 45 daily returns in a quarter to estimate volatility for that quarter.

explanation that sentiment metrics capture individual investors' demand shocks. First, if the stocks institutions buy when sentiment increases become less risky than the ones they sell, then the correlation between changes in sentiment and time-series variation in institutional investors' demand for risky stocks should be negative when using the updated "end-of-quarter" risk level. Panel A in Table III reports the correlation between changes in sentiment and time-series variation in the cross-sectional correlation between changes in institutional ownership and volatility levels when volatility is measured from daily returns in quarter t-1, t, or t+1. These figures are directly analogous to those reported in Panel B of Table II (except risk is measured with squared daily returns). Inconsistent with the explanation that changes in risk can reverse our inference, however, the relation remains essentially identical regardless of whether risk is measured in quarter t-1, t, or t+1.

[Insert Table III about here]

Our second test further examines the possibility that the stocks institutions buy when sentiment increases decline in risk. Specifically, Panel B reports the correlation between changes in sentiment and time-series variation in the cross-sectional correlation between changes in institutional ownership and two estimates of how risk changes over quarter t: the difference between risk estimated in quarters t and t-1 (first column) and the difference in risk estimated in quarters t+1 and t (second column). Further inconsistent with the hypothesis that changes in risk can resurrect the explanation that sentiment metrics capture individual investors' demand shocks, the results in both columns are positive and the relation is statistically significant in the first column, i.e., when sentiment increases, the stocks institutions buy tend to become riskier.

An increase in the institutional preference for risky stocks could arise from either (i) institutions shifting (i.e., trading) their portfolio toward more risky stocks, or (ii) an increase in the relative riskiness of the stocks already held by institutions. Thus, our third test moves the focus from stocks institutions trade to stocks institutions hold. Specifically, we examine if the stocks held by institutions become less risky when sentiment increases. Panel C of Table III reports the correlation between changes in sentiment and time-series variation in the cross-sectional correlation between institutional ownership levels (measured at either the beginning or end of quarter *t*) and the two estimates of quarter *t* changes in risk. The results in the first column reveal no evidence that changes in sentiment are associated with systematic increases or decreases in the riskiness of securities held by institutions at either the beginning or end of the quarter. The results in the second column, based on changes in risk estimated from returns over quarter *t*+1 and quarter *t*, suggest that securities held by institutions tend to get riskier when sentiment increases. Both results are inconsistent with the hypothesis that changes in risk can resurrect the explanation that sentiment metrics capture individual investors' demand shocks.

Last, we consider an alternative specification for measuring changes in institutional investors' attraction to volatile stocks. Specifically, we measure the change in institutional demand for risky stocks as the difference in the correlations between institutional ownership *levels* and risk *levels* measured at the end and beginning of quarter *t*, i.e., $\rho(Inst_{i,1}, \sigma_{i,1}) - \rho(Inst_{i,0}, \sigma_{i,0})$. As above, we use two different estimates of beginning and end of quarter *t* risk levels (based on realized returns in (*t* and *t*-1) or (*t*+1 and *t*)). Panel D reports the correlation between changes in sentiment and time-series variation in the difference in correlations measure. Although the first column reveals no evidence of a systematic relation between changes in sentiment and the difference in correlations, the results in the second column continue to support the hypothesis that sentiment metrics capture the demand shocks of institutional investors. Once again, the results in both columns are inconsistent with the hypothesis that sentiment metrics capture individual investors' demand shocks.

To reconcile the results in Panels A and D, note that the difference in correlations measure used in Panel D can be decomposed (see Internet Appendix) into a measure of (i) the relation between changes in institutional ownership and estimated volatility levels (analogous to the measure used in

Panel A) and (ii) the relation between institutional ownership levels and changes in estimated volatility (the measure used in Panel C). Two related factors, however, limit the ability of the difference in correlations measure to capture time-series variation in institutional investors' attraction to volatile stocks. First, time-series variation in the difference in correlations (the demand measure in Panel D) primarily reflects time-series variation in the relation between institutional ownership levels and changes in risk (the measure in Panel C) rather than time series variation in the extent to which institutions buy and sell risky stocks (analogous to the measure in Panel A).[16] Thus, it is not surprising that there exists little evidence supporting a systematic relation in Panel D given the little evidence of a systematic relation between changes in sentiment and time-series variation in the relation between institutional ownership levels and changes in estimated volatility (Panel C). This also explains why the results in Panel D align closely with the results in Panel C.

Second, observed volatility is measured with error and these errors have a much larger impact on the relation between institutional ownership levels and estimated changes in volatility (Panel C) than the relation between changes in institutional ownership and estimated volatility levels (Panel A). To understand why, consider first the relation between changes in institutional ownership and volatility levels estimated with error (e.g., the demand measure used in Panel A)—given cross-sectional variation in institutional ownership levels at the end of the quarter is highly correlated with beginning of quarter institutional ownership levels, the cross-sectional covariance of end of quarter institutional ownership and a vector of estimation errors is similar to the cross-sectional covariance of beginning of quarter institutional ownership and the *same* vector of estimation errors. As a result, their difference is close to zero each quarter (i.e., $(\text{cov}(Inst_{i,1},\varepsilon_{i,0}) - \text{cov}(Inst_{i,0},\varepsilon_{i,0}))\rightarrow 0$ as

[16] For instance, as shown in the Internet Appendix, the relation between institutional ownership levels and changes in volatility is 422% more important than the relation between changes in institutional ownership and volatility levels in explaining time-series variation in the difference in correlations.

$\rho(Inst_{i,1},Inst_{i,0})\rightarrow 1$). In contrast, the cross-sectional correlation between institutional ownership levels and changes in volatility (the measure used in Panel C) captures the relation between institutional ownership at a point in time and *two independent* error vectors, i.e., the error in volatility measured at the end of the quarter and the error in volatility measured at the beginning of the quarter. Because these errors are uncorrelated, they will not tend to cancel, i.e., $\mathrm{cov}(Inst_{i,1},\varepsilon_{i,0}) \neq \mathrm{cov}(Inst_{i,1},\varepsilon_{i,1})$) even though $\rho(Inst_{i,1},Inst_{i,1})=1$. In fact, because the expected variance of the sum of two random variables is the sum of the variances of the two variables, the effects are additive.[17]

In short, the results in Panel D differ from those in Panel A because time-series variation in the measure used in Panel C drives time-series variation in the measure used in Panel D (and there is little evidence that changes in sentiment systematically relate to time-series variation in the relation between institutional ownership levels and estimated changes in risk), and errors in volatility estimates have a much larger impact on the results in Panel C (and therefore Panel D) than those in Panel A.

III. Alternative Measures of Sentiment and Institutional Investor Demand

Although the BW sentiment metric is ubiquitous in recent research, there are a number of alternative proxies that may better capture individual investors' sentiment-induced demand shocks. Specifically, we consider six sets of alternative proxies: the individual components of the BW sentiment metric, mutual fund flows, consumer confidence, a survey-based measure of individual investor sentiment, venture capital flows, and changes in economic conditions. We examine two questions with regard to these alternatives: (i) does the measure capture both the contemporaneous

[17] The Internet Appendix also provides simulations detailing the impact of noise on these estimates. Although the expected value of the covariance terms with errors is zero (e.g., $E(\mathrm{cov}(Inst_{i,0},\varepsilon_{i,0})))=0$), the realized value is non-zero, i.e., adding noise to data will impact the point estimate and the greater the noise, the greater the expected deviation of the estimate from its true value.

and subsequent returns patterns documented by BW? And (ii), does the measure capture institutional or individual investors' demand shocks?

To construct the sentiment metric based on mutual fund flows, we follow the method and naming convention in BW (2007) and employ the first (denoted "general demand") and second (denoted "speculative demand") principal components of changes in mutual fund flows across seven mutual fund categories (aggressive growth, growth, balanced, growth and income, sector, income equity, and income mixed) using available Investment Company Institute (ICI) flow data over the 1984 to 2010 period.[18] Consistent with BW, the first principal component loads positively on all fund categories while the second principal component loads positively on only the more aggressive fund categories. As an alternative mutual fund sentiment metric, we compute net exchanges from bond and money market funds to equity funds. Ben-Rephael, Kandel, and Wohl (2012) propose this measure better captures retail investor sentiment because it directly reflects mutual fund investors' asset allocation decisions.

The two measures of changes in consumer confidence we employ (the University of Michigan Survey of Consumer Expectations and the Conference Board Consumer Confidence Index) have been used as sentiment proxies in previous work (e.g., Fisher and Statman (2003), Lemmon and Portniaguina (2006)). We also examine a commonly used proxy for changes in individual investors' sentiment—innovations in the American Association of Individual Investors (AAII) survey.[19]

The metrics discussed above focus on individual investors. We add to this a novel measure of changes in sophisticated investors' sentiment—venture capital "flows." Specifically, we assume

[18] The Internet Appendix provides details of the mutual fund flow measures. As detailed in the Appendix, to extend the mutual fund flows period, our data differ slightly from that used by BW.

