Who are the sentiment traders?

Evidence from the cross-section of stock returns and demand

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ABSTRACT

Recent work suggests that sentiment traders shift from less volatile to speculative stocks when sentiment increases. Given that the market clearing condition requires a buyer for every seller, we exploit these cross-sectional patterns and changes in share ownership to test whether investor sentiment metrics capture individual investors' demand shocks. In contrast to theoretical assumptions and common perceptions, we find no evidence that individual investors' trading is responsible for sentiment induced demand shocks and mispricing. Our results suggest that either these metrics do not capture "investor sentiment" or that institutional, rather than individual, investors are the sentiment traders whose demand shocks drive prices from value.

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*"There is simply no reason to believe that institutional investors are less subject to
social influences on opinion than other investors, and there are substantial grounds
for thinking that they may be even more so."* (Friedman, 1984)

A burgeoning theoretical and empirical literature posits that demand shocks by uninformed

"sentiment traders" impact security prices, which has important implications for both asset pricing

and corporate finance.[1] This research commonly assumes irrational individual investors are the

source of sentiment-based demand shocks captured by sentiment metrics.[2] In this paper, we

examine this assumption by building upon the recent insight that investor sentiment has both cross-

sectional and time-series implications. Specifically, Baker and Wurgler (henceforth, BW) (2006,

2007) propose that securities with "highly subjective valuations" are more susceptible to the vagaries

of sentiment. Consistent with their hypothesis, high volatility stocks display a strong positive relation

between the BW metric for changes in investor sentiment and contemporaneous stock returns while

low volatility stock returns move inversely with contemporaneous changes in sentiment.[3] That is,

"sentiment betas" are positive for speculative stocks and negative for safe stocks. The authors also

find speculative stocks tend to underperform safe stocks following high sentiment levels, but

outperform safe stocks following low sentiment levels. They conclude that the combined results are

consistent with the hypothesis that sentiment traders' demand shocks impact prices and result in

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[1] See, for example, the recent (May 2012) special issue of the *Journal of Financial Economics* devoted to investor sentiment.
[2] See, for example, Shiller (2000), De Long, Shleifer, Summers, and Waldmann (1990a,1990b), Lee, Shleifer, and Thaler (1991), Nagel (2005), Barberis and Xiong (2012), and Stambaugh, Yu, and Yuan (2012a). Moreover, Baker and Wurgler (2007, p. 136) note, "The inexperienced retail or individual investor is more likely than the professional to be subject to sentiment." A few early theoretical models, however, suggest institutional investors may engage in noise trading because clients cannot fully distinguish noise trading from informed trading (e.g., Allen and Gorton (1993), Dow and Gorton (1997), and Trueman (1988)). The introductory quote (Friedman (1984)) is the sole exception we are aware of that posits institutional investors are more susceptible to sentiment than individual investors.
[3] BW (2006, 2007) propose that greater limits to arbitrage for speculative stocks (relative to safe stocks) also contributes to speculative stocks' larger sentiment betas. We discuss this point in greater detail below.

pushing speculative stocks' valuations too high relative to the valuations of safe stocks when sentiment is high (and too low when sentiment is low).

The investor sentiment hypothesis is a demand shock story—it requires *changes* in demand (i.e., in the words of BW (2007, p. 131), "sentiment-based demand shocks") and finite demand and supply elasticities.[4] That is, demand shocks imply net buying or selling by sentiment traders which results in *changes* in their ownership levels. Moreover, because the market clearing condition requires a buyer for every seller, sentiment traders' net demand shocks must be offset by supply from traders who are less subject to changes in sentiment. For ease of exposition, we denote these latter traders as "liquidity" traders. Of course, at least some of the liquidity traders' supply may be motivated by fundamental trading, e.g., selling overvalued speculative stocks to sentiment traders when sentiment increases.

It is these two insights from the sentiment literature—speculative stocks are more susceptible than safe stocks to the vagaries of sentiment and sentiment traders' demand shocks must be offset by liquidity traders' supply—that drive our primary hypothesis—*changes* in sentiment will be positively related to *changes* in sentiment traders' demand for speculative stocks (and inversely related to their demand shocks for safe stocks). An increase in sentiment, for example, causes sentiment traders to *purchase* risky stocks and *sell* safe stocks (i.e., their buying and selling—their demand shocks—are the drivers of the mispricing in the sentiment literature).

Despite the near universal assumption that, as a group, individual investors are more prone to sentiment induced frenzies while institutions are smart-money rational investors, we demonstrate that an increase in sentiment is associated with an increase in aggregate institutional demand for speculative stocks and a decrease in their aggregate demand for safe stocks. Equivalently, individual

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[4] In most sentiment models, market frictions (e.g., short sale restrictions, transaction costs, capital constraints, or noise trader risk) keep rational speculators from immediately correcting mispricing (see, for example, Miller (1977), DeLong, Shleifer, Summers, and Waldmann (1990a), and Shleifer and Vishney (1997)).

investors (as a group) buy safe stocks and sell risky stocks when sentiment increases. Thus, our key result suggests that either these metrics do not capture investor sentiment or that institutional investors (in aggregate), rather than individual investors, are the sentiment traders that drive sentiment induced mispricing.