[19] Specifically we calculate the difference between the fraction of individual investors who forecast the market to increase in the next six months and the fraction who forecast the market to decline in the next six months.

venture capitalists are sophisticated (relative to individual investors) and we compute (from PWC/National Venture Capital Association data): (i) the percentage change in the dollar value of "cash-for-equity investments by the professional venture capital community in private emerging companies in the US" and (ii) the change in the number of venture capital deals.

Qiu and Welch (2006) point out that sentiment *should* be related to economic conditions, e.g., sentiment traders likely view prospects more favorably when unemployment falls or GDP growth increases. Thus, we examine two measures of changes in economic conditions—changes in the Chicago Fed's National Activity Index (the first principal component of 85 economic series that capture economic growth) and changes in the St. Louis Fed's Financial Stress Index (the first principal component of 18 variables that capture financial stress).

The first column of Table IV reports the time-series correlation between changes in each of these alternative sentiment metrics and the BW orthogonalized change in sentiment metric.[20] The second column reports the sentiment beta for a portfolio long high volatility stocks (top decile) and short low volatility stocks (bottom decile), where we compute, following BW, each sentiment beta using a time-series regression of returns on the market portfolio and the standardized (i.e., unit variance) change in each of the sentiment metrics. The third column reports the coefficient (and associated *t*-statistic) from a regression of the quarterly return difference for the portfolio of high volatility stocks and the portfolio of low volatility stocks on sentiment levels at the beginning of the quarter.[21] These tests are directly analogous to Table III in BW (2006) and examine whether high

[20] For consistency in the expected signs of the relationships, we multiply several measures (closed-end fund discounts, the dividend premium, and the stress index) by -1 throughout Table IV.

[21] The results in the third column are based on sentiment levels (results in the other columns are based on changes in sentiment). Following BW (e.g., see footnote 5 in BW (2007)), we use the beginning of quarter *t* values for closed-end

volatility securities underperform low volatility securities following high sentiment *levels*. The last column in Table IV reports the correlations between the quarterly changes in each of the sentiment metrics and the time-series variation in institutional investors' demand shocks for risky stocks (i.e., the cross-sectional correlations summarized in Panel A of Table II).

Our results are easily summarized. First, most of the metrics are positively related to the BW sentiment measure (first column). Second, the relations between the BW metric and contemporaneous (second column) and subsequent (third column) returns are largely consistent with the results in BW. Specifically, risky stocks tend to outperform safe stocks (positive coefficient) when sentiment *increases* as 13 of the 17 coefficients in the second column are positive and six of those differ significantly from zero. In contrast, none of the four negative point estimates in the second column differ meaningfully from zero. Further consistent with BW, risky stocks tend to underperform safe stocks following high sentiment *levels* as 14 of the 17 coefficients reported in the third column are negative and six differ significantly from zero (and none of the three positive point estimates differ statistically from zero). The fact that some of the coefficients reported in the first three columns do not differ meaningfully from zero means that either: (i) the metric does not capture investor sentiment, (ii) sentiment traders' demand shocks do not drive return differences between risky and safe stocks, or (iii) the measure is simply too noisy, i.e., as BW point out, any sentiment proxy contains both a sentiment component and an idiosyncratic component.[22]

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fund discount, the equity share, and IPO volume, and beginning of quarter *t*-1 values for IPO returns, turnover, and the dividend premium. (We find similar results when using beginning of quarter *t* values for these variables as well.)

[22] If a metric does not capture sentiment, then it should not generate the return patterns documented by BW. Similarly, if a metric contains a sentiment component, but the idiosyncratic component plays a large role in driving time-series variation in the metric, then the relations between the metric, the BW return patterns, and institutional/individual investors demand shocks will be weak.

The last column examines our central question of whether these alternative sentiment measures capture institutional or individual investors' demand shocks. A positive (negative) value indicates that institutions (individual investors) tend to increase their demand for risky stocks when sentiment increases, i.e., institutional (individual) investors are the traders captured by these metrics. The results reveal that the sentiment measures capture institutional, rather than individual, investors' demand shocks. Specifically, 13 of the 17 correlations are positive and nine of the 13 positive correlations differ meaningfully from zero at the 5% level or better (and a tenth is marginally significant at the 10% level). None of the four negative correlations differ meaningfully from zero.

In short, the results in the last column reveal no evidence that *any* of the 17 sentiment metrics capture individual investors' demand shocks. Seven metrics, however, are largely independent of institutional investors' demand shocks. Consistent with the hypothesis that these metrics do not capture investor sentiment, six of the seven metrics (closed-end fund discount, share turnover, the three measures of mutual fund flows, and AAII sentiment surveys) generate no evidence that they are related to the contemporaneous (second column) or subsequent (third column) return patterns documented by BW. Interestingly, this group includes the metrics that should best capture individual investors' sentiment (closed-end fund discounts, the three mutual fund flow metrics, and AAII sentiment). One of the seven measures (IPO first day returns) does capture contemporaneous return differences between risky and safe stocks (second column), suggesting that IPO first day returns contain a sentiment component—but the remaining columns suggest that the measure is noisy enough such that there is no statistically meaningful support for the BW hypothesis that the metric predicts returns or that the metric captures institutional or individual investors' demand shocks.

IV. What Drives the Relation Between Institutions' Demand and Sentiment?

The balance of our study focuses on understanding why, contrary to conventional wisdom, the sentiment metrics capture institutional, rather than individual, investors' demand shocks.

A. Are Individuals' Demand Shocks Captured by the Inverse of 13(f) Demand Shocks?

One potential interpretation of our results is that the inverse of 13(f) investors' demand shocks do not capture individual investors' demand shocks due to limitations of the 13(f) data such as exclusion of small institutions and small institutional positions. Of course, this possibility does not change the fact that the BW sentiment metric *does* capture the aggregate demand shocks of those institutions filing 13(f) reports.

Both academic (e.g., Cohen, Gompers, and Vuolteenaho (2002)) and industry (e.g., Goldman Sachs; see Sneider et al. (2013)) authors argue that the complement of 13(f) demand is a strong proxy for individual investors' demand.[23] In addition, two previous studies examine this issue. Using proprietary NASDAQ trade-by-trade data, Griffin, Harris, and Topaloglu (2003) find strong evidence that the complement of 13(f) demand shocks captures individual investors' direct trading. Malmendier and Shanthikumar (2007) use trade size and the Lee and Ready (1991) algorithm to infer impatient demand shocks by individual investors and confirm that small (large) investor order imbalance is strongly inversely (positively) related to the 13(f)-inferred institutional demand shock.

To further investigate the relation between 13(f) demand shocks and individual investors' direct trades, we compute quarterly estimates of individual investors' demand shocks from a dataset of more than 1.9 million trades from over 66,000 households at a large discount broker between January 1991 and November 1996 (n=24 quarters).[24] Specifically, we compute the net fraction of outstanding shares purchased by the sample of individual investors (in the discount broker dataset) for each stock quarter. Following Barber, Odean, and Zhu (2009), we limit the sample to securities

[23] As detailed in the Internet Appendix, we also compare estimates of individual investor aggregate equity ownership computed from 13(f) data with estimates computed from Fed Flow of Funds data. The results confirm that aggregate 13(f) inferred retail equity ownership broadly tracks Flow of Funds inferred aggregate retail equity ownership.

[24] See Barber and Odean (2000) for a description of this dataset.

with at least ten individual investors trading over the quarter to ensure a meaningful proxy for aggregate individual investor demand shocks. We then compute the cross-sectional correlation between individual investor demand shocks (from the discount broker data) and institutional demand shocks (from the 13(f) data). Although we expect the cross-sectional correlation to be negative, we do not expect it to be perfectly negative, i.e., -1, for at least two reasons. First, because the discount broker data are only a small sample of individual investors' aggregate trades, the data only proxy for individual investors' aggregate demand shocks. Second, 13(f) offsetting demand can occur from at least three other sources—the company itself, insiders (assuming one defines insiders as neither individuals nor institutions), and institutional investors under the $100M 13(f) hurdle.[25]

As detailed in the Internet Appendix, consistent with the hypothesis that the complement of 13(f) demand captures individual investors' demand shocks, we find a strong inverse relation between institutional and individual investors' demand shocks—across the 24 quarters in the overlapping sample period, the cross-sectional correlation averages -22% (t-statistic=-19.59). The analysis by 13(f) manager type reveals that individual investors' demand shocks from the discount broker data are significantly inversely related to demand shocks by insurance companies, banks, mutual funds, independent advisors, and hedge funds. In contrast, individual investors' demand shocks are positively related to pension funds' demand shocks and largely independent from unclassified institutions' demand shocks. The results demonstrate that, despite the fact that 13(f) mutual funds primarily trade on behalf of individual investors, individual investors' direct trading serves, on average, as the counterparty to mutual funds' trades. In fact, retail investors' direct trading

[25] In the Internet Appendix, we further investigate this issue by partitioning the institutional demand shock into the portions offset by changes in company shares outstanding, insider trades, and individual investors' demand shocks (i.e., the residual). The results show that although both companies and insiders appear to trade against sentiment, individual investors account for the vast majority (>75%) of the offsetting demand.

exhibits the strongest (negative) correlation with mutual funds' demand shocks (-26%, *t*-statistic=-17.66) relative to the other 13(f) investor types. In short, the analysis provides strong support for the hypothesis that the inverse of the 13(f) demand shocks captures individual investors' direct trading.