Although we primarily focus on institutional and individual investors' demand shocks, we also investigate the relation between sentiment *levels* and institutional and individual investors' ownership *levels* of speculative and safe stocks.[5] Further inconsistent with the hypothesis that sentiment metrics capture irrational individual investor demand, institutional investors' ownership *levels* (i.e., the fraction of shares held by institutions) of speculative stocks (relative to their ownership levels of safe stocks) are higher when sentiment levels are higher. Equivalently, high sentiment levels are associated with (relatively) lower individual investor ownership levels of speculative stocks.

We conduct a number of robustness tests that continue to support the hypothesis that sentiment metrics capture innovations in institutional, rather than individual investors' (direct), demand. First, although we focus on the BW sentiment metric because it is the dominant measure in recent research on sentiment (e.g., Antoniou, Doukas, and Subrahmanyam (2013), Rosch, Subrahmanyam, and van Dijk (2013), Moskowitz, Ooi, and Pedersen (2012), Karolyi, Lee, and van Dijk (2012), Ramadorai (2012), Hribar and McInnis (2012), McLean and Zhao (2012), Novy-Marx (2012), and Stambaugh, Yu, and Yuan (2012a, 2012b), Baker, Wurgler, and Yuan (2012), and Yu and Yuan (2011)), we find similar results using consumer confidence measures as an alternative proxy for sentiment (see, for instance, Fisher and Statman (2003), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), and Schmeling (2009)).

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[5] We focus on institutional and individual investors' demand shocks and changes in sentiment, because both institutional investors' ownership levels and sentiment levels are highly persistent which can lead to problems in inference (see Yule (1926), Granger and Newbold (1974), Ferson, Sarkissian, and Simin (2003), and Novy-Marx (2012)). Our tests based on changes in sentiment (and changes in institutional/individual investor ownership) largely avoid this issue.

Second, one of the components of the BW sentiment measure—the dividend premium—is computed from the cross-section of securities. That is, BW (2004, 2006, 2007) posit a rise in sentiment causes sentiment traders to increase their demand for speculative non-dividend paying stocks and decrease their demand for safe dividend paying stocks, resulting in a decline in the dividend premium. Further inconsistent with the hypothesis that these metrics capture sentiment trading by irrational individual investors, changes in the dividend premium are negatively related to individual investors' demand shocks. That is, the dividend premium increases when institutions buy dividend paying stocks from individual investors and sell non-dividend paying stocks to individual investors.

Although the primary focus of our study is identifying whose demand shocks sentiment metrics capture, our empirical results naturally bring up another question—why do investor sentiment metrics capture institutional, rather than individual, investor demand shocks? In the second part of the paper, working *under the assumption* that the BW metric does indeed capture investor sentiment, we run four additional tests to better understand the underlying mechanisms that may drive the relation between sentiment innovations and aggregate institutional demand shocks.[6]

First, we evaluate the relation between sentiment and institutional demand shocks by institutional type (hedge funds, mutual funds, independent investment advisors, and other institutions) to examine two fundamental hypotheses regarding institutions trading on sentiment: (1) institutions trade on sentiment in an attempt to ride bubbles in asset prices, and (2) institutions trade on sentiment due to their reputational concerns. Specifically, following previous work, we hypothesize that hedge funds are the most likely institutional type to attempt to ride bubbles and mutual funds and independent advisors should be the institutions most concerned with reputation. Inconsistent with the bubble riding explanation, we find no evidence that the relation between time-

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[6] An alternative interpretation is that sentiment metrics do not capture investor sentiment. We discuss this possibility in the last section.

series variation in hedge funds' attraction to speculative stocks and changes in sentiment is stronger for hedge funds than other institutions. In contrast, consistent with the hypothesis that reputational concerns play a role in driving institutional sentiment trading, changes in sentiment are strongly related to time-series variations in mutual funds' and independent advisors' demand shocks for risky securities.

Second, we examine the possibility that underlying investor flows—both underlying individual investor flows and/or underlying institutional client flows—drive the relation between institutions and sentiment.[7] Partitioning 13(f) institutional investors' trades into managers' decisions and flow-induced trades, we find the relation between time-series variation in institutional demand shocks for risky stocks and changes in sentiment is primarily driven by managers' decisions. In contrast, we find no evidence that investor flows to and from 13(f) institutions can explain their sentiment trading. Further consistent with the hypothesis that managers' decision primarily drive institutional sentiment trading, we demonstrate that 13(f) institutions' entry and exit trades (which, by definition, are due to manager decisions), are also strongly related to changes in sentiment.

We further investigate the role of investor flows by using the Thomson Financial/CRSP mutual fund data to examine the relation between changes in sentiment and mutual fund demand shocks for riskier stocks. Consistent with the tests using the 13(f) data, we document a strong positive relation between time-series variation in aggregate mutual fund demand shocks for risky stocks and changes in sentiment. We find that although mutual fund managers' decisions account for the majority of the relation between mutual fund demand shocks and changes in sentiment, flows to mutual funds account for an estimated approximately 40% of the relation (marginally statistically significant at the

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[7] A large literature finds the mutual fund investors chase mutual fund returns, but the relation is not symmetric—good performance yields strong inflows, while bad performance yields minimal outflows (e.g., Ippolito (1992), Goetzmann and Peles (1997), Sirri and Tufano (1998)). Similarly, a number of studies (e.g., Del Guercio and Tkac (2002), Heisler, Knittel, Neumann, and Stewart (2009), and Goyal and Wahal (2008)) find that the underlying pension plan sponsors also chase returns.

10% level). Nonetheless, overall, our evidence suggests that managers' decisions, rather than investor flows, plays the key role in driving institutional sentiment trading.

Third, given sentiment is "systematic," we expect that most institutions will engage in sentiment trading if changes in sentiment influence their trading. Nonetheless, given every sentiment induced trade must be offset by a trader less subject to sentiment, and estimates suggest that institutional investors have long accounted for 70-96% of trading volume (e.g., Schwartz and Shapiro (1992), Jones and Lipson (2005)), it is likely that some institutions trade with sentiment while other institutions provide much of the necessary liquidity to offset their demand, even if institutions, in aggregate, trade with sentiment. To examine this issue, we partition institutions into those that positively contribute to our measure of aggregate institutional sentiment trading and those that provide liquidity to sentiment traders (i.e., contribute negatively to our measure of aggregate institutional sentiment trading). Consistent with our hypothesis, we find that although most (57%) institutions are classified as sentiment traders, 43% are classified as liquidity traders. Thus, although most institutions (and institutions in aggregate) trade on sentiment, the practice is far from universal.

Fourth, theory suggests that sentiment traders trade excessively. Thus, if the relation between institutional demand shocks and sentiment results from institutions trading on sentiment, we expect that those institutions most subject to sentiment will exhibit higher turnover than other institutions. Consistent with theory, those institutions who contribute most strongly to our measure of aggregate institutional sentiment trading average higher turnover than the institutions that most offset sentiment trading (or more passive managers).

In sum, our results reveal that either these metrics do not capture investor sentiment or that institutional investors (in aggregate), rather than individual investors, are the sentiment traders that drive sentiment induced mispricing. Moreover, although intramanager flows may play some role in driving institutional sentiment trading, institutional investors' decisions play the primary role.

1. Data

A. *Investor sentiment*

BW compute "investor sentiment" as the first principal component of six common sentiment proxies—closed-end fund discounts, NYSE share turnover, the number of IPOs, the average first day return for IPOs, the share of equity issues in total debt and equity issues, and the difference between the average market-to-book ratios for dividend payers and nonpayers (the "dividend premium").[8] BW define a second proxy, termed orthogonalized sentiment, which is computed as the first principal component of the residuals from regressions of each of the six sentiment proxies on a set of variables related to business cycles: growth in industrial production, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions.

Analogously, the authors measure the change (both raw and orthogonalized) in investor sentiment as the first principal component of changes in the six proxies (rather than changes in the sentiment level index).[9] As a result, the BW "change in sentiment" measure is not equal to the changes in their "sentiment levels" index.[10] 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 (both raw and orthogonalized) metric over the quarter.[11]

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[8] See BW (2006) for a detailed discussion of the six individual sentiment proxies.

[9] See BW (2007) footnote 6 for additional detail. The authors point out that different proxies have different levels of noisiness when moving from levels to changes. A proxy, for instance, may have low error in its levels data (and therefore an important role in the sentiment levels index), but higher error in its changes (and therefore a less important role in the sentiment change index).

[10] In addition, BW (2006, 2007) allow both lag and contemporaneous values (depending on which works better) of the six sentiment proxies in forming the principal component for sentiment levels. BW's changes in sentiment metric, however, is based only on contemporaneous values.

[11] In untabluated analysis, we repeat our primary tests based on quarterly (raw and orthongalized) changes in sentiment computed from the first principal component of the quarterly changes in the six underlying series. Our conclusions remain unchanged.

B. Stock, institutional ownership, and mutual fund data

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

We use institutional investors' quarterly 13(f) reports to measure institutional and individual investors' aggregate demand for each stock-quarter between 1980 and 2010.[13] For each security-quarter, we measure institutional ownership levels as the fraction of outstanding shares held by institutional investors and the institutional demand shock as the change in the fraction of shares held by institutional investors over the quarter.[14] Following previous work (e.g., Nofsinger and Sias (1999), Gompers and Metrick (2001), Cohen, Gompers, and Vuolteenaho (2002), Gibson, Safieddine, and Sonti (2004), San (2010), Choi and Sias (2012)), the negative of institutional demand shocks proxies for individual investors' demand shocks. If, for example, IBM's aggregate 13(f) institutional ownership moves from 60% to 65%, then the institutional demand shock is 5% and the individual investor demand shock is -5%.