B. Evidence from Institutions' Client Base

An alternative explanation for institutional sentiment trading is that it is driven by the institution's underlying retail investors, e.g., retail investors shifting from managers holding more conservative securities to managers focusing on less conservative securities when sentiment increases. We take two general approaches to examining this possibility. First, for a subset of institutions with adequate data, we compare sentiment trading for managers with a focus on retail clients versus those with a focus on institutional clients. Second, in subsequent sections, we examine underlying investor flows and institutions' entry and exit trades.

We use data from *Pensions & Investments*' (*P&I*) annual surveys of investment managers to classify the 13(f) institutions' clientele. *P&I* surveys money managers who want to be included in their annual "Investment Adviser Profile Issue" and those managers who provide "quarterly performance data to PIPER" (*P&I*'s Performance Evaluation Report). Between 1999 and 2012, 1,480 unique managers complete *P&I* surveys at some point. On average, 732 institutional investors complete surveys (range 670 to 777) each year. Beginning with the 1999 surveys, *P&I* asked managers to report what fraction of their total worldwide assets was from "retail clients" versus "institutional clients." Because these surveys are voluntary, they may suffer from several biases including the facts that (i) only managers attempting to expand their client base have an incentive to complete surveys, and (ii) the data are voluntarily reported (rather than mandated) and therefore reporting errors may be more likely to occur in the data. For example, managers may be slow to update figures and institutions closed to new investors are unlikely to complete *P&I* surveys. (See Christoffersen et al.

(2005), Sialm and Starks (2012), and Sialm, Starks, and Zhang (2015a, 2015b) for additional discussions of the *P&I* data.) Despite these limitations, the results of sorting institutions by their client base can be suggestive of whether the institutions' sentiment trading is related to whether the underlying clients are primarily institutional or retail investors.

We merge (by manager name) 817 institutions that appear in both our 13(f) sample and the *P&I* data. Not surprisingly, we find that the reported institutional/retail client split is highly persistent.[26] Thus, we assign the closest (in calendar time) reported fraction of institutional clients for each manager for all quarters with adequate 13(f) data. Our sample of 13(f) institutions with *P&I* data averages 331 institutions each quarter (henceforth the "*P&I* sample").

Each quarter we partition the *P&I* sample into three groups by the fraction of their assets under management for institutional (versus retail) clients. The top row of Panel A in Table V reports the time-series mean fraction of assets attributed to institutional clients for each of the three groups: institutional client focused, mixed clientele, and retail client focused. For instance, on average, only 30% of assets are from institutional clients for retail-focused managers versus 97% of assets for institutional-client focused managers. The second row in Panel A reports the time-series average of the fraction of the aggregate *P&I* institutional equity portfolio accounted for by each of the three manager groups.

[Insert Table V about here]

We then measure, each quarter, changes in *P&I* institutions' attraction to volatile stocks. Consistent with the broader sample, institutions in the *P&I* sample exhibit substantial time-series variation in their buying and selling of risky stocks (specifically, analogous to Table II Panel A, the

[26] The cross-sectional correlations between the current fraction of assets managed for institutional clients and the fraction of assets managed for institutional clients one, two, or three years previously averages 97%, 94%, and 91%, respectively.

cross-sectional correlation between *P&I* demand shocks and volatility ranges from -11% to 13%). The first column in Panel B of Table V reports the correlation between time-series variation in changes in aggregate *P&I* institutions' attraction to risky stocks and time-series variation in the 17 changes in sentiment metrics, i.e., the first column in Table V is analogous to the last column in Table IV. The results based on the *P&I* institutions are largely consistent with those for the broader sample, e.g., of the 10 metrics in Table IV that capture aggregate institutional demand shocks, nine capture aggregate *P&I* institutions' time-varying demand for risky stocks. For instance, the correlation between changes in orthogonal sentiment and time-series variation in the extent that *P&I* institutions shift toward risky stocks is 29% (Table V) versus 37% for the full sample of 13(f) institutions (Table IV).

Because *P&I* aggregate demand is the sum of demand across the three manager categories and covariances are linear in the arguments, the correlation between changes in each of the sentiment metrics and time-series variation in *P&I* institutions' demand shocks can be partitioned (each quarter and over the entire period) into the portion attributed to managers with an institutional client focus, managers with a mixed clientele, and managers with a retail client focus (see Internet Appendix for proof). Under the null that client type is independent of contribution to sentiment trading, the expected contribution for each manager type-quarter is the product of their beginning of quarter weight in the aggregate *P&I* portfolio and that quarter's contribution to aggregate *P&I* sentiment trading (i.e., the values reported in the first column).[27] The second two columns in Panel B report the abnormal contribution (actual contribution less expected contribution) to *P&I* sentiment trading by managers with an institutional client focus and managers with a retail client focus,

[27] For instance, if, in a given quarter, retail client focused institutions have twice the aggregate institutional portfolio weight as institutional focused institutions, the former should account for twice the contribution of the latter if sentiment trading is unrelated to client type.

respectively. The last column reports the difference in abnormal contributions between institutional focused managers and retail focused managers (t-statistics are computed from the time-series standard error of the difference). Inconsistent the explanation that underlying retail investors are primarily responsible for the relation between institutions and sentiment, the results show that managers with an institutional client base disproportionally contribute to sentiment trading. Specifically, the abnormal contribution from institutional client focused managers is significantly greater (at the 10% level or better) than the abnormal contribution from retail client focused managers for nine of the 17 sentiment metrics (and eight of the 10 metrics that appear to capture institutional demand shocks based on the Table IV analysis).

C. *Underlying Investor Flows*

Perhaps the simplest explanation for institutional sentiment trading is that it reflects underlying investor flows. The analysis is complicated by the facts that: (i) flows to 13(f) managers reflect flows from both retail and institutional clients, (ii) flows within a fund family are not captured by the 13(f) data, and (iii) even when focusing on mutual funds, flows are determined by underlying individual investors, their advisers, and defined contribution plan sponsors. For instance, Sialm, Starks, and Zhang (2015) find that mutual funds' flow-performance relation is driven by both underlying investors' decisions and the decisions of (presumably sophisticated) DC fund sponsors and they find a stronger flow-performance relation for the latter rather than the former.

Our initial investigation into the contribution of underlying investors' flows to sentiment trading uses the Griffin et al. (2011) method (details given in Internet Appendix) to estimate three components of institutional demand shocks: trades that result from investor flows, trades that result from managers' decisions, and trades that result from reinvested dividends. This method assumes that flows are used to purchase and sell existing securities held by the manager and in direct proportion to the manager's portfolio weights.[28] Therefore, the method defines net active buying to be any trade that causes deviations from existing portfolio weights regardless of whether flows influence managers' decisions. Again, exploiting covariance linearity and the fact that aggregate institutional demand is the sum of the three components, the correlation between changes in sentiment and time-series variation in institutional demand shocks for risky stocks (i.e., the correlation reported in Panel B of Table II) can be partitioned into the portion attributed to each component (see Internet Appendix for proof).

The first column of Panel A in Table VI reports the time-series correlation between changes in orthogonalized sentiment and changes in institutional investors' attraction to risky stocks, i.e., the 37.27% figure reported in Panel B of Table II. The last three columns report the portion of the correlation due to investor flows, manager decisions, and reinvested dividends. The *p*-values reported in the last three columns are based on bootstrapped estimates with 10,000 iterations (see Internet Appendix for details). The results provide little evidence that managers investing net flows into their existing portfolios play a meaningful role in driving the relation between institutional demand shocks and changes in sentiment. Rather, managers' decisions account for 97% of the time-series correlation reported in the first column (i.e., 0.3615/0.3727).