The 13(f) data are, however, only a proxy for institutional investor ownership levels as small institutions (e.g., less than $100 million in 13(f) securities) and small positions (less than $200,000 and 10,000 shares) are excluded. Moreover, a few institutions are sometimes able to file confidential reports with the SEC (that do not show up in the Thomson Reuters/WRDs 13(f) data).[15]

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[12] In Appendix A, 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] Since 1980, regulation requires those investors with more than $100 million under management (in 13(f) securities) to disclose their end-of-calendar quarter positions (greater than $200,000 or 10,000 shares) within 45 days of quarter-end.
[14] Following Yan and Zhang (2009) we exclude observations where reported institutional ownership exceeds 100% of shares outstanding (about 1% of observations).
[15] This is a relatively small group. Agarwal, Jiang, Tang, and Yang (2013) report that there are only 3.37 confidential reports per 100 13(f) reports. Moreover, these confidential reports account for less than 14% of the reporting institution's positions.

We use two sources for the 13(f) manager classification data. First, we use the "Type" classifications maintained by Brian Bushee to identify mutual funds (Type=3) and independent investment advisors (Type=4).[16] Second, our sample of hedge funds is based on a proprietary Thomson Financial dataset that identifies all hedge fund companies filing 13(f) reports (see Reca, Sias, and Turtle (2013) for details regarding this data). All remaining institutions (e.g., banks, insurance companies, foundations, internally managed pension funds, etc.) are classified as "others."

We merge (using WRDs MFlinks) Thomson Financial N-30D and CRSP mutual fund data to form the mutual fund sample. Our sample construction follows Griffin, Harris, Shu, and Topaloglu (2011) and Ben-David, Franzoni, and Moussawi (2012). Appendix B provides details of the mutual fund sample construction. Analogous to institutional demand shocks, we define the aggregate mutual fund demand shock for security i in quarter t as the change in the fraction security i's shares held by mutual funds over quarter t.

We require securities to have at least five 13(f) institutional owners at the beginning or end of the quarter to ensure an adequate proxy for institutional/individual investor demand levels and shocks.[17] The number of securities in our sample averages 3,953 stocks each quarter (ranging from 1,711 to 5,537) between June 1980 and December 2010 (n=123 quarters). Table 1 reports the time-series average of the cross-sectional descriptive statistics for our sample. The median firm has 34% of its shares held by institutional investors and 32 institutions trading its stock during the quarter. 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

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[16] The type codes from the Thomson Financial 13(f) data available on WRDs are not reliable after 1998. Brian Bushee has taken "reliable" pre-1998 codes and carried them forward. In addition, he hand-classifies managers that enter the database after 1998. Professor Bushee's institutional classification data are available on his website: http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html.

[17] As noted above, institutions are not required to report holdings less than 10,000 shares and $200,000. As a result, we cannot be certain that 13(f) data adequately proxies for institutional ownership levels/demand for stocks with very low levels of institutional ownership.

"institutional demand shock" as the raw change in institutional ownership for firm i in quarter t less the mean change in the fraction of shares held by institutions across all stocks in quarter t.[18]

[Insert Table 1 about here]

2. Empirical results

We begin by confirming the BW (2007) findings (based on monthly data from 1966-2005) that: (1) high volatility stocks exhibit larger "sentiment betas" than low volatility stocks, and (2) high volatility stocks tend to underperform (outperform) low volatility stocks following high (low) sentiment levels, holds for our quarterly data from 1980-2010.[19] Specifically, we form volatility deciles (based on NYSE breakpoints) at the beginning of each quarter and compute the equal-weighted return for securities within each volatility decile portfolio. We then estimate time-series regressions of quarterly portfolio returns on the value-weighted market portfolio and the (raw or orthongalized) quarterly sentiment change index. Consistent with BW (2007), the results (detailed in Appendix A) suggest that an increase in sentiment causes sentiment traders to sell safe stocks and buy risky stocks and these sentiment induced demand shocks impact prices, i.e., high volatility stocks have positive sentiment betas, low volatility stocks have negative sentiment betas, and the difference in sentiment betas is statistically meaningful.[20]

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[18] Because the same constant is subtracted from all firms (within a quarter), statistics computed from differences (e.g., the mean change for high volatility stocks less the mean change for low volatility stocks) are not impacted. Similarly, cross-sectional correlations (e.g., Table 5) are not impacted by this de-meaning.

[19] Because the 13f data is only available beginning in December 1979, we cannot include the earlier BW sample years in our sample.