[Insert Table VI about here]

Because 13(f) filings reflect the institution's aggregate portfolio, it is possible that a given 13(f) institution's net active buying reflects within-family flows. To examine whether these flows can

[28] Consistent with this assumption, Pollet and Wilson (2008) find, "…that funds overwhelmingly respond to asset growth by increasing their ownership shares rather than by increasing the number of investments in their portfolio." Coval and Stafford (2007) and Khan, Kogan, and Serafeim (2012) also find supporting evidence. In addition, a manager experiencing an outflow has (effectively) no choice but to sell existing positions (although not necessarily in proportion to portfolio weights).

explain institutional sentiment trading, we follow Edelen, Ince, and Kadlec (2016) and recalculate aggregate institutional demand shocks using only entry and exit trades that, by definition, are due to manager decisions. Accordingly, we compute the cross-sectional correlation between aggregate institutional entry/exit demand shocks and securities' return volatility each quarter (these correlations range from -14.48% to 14.29%). We then calculate the correlation between time-series variation in institutions' entry/exit demand shocks for risky stocks and changes in orthogonalized sentiment. Panel B in Table VI reports the correlation is 48.58%, providing further evidence that managers' decisions play an important role in driving the relation between changes in sentiment and time-series variation in institutional demand shocks for volatile stocks.

We next repeat the above analyses using the merged Thomson Financial/CRSP mutual fund data (see Internet Appendix for details). Because the data are at the fund level, these estimates capture flows between funds in the same family as well as across families. Panel C in Table VI reports the correlation between changes in sentiment and time-series variation in changes in mutual funds' attraction to volatile stocks (as captured by the cross-sectional correlation between mutual fund demand shocks and stock volatility) is 35.67%.[29] Thus, consistent with our results based on 13(f) data, mutual funds buy risky stocks and sell safe stocks when sentiment increases.

The next three columns in Panel C partition the Thomson Financial/CRSP mutual fund correlation into the three components. Although managers' decisions account for the largest share of the correlation (statistically significant at the 1% level), investor flows to mutual funds account for a substantial component of the correlation (approximately 43%=0.1536/0.3567) and are also statistically significant at the 1% level. As a final test, Panel D reports that the correlation based on

[29] For consistency, we limit the sample to stocks that are held by at least five mutual funds. The sample size averages 2,061 stocks per quarter.

mutual funds' entry and exit trades is 42.81% (statistically significant at the 1% level), further consistent with the explanation that mutual fund managers' decisions play an important role in driving the relation.

The relation between mutual fund flows and changes in sentiment suggests that (in aggregate) individual investors who invest via mutual funds differ from those who invest in stocks directly, consistent with our earlier evidence that retail investors' direct trades serve as the counterparty to mutual fund trades. This could result, at least in part, because mutual fund investors are influenced by their advisors or because defined contribution plan sponsors' menu decisions are related to changes in sentiment.[30,31]

D. Explaining Institutional Demand Shocks Across Stock-Quarters

Previous work demonstrates that institutional demand shocks are a function of their investment style as such demand shocks are related to their reluctance to deviate from benchmarks, lag returns, and lag institutional demand shocks. Demand shocks are, of course, also related to underlying investors' flows. Thus, sentiment metrics are either correlated with the portion of the institutional demand shock associated with these factors or the portion of the institutional demand shock orthogonal to these factors. In this section, we consider how these known institutional investment styles and investor flows contribute to the relation between changes in sentiment and institutional

[30] According to the 2016 ICI Fact Book, 77% of mutual fund shareholders own shares through their employer-sponsored retirement plan, 46% own shares through an investment professional (these are overlapping percentages). Only 3% reported that they purchased funds outside of a retirement plan without an investment professional (5% did not report the source.) http://www.icifactbook.org/ch6/16_fb_ch6.

[31] This does not imply plan sponsors are necessarily irrational. For instance, Christoffersen and Simutin (2017) argue that ERISA provisions make plan sponsors especially concerned about deviations from benchmark and, as discussed below, such benchmark concerns can lead to institutional sentiment trading.

investors' demand shocks. Recognize, however, that although it is possible that these factors and unknown omitted variables may help explain why sentiment metrics capture institutional investors' demand shocks, they cannot resurrect the traditional interpretation of the investor sentiment hypothesis. That is, one cannot argue that sentiment metrics capture individual investors' demand shocks if individuals sell volatile stocks to institutions when sentiment increases.

We begin the analysis by partitioning our 123 quarters of data into quintiles based on the extent of institutional sentiment trading. The extreme "up sentiment" quarters are those in which sentiment increases and institutions shift from safe to speculative stocks, which we define as the 24 quarters (top quintile) that contribute the most to the correlation between changes in sentiment and time-series variation in institutional demand shocks for high volatility stocks (i.e., the 37.27% correlation reported in Table II). Analogously, the extreme "down sentiment" quarters are defined as the 24 quarters that contribute the most to the correlation because sentiment decreases and institutions shift from volatile to safe stocks. We then estimate a panel regression of institutional demand shocks on stock volatility and stock volatility interacted with indicators for up-sentiment quarters and down-sentiment quarters (standard errors are clustered at the stock level). To allow for variation over time, we standardize both the dependent variable (the aggregate institutional demand shock) and the independent variables each quarter.[32] Consistent with Table II, the results in the first column of Table VII show that, on average, institutions in aggregate shift toward volatile stocks over our sample period (first row), institutions' attraction to volatile stocks is much stronger in the extreme up sentiment quarters (second row), and reverses for the extreme down sentiment quarters (third row).

[32] Subtracting the mean each quarter is identical to adding quarterly fixed effects in the panel. Because institutional ownership grows dramatically over our sample period, we also divide by the standard deviation each quarter. In addition, all variables in Table VII are winsorized at the 0.05% and 99.5% levels.

[Insert Table VII about here]

Our strategy in this section is to test whether known institutional investment styles and underlying flows can reduce or eliminate the relation between changes in sentiment and institutional investors' demand shocks. We begin by further investigating the role of underlying investors' flows in driving the relation by adding flow-induced demand shocks for each stock-quarter observation to the regression. As discussed above, the flows methodology assumes that institutions invest flows in their current portfolio. We expect this assumption will better hold for outflows than inflows because an institution with outflows has no choice but to sell existing holdings. Thus, we estimate, for each stock-quarter, expected flow-induced demand shocks by managers experiencing inflows (values ≥ 0) and expected flow-induced demand shocks by managers experiencing outflows (values ≤ 0).

The results in the second column reveal strong evidence (i.e., both coefficients have *t*-statistics greater than 25) that flows impact institutional demand shocks, and, as expected, the impact of outflows is greater than the impact of inflows. Although an important component in explaining which stocks institutions buy from individual investors, flows have almost no impact on the coefficients associated with stock volatility in up sentiment or down sentiment periods, e.g., the coefficient in the second row falls from 0.072 to 0.071 and the coefficient in the third row "falls" from -0.052 to -0.050. The results are consistent with the evidence in Table VI and suggest that underlying investor flows are not the primary mechanism driving the relation between institutions and sentiment.

We next consider the role of known institutional investment styles. A number of previous studies demonstrate that institutional investors are reluctant to deviate from their benchmarks due to both risk-management constraints and reputational concerns (e.g., Cao, Han, and Wang (2017), Almazan et al. (2004), Maug and Naik (2011), Arnott (2003)). In particular, risk budgeting and asset allocation rebalancing would cause some institutional investors to reduce their equity risk exposure when sentiment is decreasing either by shifting from risky stocks to safer stocks or by shifting away from equities. This particularly holds for those institutional investors unable or unwilling to take on leverage (see Asness, Frazzini and Pedersen (2012) and Frazzini and Pedersen (2014)). Moreover, a small stock with a large price spike becomes a much larger stock and, absent trading, institutions with no initial position in the stock will be making a much larger active bet after the spike. Thus, institutions concerned about active weights will tend to buy the stock.[33]

We generate two measures of the aggregate institutional portfolio's deviation from the market portfolio to capture institutions' trading style associated with risk management/reputational concerns: (i) the aggregate institutional active weight at the beginning of the quarter (the difference between the stock's weight in aggregate institutional portfolio and the stock's weight in the market portfolio), and (ii) the expected change in active weight assuming no trading. The latter measure accounts for the fact that if institutions are underweight a given stock at the beginning of quarter t and the stock outperforms the market in quarter t, then, absent trading, institutions will be even more underweight at the end of the quarter t. We expect negative coefficients associated with both measures.

[33] Consider, for example, BEA Systems during the TMT bubble period (as defined by Griffin et al. (2011)) from the end of March 1999 to end of March 2000. BEA was in the top volatility decile throughout this period. At the beginning of the period BEA with a market weight of 0.0084%, was held by 4% of institutions and had a 0.0027% weight in the aggregate institutional portfolio. Over the next year, BEA had a return of 839% (its cumulative return peaks in February of 2000 at 1,520%) and a market weight 0.0799% by the end of March 2000 when 216 of 1,669 institutional investors (13%) hold 55% of BEA shares. By the end of March 2000, BEA's weight in the aggregate institutional portfolio, at 0.0763%, was nearly identical to its market weight of 0.0799%. In sum, most institutions had a small negative active weight in BEA at the beginning of the period when BEA is a small company. As sentiment and BEA's market weight increases, institutions who initially underweight the stock must either purchase it or increase their active bet against the stock.

Previous work (e.g., Sias (2004)) also demonstrates that institutions tend to follow lag returns (momentum trade) and other institutions (herd). Thus, given these patterns help explain institutional demand shocks, it is possible they contribute to the relation between institutional demand shocks and changes in sentiment. We measure lag return as the stock's return in quarter *t*-1 (i.e., months -1 to -3) and lag institutional demand as the institutional demand shock in quarter *t*-1.[34]

The third column in Table VII adds lag institutional demand, lag return, beginning of quarter active weight, and the expected change in active weight as independent variables to the regression of institutional demand shocks. All coefficients have the expected sign—institutional demand shocks are positively related to lag institutional demand (institutional herding) and lag returns (institutional momentum trading) and inversely related to the aggregate institutional active weight and the expected change in active weight (consistent with the risk management/reputation concerns). Moreover, adding these variables to the regression results in a noticeable reduction in the magnitude of the coefficients associated with extreme up and down sentiment periods—the coefficient associated with extreme up sentiment falls by 25% and the coefficient associated with extreme down sentiment periods falls by 41%. In sum, the results in Table VII suggest that common, and previously documented, institutional investment styles contribute to institutional sentiment trading.[35]

[34] We also estimated the regression in the third column of Table VII using lag returns measured over months -2 to -12 (rather than months -1 to -3) and found similar, albeit slightly weaker, results.

[35] The evidence of institutional momentum trading brings up the related possibility that perhaps institutional investors are short-term (intraquarter) momentum traders who simply chase lag returns and their demand shocks do not impact prices. Although this explanation could explain why institutions buy volatile stocks from, and sell safe stocks to, individual investors when sentiment increases, it would not change our primary conclusion that sentiment metrics do not capture individual investors' demand shocks. Moreover, this explanation is inconsistent with the sentiment hypothesis because the sentiment hypothesis requires that demand shocks from those investors that are buying speculative stocks

E. Evidence from Institution Types

As detailed in the Internet Appendix, we find substantial variation in holdings across investor types (consistent with Bennett, Sias, and Starks (2003))—insurance companies, pension funds, banks, and unclassified institutions: (i) tend to avoid risky stocks and (ii), are less willing to make adjustments to their exposure to risky stocks. Because these investors play a *relatively* minor role in the holding and trading of high volatility securities, we predict that they will play a relatively small role (versus the role of mutual funds, independent advisors, and hedge funds) in accounting for time-series variation in the aggregate institutional investor shifts between low and high volatility securities.

Tests reported in the Internet Appendix also suggest that mutual funds and independent investment advisors are the institution types most concerned about reputations which is consistent with previous work (see Sias (2004) and Dasgupta, Prat, and Verardo (2011)). Thus, if reputational concerns contribute to institutional sentiment trading, we expect that these two investor groups will play a disproportionately large role in driving aggregate institutional sentiment trading. Note that the implications of the reputational concerns channel are identical to the preferred habitat channel—both predict that insurance companies, pensions, banks, and unclassified institutions will tend to contribute less to aggregate sentiment trading than mutual funds and independent advisors. In fact, the two explanations are not mutually exclusive. An institution may have a preferred habitat because of reputational concerns.

Some institutions may attempt to ride bubbles to exploit less sophisticated investors. Although the idea of profitably riding a bubble appears, at least initially, straightforward, market clearing still

(and selling safe stocks) when sentiment increases is what causes the misvaluation (and the associated return patterns documented by BW).

requires that someone offsets these trades. That is, if both sentiment traders and rational speculators (attempting to ride bubbles) buy speculative stocks, some third group of traders must sell speculative stocks.[36] Nonetheless, previous work (e.g., Brunnermeier and Nagel (2004)) suggests that hedge funds are more likely to attempt to ride bubbles than other types of institutions. Complicating the issue, however, Brunnermeier and Nagel also argue that hedge fund bubble riding results, at least in part, from reputational concerns. Note that other institutions may attempt to ride bubbles—we simply expect hedge funds to be the most likely institutional type to attempt to ride bubbles. Regardless, if such behavior contributes meaningfully to the relation between institutions and sentiment, we expect hedge funds will also play a disproportionately large role in contributing to aggregate institutional sentiment trading.

Examining contributions by manager type (detailed results reported in Internet Appendix), we find, consistent with the hypotheses that preferred habitats, reputational concerns, and bubble riding help explain institutional sentiment trading, mutual funds, independent advisors, and hedge funds account for a disproportionately large share of the aggregate institutional sentiment trading. In fact, these three investor groups account for 89% of the aggregate institutional sentiment trading even though (on average) they account for only half of the institutional ownership.[37]

[36] For example, DeLong et al. (1990) model three investor classes—informed rational speculators, positive feedback traders, and passive investors.

[37] Because mutual funds and independent advisors account for a much greater fraction of institutional equity ownership, they contribute much more to the aggregate sentiment trading than hedge funds. As detailed in the Internet Appendix, however, once accounting for size, hedge funds exhibit the greatest propensity for sentiment trading. One potential concern regarding the strong relation between hedge fund demand shocks and changes in sentiment is that hedge funds often employ substantial short positions. Thus, it is possible that hedge funds increase both their long and short exposures to risky stocks when sentiment rises (and therefore do not have positive "net" demand for risky stocks when sentiment rises). To investigate this possibility, we reexamine the relation between institutional demand shocks and

F. *Evidence from Variation Across Individual Institutions*

Most trading is between institutions (rather than between institutions and individual investors). Thus, many institutions likely provide offsetting liquidity for institutions trading on sentiment even if institutions in aggregate sentiment trade (we investigate the breadth of institutional sentiment trading in the Internet Appendix). In this section, we investigate differences across individual institutional investors to help understand if investment styles can help explain both why institutions in aggregate sentiment trade and why the behavior varies across individual institutions. Because our focus is on understanding variation in sentiment trading across institutions and time, we focus on a measure of sentiment trading at the manager-quarter level—the extent that their trading shifts *their own* portfolio toward risky stocks within a given quarter.

Analogous to our examination of variation across stocks and time (Table VII), we estimate a panel regression of the extent that individual managers shift their portfolios toward high volatility stocks (computed as the sum of the products of stock volatility measured at the beginning of quarter t and changes in the manager's portfolio weight due to trading in quarter t) on a set of explanatory variables related to manager characteristics and those characteristics interacted with dummy variables for the quintiles of extreme up sentiment quarters and extreme down sentiment quarters (as defined previously). Our panel includes five independent variables (plus the interaction effects): (i) the extent that the manager's portfolio is "tilted" toward volatile stocks at the beginning of the quarter (computed as the sum of the product of the manager's beginning of quarter weights and security return volatility), (ii) a dummy variable for transient institutions, (iii) a dummy variable for non-transient institutions, (iv) manager flows the previous quarter, and (v) manager size at the beginning

changes in sentiment when controlling for changes in short interest. The results, detailed in the Internet Appendix, reveal our results are effectively unchanged.

of the quarter.[38]

Both the dependent and independent variables (except the transient and non-transient dummy variables) are measured relative to other investors of the same type each quarter. Specifically, we subtract the median value for the same type managers. Thus, for instance, the extent to which an insurance company tilts a portfolio toward high volatility stocks is measured relative to other insurance companies in the same quarter. All variables (except the transient and non-transient indicator variables) are standardized (rescaled to unit variance and zero mean) each quarter.

We hypothesize that, due to risk management/reputation concerns, managers' beginning of quarter tilts toward volatile stocks will be inversely related to the extent that they shift their portfolios toward risky stocks over the quarter. For instance, a manager who already underweights risky stocks relative to their peers will be more likely than their peers to increase their exposure than decrease it.

Second, we expect that institutions with a short-term focus will be more likely to trade on sentiment given they are more likely to focus on the trades of other investors than longer-term fundamentals (e.g., Cella, Ellul, and Giannetti (2013)). We use Brian Bushee's data to identify transient institutions (those with high portfolio turnover and relatively small stakes in the companies they hold). We expect the coefficient on transient to be positive for up sentiment quarters (i.e., transient institutions will tend to shift to riskier stocks) and negative for down sentiment quarters

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[38] We measure changes in weights due to trading as the differences in end-of-quarter and beginning-of-quarter (split adjusted) shares held times beginning of quarter prices scaled by portfolio value. We measure security volatility as the natural logarithm of one plus monthly return standard deviation over quarters t-4 to t-1 To ensure outliers do not impact our results we limit the sample to managers that hold at least 20 eligible securities (e.g., share code 10 and 11) worth at least $50M. As discussed above, we winsorize flows following the method in Griffin et al. (2011) (see Internet Appendix for detail). We also winsorize type-adjusted manager tilt and size at 1% and 99% levels.