[20] As noted in footnote 3, BW (2006, 2007) point out that speculative stocks also have greater sensitivity to changes in sentiment because they are hard to arbitrage. One could propose, therefore, that low volatility stocks may experience larger shifts in ownership by sentiment traders (but smaller associated return shocks) than high volatility stocks. For instance, assuming both low and high volatility stock had positive sentiment betas, an increase in sentiment could theoretically cause sentiment traders to purchase more shares of low volatility stocks (because liquidity traders may provide many shares in these "easy to arbitrage" stocks) than high volatility stocks. However, BW (2007) demonstrate (and we confirm) that low volatility stocks have negative sentiment betas and high volatility stocks have positive sentiment betas. As a result (assuming, as the sentiment literature proposes, these return patterns are driven by demand shocks induced by changes in sentiment), an increase in sentiment is associated with sentiment traders buying high volatility stocks from liquidity traders and selling low volatility stocks to liquidity traders. That is, the different signs on

As further detailed in Appendix A, we also confirm that sentiment levels are inversely related to the subsequent return difference for high and low volatility stocks, e.g., high volatility stocks underperform low volatility stocks following high sentiment levels. In sum, although based on a different sample period and periodicity, our results are fully consistent with BW and Baker, Wurgler, and Yuan (2012).

A. Changes in sentiment and institutional/individual investor demand shocks

We begin our examination of the relation between changes in sentiment and institutional/ individual investor demand shocks by computing the cross-sectional mean institutional demand shock (i.e., the change in the fraction of shares held by institutions for stock i less the mean change across all stocks in quarter t) for securities within each volatility decile. We then calculate the time-series correlation between changes in sentiment and the contemporaneous quarterly cross-sectional average institutional demand shocks (or, equivalently, individual investors' supply shocks) for each volatility portfolio.[21]

The results, reported in Table 2, reveal the pattern in institutional investor demand shocks matches the pattern in contemporaneous returns. 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 orthogonal sentiment is 31.8%) and sell low volatility stocks to individual investors (i.e., the correlation between time-series variation in institutional demand shocks for low volatility stocks and changes in orthogonal sentiment is -29.1%). As shown in the last column of Table 2, the correlations between the difference in

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the high and low volatility portfolios' sentiment betas are inconsistent with the explanation that differences in arbitrage costs account for the relations between institutional investors' demand shocks and changes in sentiment for low and high volatility stocks.

[21] We recognize that other factors may influence institutional or individual investors' demand shocks. Because our goal is to determine whose demand shocks are captured by these sentiment metrics (e.g., who are buying high volatility stocks when sentiment increases regardless of whether other factors influence those decisions), we purposely do not control for other factors.

institutional demand shocks for high and low volatility stocks and changes in sentiment is positive (and statistically significant at the 1% level using either raw or orthogonal sentiment).

[Insert Table 2]

In sum, institutional investors buy volatile stocks from, and sell safe stocks to, individual investors when sentiment increases. That is, institutional demand shocks move with, and individual investors' demand shocks move counter to, changes in sentiment for high volatility stocks. Further, just like returns, the relation is reversed for low volatility stocks. The results are inconsistent with the hypothesis that the BW metric captures individual investors' demand shocks. Rather, if the BW metric captures investor sentiment, then institutions, rather than individual investors, are the sentiment traders.

B. *Sentiment levels and institutional/individual investor ownership levels*

If sentiment metrics capture the demand of institutional rather than individual investors, 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.[22] Because institutional ownership grow substantially throughout this period (see, for example, Blume and Keim (2011)), we detrend institutional ownership levels (by regressing mean institutional ownership levels for each volatility portfolio on time) and compute the mean (detrended) institutional ownership level (i.e., the fraction of shares held by institutions) across stocks within each volatility decile at the beginning of each quarter.[23] We then partition the sample into low (below median) and high beginning of quarter sentiment level periods and compute the time-series mean of the cross-sectional average detrended

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[22] In a working paper we were not aware of when beginning our study, Cornell, Landsman, and Stubben (2011) examine *changes* in institutional ownership (i.e., institutional demand shocks) following high sentiment *levels* and find that institutional investors tend to buy speculative stocks and sell safe stocks following high sentiment levels. Although both studies examine institutional ownership and sentiment, we differ both empirically and theoretically. Appendix C provides a full discussion and additional tests.

[23] In Appendix A, we repeat these tests without detrending institutional ownership levels and find similar results.

institutional ownership levels for stocks within each volatility decile during high and low sentiment periods.

Panels A and B in Table 3 report the mean detrended ownership level within each volatility portfolio during high and low sentiment and orthogonal sentiment periods, respectively. Because the average detrended ownership level is zero by definition (i.e., it is a regression residual), the mean value across high and low sentiment periods (for each volatility portfolio) is zero.[24] The results reveal that detrended institutional ownership levels for high volatility stocks relative to their ownership levels for low volatility stocks (i.e., last column) are greater when sentiment is high using either raw or orthogonalized sentiment levels (statistically significant at the 1% level). In sum, the levels analysis (Table 3) is consistent with the demand shock analysis (Table 2). Both tests indicate that if the BW metric captures investor sentiment, then institutions, rather than individual investors, are the sentiment traders.