(i.e., transient institutions will tend to shift to safe stocks). If non-transient institutions help offset the trades of transient institutions, then the signs will be opposite for non-transient institutions. We propose that managers who recently suffered outflows and small managers could be more concerned about reputation relative to other managers. Thus, we use manager's quarter *t*-1 flows (scaled by portfolio value) and size (natural logarithm of total equity portfolio value) to proxy for managers with strong reputational concerns.

The panel regression results are reported in Table VIII (standard errors are clustered at the manager level). The coefficient reported in the first column of the first row is consistent with the hypothesis that managers' risk management/reputation concerns impact their decisions to shift toward or away from risky stocks. A manager with a one standard deviation larger tilt toward risky stocks at the beginning of the quarter averages a -0.12 standard deviation shift away from risky stocks over the quarter. Thus, managers who underweight risky stocks are more likely to sentiment trade (i.e., shift toward risky stocks) when sentiment increases and managers who overweight risky stocks are more likely to sentiment trade (i.e., shift away from risky stocks) when sentiment declines. The next two columns reveal, however, that this effect is not magnified in extreme sentiment quarters.

[Insert Table VIII about here]

The results in the second and third rows are consistent with the hypothesis that transient institutions are more likely to sentiment trade and non-transient institutions are more likely to offset the sentiment trading. In general, transient institutions are more likely to shift toward riskier stocks than other institutions (first column). This effect is even greater when sentiment increases (i.e., the sum of the first and second columns) and reverses when sentiment declines (the sum of the first and third columns differs meaningfully from zero at the 1% level).[39] If flows and size are representative of the reputation hypothesis, the results reveal no evidence supporting the hypothesis as lag flows and manager size do not impact the extent to which a manager shifts toward risky stocks in either large sentiment increase or decrease quarters (last two columns).

V. Conclusions

When sentiment increases, institutions, in aggregate, buy volatile stocks from, and sell safe stocks to, individual investors. The results are inconsistent with the hypothesis that individual investors' sentiment-induced demand shocks drive prices from fundamental value. If these metrics capture sentiment and the cross-sectional return patterns documented in the sentiment literature are due to sentiment-induced demand shocks, then institutions, rather than individual investors, are the sentiment traders. Although our results are inconsistent with the traditional *interpretation* that sentiment metrics capture individual investors' irrational demand shocks, our results are largely consistent with the empirical evidence in the sentiment literature.[40]

The second part of our study focuses on understanding why sentiment metrics capture institutional rather than individual investors' demand shocks. We find no evidence that mis-measurement of individual investors' demand shocks (via the inverse of 13(f) demand shocks) drive our results. Further inconsistent with the traditional interpretation of the investor sentiment hypothesis, managers with a focus on institutional clients contribute proportionally more to aggregate institutional sentiment trading than managers with a retail client focus.

[39] Not surprisingly, hedge funds exhibit the greater tendency to be classified as transient institutions (46% of hedge funds in our sample are classified as transient). Because hedge funds account for only 16% of institutions in our sample, however, most transient institutions are not hedge funds.

[40] For example, as detailed in the Internet Appendix, most previous studies find no evidence that mutual fund flows forecast subsequent market returns or the subsequent size premium.

Our tests support the hypothesis, however, that previously documented institutional trading styles contribute to the relation between sentiment metrics and institutional investors' demand. We also find that although underlying investors' flows have a large impact on institutional investors' demand shocks (see Table VII), there is little evidence that underlying investors' flows play the central role in driving the relation between 13(f) institutions and sentiment. Nonetheless, our results suggest that individual investors may still play an indirect role in institutional sentiment trading—mutual fund flows within a family contribute to institutional sentiment trading—although managers' decisions play the dominant role.

While our results demonstrate correlation, they do not necessarily demonstrate causation—it is possible omitted variables drive both changes in the sentiment metrics and institutional investors' demand shocks. If that is the case, however, then sentiment-induced demand shocks are not the underlying cause of the return patterns documented by BW. Regardless, the relation between individual investors, institutions, and sentiment metrics is more nuanced than previously recognized and deserves further study.

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Table I
Institutional Investor Demand and Investor Sentiment by Volatility Decile

The first column reports the time-series correlation between quarterly orthogonalized changes in sentiment ($\Delta Sent_t^{\perp}$) and cross-sectional average institutional investor demand shocks ($\overline{\Delta Inst_{i,t}}$) for stocks within each volatility decile (where volatility is estimated using monthly returns over the previous 12 months). The bottom row in the first column reports the correlation for the difference in mean institutional demand shocks for high versus low volatility stocks and orthogonalized changes in sentiment. We sort the 123 quarters (June 1990-December 2010) into high (above median) and low orthogonalized sentiment periods and report the time-series mean of the cross-sectional average detrended institutional ownership levels (i.e., fraction of shares held by institutions) for securities within each volatility decile (sentiment levels and ownership levels are measured at the same point in time) for high sentiment periods (second column), low sentiment periods (third column), and their difference (final column). Detrended levels are the residuals from regressions for each volatility-sorted portfolio of cross-sectional mean institutional ownership levels (in percent) on time. The final row in columns two and three reports the difference in institutional ownership levels for the high volatility portfolio and the low volatility portfolio. The final row in the last column reports the difference between high and low sentiment periods and associated *t*-statistics (based on a *t*-test for difference in means). Statistical significance at the 1% is indicated by ***.

Table I (continued)
Institutional Investor Demand and Investor Sentiment by Volatility Decile

	$\rho\left(\overline{\Delta Inst_{i,t}}, \Delta Sent_t^{\perp}\right)$ (*p*-value)	High sentiment periods	Low sentiment periods	High sentiment – low sentiment (*t*-statistic)
Low vol. stocks	-0.287 (0.01)	-0.45	0.46	-0.90
2	-0.293 (0.01)	-0.04	0.04	-0.08
3	-0.370 (0.01)	-0.11	0.11	-0.22
4	-0.272 (0.01)	0.30	-0.31	0.61
5	-0.234 (0.01)	0.04	-0.04	0.09
6	-0.144 (0.12)	0.53	-0.54	1.07
7	-0.112 (0.22)	0.69	-0.70	1.39
8	0.076 (0.39)	0.87	-0.89	1.76
9	0.202 (0.03)	0.88	-0.90	1.78
High vol. stocks	0.315 (0.01)	1.39	-1.42	2.81
High σ – low σ	0.339 (0.01)	1.84	-1.87	3.71 (4.72)***

Table II
Time-series Variation in Institutional Demand Shocks for Volatile Stocks and Changes in Sentiment

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between institutional demand shocks ($\Delta Inst_{i,t}$) and security return volatilities ($\sigma_{i,t}$) for all stocks in the sample. Volatility is estimated using monthly returns over the previous 12 months. Panel A reports the time-series mean, standard deviation, minimum, and maximum of the cross-sectional correlation and associated *t*-statistics (in parentheses) computed from the time-series of cross-sectional correlations. Panel B reports the correlation between time-series variation in changes in institutional investors' attraction to volatile stocks (i.e., the cross-sectional correlation between volatility and changes in the fraction of shares held by institutions summarized in Panel A) and changes in raw or orthogonalized investor sentiment (and associated *p*-values). Statistical significance at the 1% level is indicated by ***.

Panel A: Descriptive Statistics for Cross-sectional Correlation between Institutional Demand Shocks and Stock Volatility

	Mean (*t*-statistic)	Standard Deviation	Minimum	Maximum
$\rho_t(\Delta Inst_{i,t}, \sigma_{i,t})$	2.55% (5.20)***	5.44%	-16.87%	17.65%

Panel B: Correlation between Changes in Sentiment and Time-series Variation in Changes in Institutional Investors' Attraction to Volatile Stocks (*n*=123 quarters)

	ΔSentiment (*p*-value)	Orthogonalized ΔSentiment (*p*-value)
$\rho(\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta Sent_t)$	37.34% (0.01)	37.27% (0.01)

Table III
Examination of Changes in Risk and Alternative Risk Metrics

Volatility is estimated for each stock-quarter (between June 1980 and December 2010) as the natural logarithm of estimated monthly standard deviation of returns computed from squared daily returns in quarter *t*-1 ($\sigma_{i,t-1}$), quarter *t* ($\sigma_{i,t}$), and quarter *t*+1 ($\sigma_{i,t+1}$). Panel A reports the correlation between changes in investor sentiment ($\Delta Sent_t^{\perp}$) and time-series variation in the cross-sectional correlation between changes in institutional ownership levels ($\Delta Inst_{i,t}$) and volatility levels (where volatility is measured in quarter *t*-1, *t*, or *t*+1). Panel B reports the correlation between changes in investment sentiment and time-series variation in the cross-sectional correlation between changes in institutional ownership and estimated changes in volatility (where the change in quarter *t* volatility is estimated as either the difference in realized volatility in quarters *t* and *t*-1 or quarters *t*+1 and *t*). Panel C reports the correlation between changes in investment sentiment and time-series variation in the cross-sectional correlation between institutional ownership levels (measured at the beginning or end of the quarter) and estimated changes in volatility. Panel D reports the correlation between changes in investment sentiment and time-series variation in the difference in the cross-sectional correlations between institutional ownership levels and estimated stock volatility at the end and beginning of quarter *t*. The *p*-values for the correlations are reported parenthetically.