[Insert Table 3 about here]

C. An alternative test—Time-series variation in institutional demand for volatile stocks and sentiment

Although the above tests reveal no evidence that individual investors' demand shocks are encapsulated by sentiment metrics, these tests focus on time-series variation in cross-sectional averages in the extreme volatility deciles. To broaden our results, we construct an alternative test that uses all securities. We begin by computing the cross-sectional correlation (across all securities in our sample), each quarter, between institutional demand shocks and securities' return volatility (measured over the previous 12 months). Following BW (2006), we winsorize return volatility at the 0.5% and 99.5% levels each quarter. Panel A in Table 4 reports the time-series descriptive statistics—the cross-sectional correlation averages 2.15%. The correlation, however, varies

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[24] The sum does not add exactly to zero because there is an odd number of quarters (123). Given 61 low sentiment quarters and 62 high sentiment quarters, 61/123*(low sentiment value) + 62/123*(high sentiment value) = 0.

substantially over time—falling as low as -15.19% and rising as high as 17.99%. Thus, although, on average, institutions tend to buy volatile stocks (or, equivalently, individual investors tend to sell volatile stocks), the pattern varies substantially over time.

[Insert Table 4 about here]

Panel B in Table 4 reports the time-series correlation between changes in sentiment and variation in institutional demand shocks for risky stocks—as measured by time-series variation in the cross-sectional correlation between institutional demand shocks and return volatility (i.e., the cross-sectional correlations summarized in Panel A). That is, we test if institutional investors *increase* their preference for risky stocks (and decrease their preference for safe stocks) when sentiment *increases*. Consistent with our earlier tests, the results reveal the correlation between time-series variation in institutions' attraction to volatile stocks and changes in sentiment is 37.81% based on raw changes in sentiment and 36.69% based on orthogonalized changes in sentiment (statistically significant at the 1% level in both cases). Equivalently, the correlation between orthogonal changes in sentiment and time-series variation in individual investors' attraction to volatile stocks is -36.69%.

D. Consumer confidence, speculative stocks, and institutional/individual investor demand

Although the BW sentiment metric is the dominant measure in recent sentiment research, a number of studies have used an alternative proxy to capture investor sentiment, consumer confidence (e.g., Fisher and Statman (2003), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), Schmeling (2009)). Thus, we next examine the relation between institutional demand shocks for risky stocks and changes in consumer confidence. We focus on two measures of consumer confidence—the University of Michigan Survey of Consumer Expectations and the Conference Board Consumer Confidence Index. Both are based on monthly surveys (over our

sample period) to households asking for their views on current and future economic conditions (see Lemmon and Portniaguina for a detailed discussion of both surveys).

We begin by comparing the correlation between the consumer confidence indices and the BW index over our sample period (*n*=123 quarters). Panel A in Table 5 reports that the time-series correlation between quarterly changes-in-consumer-confidence indices and the quarterly BW change-in-sentiment measures ranges from 20% to 35% (all are statistically significant at the 5% level or better). Panel B reports the time-series correlation between quarterly consumer confidence levels and BW sentiment levels. Although all four estimates of the correlations are positive, only one (the correlation between BW raw sentiment levels and the Conference Board Consumer Confidence levels) differs meaningfully from zero at the 5% level.

[Insert Table 5 about here]

We next examine whether the sentiment-related return patterns documented by BW hold for the consumer confidence measures. We begin by testing whether "consumer confidence sentiment betas" differ for high and low volatility stocks. Specifically, we regress the equal-weighted portfolio returns for the highest and lowest volatility deciles on the contemporaneous market return and the standardized (i.e., rescaled to unit variance, zero mean) contemporaneous change in consumer confidence. The results, reported in Panel C of Table 5, reveal that high volatility stocks tend to outperform low volatility stocks when the Michigan Consumer Confidence increases (statistically significant at the 1% level). Although the difference in sentiment betas is in the forecasted direction (i.e., higher for high volatility stocks), it is not materially different from zero for changes in the Conference Board index.

Next, we test whether low volatility stocks outperform high volatility stocks following high consumer confidence periods. Panel D reports regression results of the quarterly return difference between the high and low volatility portfolio returns on beginning of quarter consumer confidence.

Consistent with the BW metric, the results reveal beginning of the quarter consumer confidence levels are inversely related to the subsequent quarterly return difference between high- and low-volatility stocks (statistically significant at the 1% level in both cases), i.e., volatile stocks tend to underperform safe stocks following high consumer confidence.

Although somewhat weaker than the BW metrics, the results in Panels A-D are largely consistent with the hypothesis that changes in consumer confidence captures changes in investor sentiment and volatile stocks exhibit great sensitivity to sentiment induced demand shocks. Thus, we next focus on understanding which investors' demand for volatile stocks moves with changes in consumer confidence. Specifically, we repeat the tests in Table 4, but examine whether time-series variation in the cross-sectional correlation between institutional investors' demand shocks and stock volatility (i.e., the figures summarized in Panel A of Table 4) covaries with changes in consumer confidence. Panel E of Table 5 reports the time-series correlations and reveals that institutions *increase* their preference for volatile stocks when consumer confidence increases (both measures are statistically significant at the 5% level or better).

In sum, although not as strong as the results using the BW metric, the results in Table 5 are consistent with the returns patterns documented by BW and the hypothesis that consumer confidence proxies for investor sentiment. We find no evidence, however, that consumer confidence captures individual investors' demand shocks. Rather, once again, the evidence points to institutional investors.

E. *Institutional demand and the dividend premium*

BW use six sentiment proxies to form their sentiment indices. One of the six proxies—the dividend premium—is computed from the cross-section of securities. Specifically, based on earlier work (BW (2004)), the authors propose that sentiment traders increase their demand for non-

dividend paying stocks relative to dividend paying stocks when sentiment increases. According to the sentiment hypothesis, these sentiment induced demand shocks result in the valuation of non-dividend paying stocks rising relative to the valuation of dividend paying stocks when sentiment increases. As a result, the dividend premium—measured as the natural logarithm of the difference in the average market-to-book ratio for dividend paying stocks and the market-to-book ratio for non-dividend paying stocks—falls when sentiment increases.

Because this measure is derived from the cross-section of securities, it leads to another direct test of whose demand shocks are captured by changes in this sentiment proxy. Specifically, if an increase in sentiment causes a decline in the dividend premium as a result of sentiment traders' demand shocks (as BW (2004, 2006, 2007) contend), then the difference between sentiment traders' demand shocks for dividend paying stocks and non-dividend paying stocks will be positively correlated with changes in the dividend premium. For instance, an increase in sentiment causes sentiment traders to sell dividend paying stocks to, and buy non-dividend paying stocks from, liquidity traders resulting in a decline in the dividend premium.

To examine this issue, we divide securities into two groups—those that paid a dividend in the previous 12 months and those that did not. Each quarter, we compute the cross-sectional average institutional demand shock for dividend payers and non-payers, as well as their difference. Following BW (2004), we exclude financials (SIC codes 6000 through 6999), utilities (SIC codes 4900 through 4949), firms with book equity less than $250,000, and firms with assets less than $500,000 from the dividend premium analysis.

We next examine whose demand shocks for dividend paying and non-dividend paying stocks are positively correlated with quarterly changes in BW's dividend premium sentiment variable (both raw and orthogonalized to growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator). Table 6 reports

the time-series correlation between the change in the dividend premium and the difference in the average institutional demand shock for dividend payers and non-payers. The results reveal a strong positive relation—the correlation is 42% and statistically significant at the 1% level. We find nearly identical results based on orthogonalized changes in the dividend premium. In sum, the dividend premium increases when institutional investors buy dividend paying stock from, and sell non-dividend paying stocks to, individual investors. The result is inconsistent with the hypothesis that individual investors' demand shocks drive changes in the dividend premium. In sum, if sentiment traders' demand shocks drive time-series variation in the dividend premium, then institutional investors, rather than individual investors, are the sentiment traders.

<div align="center">[Insert Table 6 about here]</div>

3. What drives the relation between institutions and sentiment?

A. Analysis by investor type

We next evaluate the relations between sentiment and institutions by institutional investor type—hedge funds, mutual funds, independent advisors, and other institutions—to examine two factors that may contribute to institutional sentiment trading. First, we propose (as maintained by Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011)) that hedge funds, compared to other institutional types, are the most likely institutional type to attempt to "ride bubbles." Thus, if such behavior contributes meaningfully to the relation between institutions and sentiment, we expect to document a strong relation between changes in sentiment and hedge fund demand shocks.

Although the idea of profitably riding a bubble appears, at least initially, straightforward (e.g., a smart investor buying NASDAQ at the beginning of 2000 earns a 25% gain over the next 70 days if she sells at the market peak on March 10, 2000), the market clearing condition still requires that

someone must offset these trades. That is, if both sentiment traders and rational speculators buy speculative stocks, some third group of traders must sell speculative stocks.[25] The key takeaway is that not all traders can simultaneously cause the "bubble." If individual investors' sentiment induced demand shocks drive mispricing, then as a group, institutional investors must provide the necessary liquidity even if some smart institutions attempt to ride the bubble. In other words, if individual investors' aggregate sentiment induced demand shocks drive mispricing, institutional investors (in aggregate) must sell speculative stocks to, and buy safe stocks from, individual investors (in aggregate) when sentiment increases.[26]

Second, it is possible that institutional clients' perceptions are influenced by sentiment. As a result, institutions may fear they will lose clients (or fail to gain additional clients) if they fail to trade on sentiment. Specifically, institutional investors ultimately invest on behalf of individuals. Thus, they answer to their firm's board or those who delegate portfolio management to them such as pension fund boards, foundation boards, individual investors, and their consultants responsible for selecting and retaining their services. If the perceptions of these individuals to whom institutional investors answer are influenced by sentiment, a rational institutional investor will act accordingly, or face termination and declining revenue. A number of studies formally model such "reputational" trading (e.g., Scharfstein and Stein (1990), Graham (1999), Dasgupta, Prat, and Verardo (2011a)). In