Table III (continued)
Examination of Changes in Risk and Alternative Risk Metrics

Panel A: Correlation between Changes in Sentiment and Changes in Institutional Investors' Attraction to Volatile Stocks			
	$\sigma_{i,t-1}$	$\sigma_{i,t}$	$\sigma_{i,t+1}$
$\rho(\rho_t(\Delta Inst_{i,t}, \sigma_{i,X}), \Delta Sent_t^{\perp})$	0.255	0.285	0.311
	(0.01)	(0.01)	(0.01)

Panel B: Correlation between Changes in Sentiment and Correlation between Changes in Institutional Ownership and Changes in Stock Volatility		
	$\Delta\sigma = \sigma_{i,t} - \sigma_{i,t-1}$	$\Delta\sigma = \sigma_{i,t+1} - \sigma_{i,t}$
$\rho(\rho_t(\Delta Inst_{i,t}, \Delta\sigma_{i,X}), \Delta Sent_t^{\perp})$	0.202	0.047
	(0.03)	(0.60)

Panel C: Correlation between Changes in Sentiment and Correlation between Institutional Ownership Levels and Changes in Stock Volatility		
	$\Delta\sigma = \sigma_{i,t} - \sigma_{i,t-1}$	$\Delta\sigma = \sigma_{i,t+1} - \sigma_{i,t}$
$\rho(\rho_t(Inst_{i,t=0}, \Delta\sigma_{i,X}), \Delta Sent_t^{\perp})$	-0.140	0.245
	(0.13)	(0.01)
$\rho(\rho_t(Inst_{i,t=1}, \Delta\sigma_{i,X}), \Delta Sent_t^{\perp})$	-0.122	0.240
	(0.18)	(0.01)

Panel D: Correlation between Changes in Sentiment and the Difference in Correlation between Institutional Ownership Levels and Stock Volatility		
	$\rho(Inst_{i,1}\sigma_{i,t}) - \rho(Inst_{i,0}\sigma_{i,t-1})$	$\rho(Inst_{i,1}\sigma_{i,t+1}) - \rho(Inst_{i,0}\sigma_{i,t})$
$\rho((\rho_t(Inst_{i,t=1}, \sigma_{i,X}) - \rho_t(Inst_{i,t=0}, \sigma_{i,X-1})), \Delta Sent_t^{\perp})$	-0.103	0.236
	(0.26)	(0.01)

Table IV
Examination of Alternative Sentiment Metrics

This table reports tests based on 17 investor sentiment metrics: the BW orthgonalized sentiment measure (Panel A), the six components of the BW metric (Panel B), three mutual fund flow measures (Panel C), two consumer confidence measures (Panel D), a survey-based measure of individual investors' sentiment (Panel E), two venture capital flow measures (Panel F), and two economic activity measures (Panel G). Variables expected to have a negative relation with investor sentiment are multiplied by -1 such that the expected sign within each column is consistent (e.g., all values in the first column are expected to be positive). All sentiment metrics (both levels and changes) are rescaled to zero mean and unit variance to allow direct comparison across the panels. The measures are discussed in the text and details are provided in the Internet Appendix. The first column reports the time-series correlation between quarterly changes in the measure and the BW orthoganalized change in sentiment measure ($\Delta Sent_t^{\perp}$). The second column reports the sentiment beta for the portfolio long the decile of most volatile stocks and short the decile of least volatile stocks (estimated from a time-series regression of the quarterly long-short portfolio return on market returns and each of the 17 change in sentiment metrics individually). The third column reports the coefficient associated with a time-series regression of the difference in quarterly returns for high and low volatility stocks on the lag level of the sentiment metric. The last column reports the correlation between time-series variation in changes in institutional investors' attraction to volatile stocks (i.e., the cross-sectional correlation between volatility ($\sigma_{i,t}$) and changes in the fraction of shares held by institutions ($\Delta Inst_{i,t}$)) and changes in each of the sentiment proxies (and associated *p*-values). Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **. and *, respectively.

Table IV (continued)

Examination of Alternative Sentiment Metrics

	Correlation with BW metric	Sentiment Beta	Predict Returns?	Capture individual or institutional demand?
	$\rho(\Delta X_t, \Delta Sent_t)$	High σ – Low σ (*t*-statistic)	Coefficient on lag levels (*t*-statistic)	$\rho(\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta X_t)$ (*p*-value)
Panel A: BW Sentiment Metric (*n*=123 quarters)				
Sentiment$^{\perp}$	100.00%	0.057	-0.043	37.27%
		(4.82)***	(-2.85)***	(0.01)***
Panel B: BW Sentiment Components (*n*=123 quarters)				
CEF discount(*-1)	-5.64%	-0.001	-0.013	0.75%
	(0.54)	(-0.07)	(-0.84)	(0.94)
Turnover	10.97%	0.014	0.021	-2.92%
	(0.23)	(1.19)	(1.36)	(0.75)
Number IPOs	23.91%	-0.001	-0.037	35.75%
	(0.01)***	(-0.10)	(-2.40)**	(0.01)***
IPO return	50.18%	0.051	-0.010	7.69%
	(0.01)***	(4.41)***	(-0.62)	(0.40)
Equity share	22.34%	0.014	-0.019	26.34%
	(0.02)**	(1.15)	(-1.25)	(0.01)***
Dividend prem.(*-1)	70.65%	0.088	-0.065	38.77%
	(0.01)***	(7.77)***	(-4.46)***	(0.01)***
Panel C: Mutual Fund Flows (*n*=106 quarters)				
MF general demand	16.48%	-0.010	-0.020	-1.27%
	(0.10)*	(-0.63)	(-1.17)	(0.90)
MF speculative	1.78%	0.008	0.017	8.15%
demand	(0.86)	(0.60)	(0.99)	(0.41)
Net exchange to	14.82%	-0.011	-0.011	-0.71%
equity funds	(0.13)	(-0.70)	(-0.61)	(0.95)
Panel D: Consumer Confidence (*n*=123 quarters)				
Michigan	19.53%	0.038	-0.043	19.12%
	(0.04)**	(3.06)***	(-2.87)***	(0.04)**
Conference	24.85%	0.018	-0.047	29.87%
Board	(0.01)***	(1.44)	(-3.14)***	(0.01)***
Panel E: American Association of Individual Investors Sentiment (*n*=93 quarters)				
AAII sentiment	19.33%	0.001	0.005	-12.30%
	(0.07)*	(0.07)	(0.26)	(0.24)
Panel F: Venture Capital Flows (*n*=63 quarters)				
Venture capital	36.58%	0.015	-0.035	37.64%
	(0.01)***	(0.75)	(-1.37)	(0.01)***
#Venture deals	40.50%	0.013	-0.034	39.37%
	(0.01)***	(0.63)	(-1.31)	(0.01)***
Panel G: Economic Indicators (sample sizes in first column)				
National activity	26.15%	0.037	-0.045	28.46%
(*n*=123 quarters)	(0.01)***	(3.28)***	(-3.00)***	(0.01)***
Econ. stress(*-1)	34.38%	0.041	-0.028	20.42%
(*n*=68 quarters)	(0.01)***	(2.11)***	(-1.18)	(0.10)*

Table V
Sentiment Trading for Managers Sorted by Client Types

Using annual *Pensions & Investments* (*P&I*) surveys, we partition a subsample of 13(f) institutions, each quarter, into three groups by their fraction of assets under management for institutional (versus retail) clients. Panel A reports the time-series mean fraction of assets managed for institutional clients (first row) and time-series mean fraction of the subsample *P&I*/13(f) institutions' aggregate portfolio accounted for by managers within each group (second row). The first column of Panel B reports the correlation between time-series variation in changes in *P&I* institutions' attraction to volatile stocks (i.e., the cross-sectional correlation between volatility and changes in the fraction of shares held by *P&I* institutions in aggregate) and changes in each of 17 sentiment proxies (and associated *p*-values) whose details are provided in the text and Internet Appendix. The second and third columns in Panel B report the abnormal contribution to sentiment trading by managers with an institutional client focus and managers with a retail client focus. The last column reports the difference in abnormal contributions to *P&I* sentiment trading (and associated *t*-statistics) between managers with an institutional client focus and managers with a retail client focus. The abnormal contribution for each manager type-quarter is defined as their actual contribution that quarter less the product of their beginning of quarter weight in the aggregate *P&I* portfolio and that quarter's contribution to the aggregate *P&I* sentiment trading (under the null that client base is independent of contribution to sentiment trading). Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **. and *, respectively.

Table V (continued)
Sentiment Trading for Managers Sorted by Client Types

Panel A: Averages across Managers with Institutional versus Retail Client Focus

	All *P&I*	Managers with Focus on Inst. Clients	Managers with Mixed Clientele	Managers with Focus on Retail Clients
%AUM Inst. clients	1.000	0.974	0.700	0.302
%Agg. *P&I* port.	1.000	0.256	0.336	0.408

Panel B: Do Institutional Client Focused Managers Disproportionally Contribute to Sentiment Trading?

Sentiment Metric	All *P&I* Sentiment Trading (*p*-value)	Abnormal Contribution to *P&I* Institutions' Sentiment Trading by:		[Abnormal Cont. Inst. Focused] - [Abnormal Cont. Retail Focused] (*t*-statistic)
		Managers with Focus on Inst. Clients	Managers with focus on Retail Clients	
Sentiment$^{\perp}$	0.294	0.034	-0.067	0.101
(*n*=123 quarters)	(0.01)***			(2.25)**
CEF discount(*-1)	-0.038	0.018	-0.011	0.029
(*n*=123 quarters)	(0.68)			(0.58)
Turnover	-0.065	0.025	-0.023	-0.048
(*n*=123 quarters)	(0.48)			(-0.91)
Number IPOs	0.389	0.023	-0.099	0.122
(*n*=123 quarters)	(0.01)***			(3.09)***
IPO return	0.112	0.040	-0.076	0.117
(*n*=123 quarters)	(0.39)			(2.46)**
Equity share	0.275	0.037	-0.050	0.087
(*n*=123 quarters)	(0.01)***			(1.56)
Div. prem.(*-1)	0.381	0.029	-0.059	0.088
(*n*=123 quarters)	(0.01)***			(1.93)*
MF gen. demand	-0.006	0.010	-0.032	0.042
(*n*=106 quarters)	(0.96)			(1.17)
MF spec. demand	0.141	-0.033	0.007	-0.040
(*n*=106 quarters)	(0.15)			(-1.24)
MF net exch. eq.	0.025	0.027	-0.027	0.053
(*n*=106 quarters)	(0.81)			(1.45)
Michigan	0.196	0.026	-0.042	0.068
(*n*=123 quarters)	(0.04)**			(1.50)
Conference Board	0.290	0.054	-0.042	0.096
(*n*=123 quarters)	(0.0 1)***			(2.06)**
AAII sentiment	-0.129	0.008	0.002	0.007
(*n*=93 quarters)	(0.22)			(0.13)
Venture capital	0.389	0.092	-0.040	0.132
(*n*=63 quarters)	(0.01)***			(2.96)***
#Venture deals	0.430	0.088	-0.011	0.099
(*n*=63 quarters)	(0.01)***			(2.18)**
National activity	0.296	0.042	-0.095	0.137
(*n*=123 quarters)	(0.01)***			(2.62)***
Econ. stress(*-1)	0.133	0.092	-0.081	0.173
(*n*=68 quarters)	(0.29)			(2.37)**

Table VI
Demand Attributed to Investor Flows, Managers' Decisions, and Reinvested Dividends for Volatile Stocks and Changes in Sentiment

Each quarter (between June 1980 and December 2010, *n*=123 quarters) we compute the cross-sectional correlations between security return volatility and demand shocks by all 13(f) institutions. Volatility is based on returns over the previous 12 months. The first column in Panel A reports the correlation (and associated *p*-value) between time-series variation in changes in institutional investors' attraction to volatile stocks and changes in orthogonalized investor sentiment (and is identical to Panel B of Table II). We then decompose the correlation into the portion attributed to demand shocks from investor flows, managers' decisions, and reinvested dividends. Thus, the sum of the last three columns equals the first column. For the last three columns, *p*-values are generated from a bootstrap procedure with 10,000 iterations (see Internet Appendix for details). Panel B repeats the analysis when aggregate institutional demand shocks are limited to 13(f) entry and exit trades. Panel C reports the estimates based on the Thomson Financial/CRSP merged mutual fund data where flows are estimated at the fund (rather than the institution) level. Panel D repeats the analysis when demand shocks are limited to Thomson Financial/CRSP mutual funds' entry and exit trades.

	$\rho\left[\rho_t\left(\Delta X_{i,t},\sigma_{i,t}\right),\Delta Sent_t^{\perp}\right]$ (*p*-value)	Contribution to $\rho\left[\rho_t\left(\Delta X_{i,t},\sigma_{i,t}\right),\Delta Sent_t^{\perp}\right]$ due to:		
		Flows (*p*-value)	Managers' decisions (*p*-value)	Reinvested dividends (*p*-value)
Panel A: All 13(f) Institutions				
All 13(f) institutions	37.27% (0.01)	0.86% (0.37)	36.15% (0.01)	0.26% (0.45)
Panel B: All 13(f) Institutions – Demand due to Entry and Exit Trades Only				
13(f) entry/exit trades	48.58% (0.01)			
Panel C: CRSP/TFN Mutual Fund Data				
Δ CRSP/TFN mutual funds	35.67% (0.01)	15.36% (0.01)	19.64% (0.01)	0.67% (0.77)
Panel D: CRSP/TFN Mutual Fund Data – Demand due to Entry and Exit Trades Only				
Δ CRSP/TFN MF entry/exit trades	42.81% (0.01)			

Table VII
Explaining Aggregate Institutional Demand Shocks

The first column reports coefficient estimates from a panel regression of the fraction of outstanding shares moving from individual investors to institutional investors for each stock-quarter on stock volatility (measured over the previous 12 months), stock volatility times an indicator for extreme up sentiment quarters, and stock volatility times an indicator for extreme down sentiment quarters. The second column repeats the analysis but adds expected flow-induced demand from institutions experiencing inflows and institutions experiencing outflows. The third column adds the following regressors: the fraction of outstanding shares moving from individual investors to institutional investors in quarter *t*-1, quarter *t*-1 (months -1 to -3) stock return, the aggregate institutional market-adjusted weight in the security at the beginning of quarter *t*, and expected change in the market-adjusted weight in the stock at the end of quarter *t* if institutions did not trade. Variables are standardized each quarter and standard errors are clustered at the stock level.

	(1)	(2)	(3)
Stock volatility	0.021	0.016	0.005
	(10.82)***	(7.81)***	(2.46)**
Stock volatility*up sent. indicator	0.072	0.071	0.054
	(18.79)***	(18.62)***	(14.56)***
Stock volatility*down sent. indicator	-0.052	-0.050	-0.031
	(-13.78)***	(-13.23)***	(-8.41)***
E(inflow-induced demand)		0.054	0.044
		(26.11)***	(21.28)***
E(outflow-induced demand)		0.121	0.124
		(42.87)***	(43.05)***
$\Delta\text{Inst.}_{t-1}$			0.081
			(31.37)***
Return_{t-1}			0.127
			(66.42)***
Agg. institutional active $\text{weight}_{t=0}$			-0.021
			(-11.09)***
E(Δinstitutional active weight_t)			-0.067
			(-19.82)***
Number of observations	478,922	478,922	478,922
Number of clusters	14,798	14,798	14,798
R^2	0.21%	1.52%	4.67%

Table VIII
Explaining Sentiment Trading across Institutions

We estimate a panel regression of the extent that an institution shifts its own portfolio toward risky stocks in the quarter (measured as the sum across the institution's holdings of the product of stock volatility and changes in the manager's portfolio weight due to trading over quarter *t*) on the extent that a manager tilts the portfolio toward volatile stocks at the beginning of the quarter, indicators for transient and non-transient institutions, each manager's quarter *t*-1 flow (scaled by portfolio value at the beginning of quarter *t*-1) and each manager's size (log of portfolio equity value) at the beginning of quarter *t*. All variables (except transient/non-transient dummy variables) are measured relative to managers of the same type by computing the difference between the value for the manager and the median value for other same type managers in the same quarter. The last two columns are the variables interacted with an indicator for the quintile of extreme up sentiment trading quarters and extreme down sentiment trading quarters. All variables (except transient/non-transient dummies) are standardized each quarter. Standard errors are clustered at the manager level. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **. and *, respectively.

		Interacted with up sentiment indicator	Interacted with down sentiment indicator
Manager high σ tilt	-0.117	0.014	-0.009
	(-17.70)***	(1.53)	(-0.86)
Transient dummy	0.059	0.035	-0.116
	(6.81)***	(2.14)**	(-6.22)***
Non-trans. dummy	-0.026	-0.013	0.049
	(-5.96)***	(-1.99)**	(7.11)***
Lag flows	0.014	0.005	0.001
	(2.77)***	(0.49)	(0.12)
Manager size	0.005	0.004	0.001
	(1.45)	(0.61)	(0.14)
Number of obs.	147,420		
Number of clusters	4,819		
R^2	1.43%		