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[25] The literature takes several approaches to solving this issue. DeLong, Shleifer, Summers, and Waldmann (1990b) model three investor classes—passive investors, informed rational speculators, and positive feedback traders. The passive investors provide the liquidity to rational speculators and rational speculators are allowed to trade prior to irrational feedback traders. Alternatively, in the Abreu and Brunermeier (2003) model, rational arbitrageurs sell overvalued shares to "irrationally exuberant behavioral traders." However, a given rational manager may not sell all shares initially (even if the manager believes the shares are overvalued) because the manager has a chance to earn a higher return by attempting to sell later in the bubble (but prior to its bursting). Note that in the Abreu and Brunermeier model, rational arbitrageurs trade against sentiment (i.e., they do provide the liquidity to offset sentiment traders' demand shocks), just not as aggressively as they would in the absence of market frictions.

[26] It is theoretically possible institutional and individual investors are equally likely to be sentiment traders. Thus, individual (or institutional) investors would be equally likely to trade on sentiment as offset sentiment traders' demand and changes in institutional/individual investor ownership would be independent of changes in sentiment. Another possibility is that all investors are subject to sentiment. Under this scenario, an increase in sentiment would increase the value of a speculative stock, but would not result in trading, e.g., if the stock's initial value was $1 and the sentiment shock caused all investors to set a new reservation price of $2 the price would immediately adjust to $2 and no trading would occur since no investor would be willing to sell the stock for less than $2.

a recent letter to clients, legendary investor and GMO founder Jeremy Grantham (2012) succinctly describes the problem: "The central truth of the investment business is that investor behavior is driven by career risk…The prime directive, as Keynes knew so well, is first and last to keep your job…To prevent this calamity, professional investors pay ruthless attention to what other investors in general are doing. The great majority 'go with the flow,' either completely or partially. Missing a big move, however unjustified it may be by fundamentals, is to take a very high risk of being fired." Following previous work (e.g., Sias (2004) and Dasgupta, Prat, and Verardo (2011b)), we propose that mutual funds and independent advisors should be most concerned about reputation.

In sum, if institutions attempting to ride bubbles largely drives the relation between sentiment and institutions, we expect a strong relation between changes in sentiment and hedge fund demand shocks. Analogously, if reputational concerns primarily drive institutional sentiment trading, then the relation between changes in sentiment and demand shocks by both mutual funds and independent advisors should be especially strong.

Analogous to our aggregate analysis, for each institutional investor type, we limit the sample to securities that are held by at least five investors of that type at either the beginning or end of the quarter. For mutual funds, independent investment advisors, and other institutions, the cross-sectional sample averages 2,582 securities each quarter (ranging from 355 stocks for mutual funds in June 1980 to 4,694 stocks for others in September 1998). Because there are relatively few hedge companies in our sample at the beginning of the period, we limit the hedge fund sample to the final 90 quarters.[27]

To test how the relation between institutional demand and sentiment varies by investor type, we repeat the examination of whether time-series variation in institutional demand for volatile stocks is

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[27] Prior to September 1998, each quarter has less than 100 stocks that are held by at least five 13(f) hedge fund companies. The hedge fund sample size in the final 90 quarters averages 1,220 securities/quarter (ranging from 89 in December 1989 to 2,769 in December 2006).

related to changes in sentiment (i.e., the analysis in Table 4) for each investor type. Specifically, each quarter we compute the cross-sectional correlation between institutional demand shocks (by each type of institutional investor, as measured by the change in the fraction of shares held by that type of institution) and stock return volatility. As shown in Panel A of Table 7, all four manager types exhibit, on average, a positive relation between demand shocks and return volatility. As with aggregate institutional demand (Table 4, Panel A), however, the cross-sectional correlation varies greatly over time for each of the four manager types.

[Insert Table 7 about here]

Panel B (analogous to Panel B in Table 4) reports the key test—the correlation between changes in sentiment and time series variation in each type of managers' demand shocks for risky stocks (as captured by the cross-sectional correlations summarized in Panel A). The results reveal strong evidence that mutual funds and independent advisors increase their demand for risky stocks when sentiment increases. Specifically, the correlations for mutual funds and independent advisors range from 32% (independent advisors and orthogonal changes sentiment) to 43% (independent advisors and raw changes in sentiment). In contrast, although the point estimates are positive, the relation between time-series variation in hedge funds' or other institutions' demand shocks for volatile stocks and changes in sentiment is not statistically significant.

The lack of a meaningful relation between sentiment and time series variation in hedge funds' attraction to volatile stocks in Table 7 suggests that institutions attempting to ride bubbles is not the primary factor driving the relation between sentiment and institutional demand. The Table 7 results, however, provide some support for the hypothesis that institutions' reputational concerns contribute to institutional sentiment trading. Those investors who are arguably most concerned about reputational effects (mutual funds and independent advisors) exhibit the greatest propensity for sentiment trading.

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B. Flows, net active buying, and passive trades

Another possible scenario is that sentiment induced underlying investor flows drives aggregate institutional sentiment trading. An increase in sentiment, for instance, may cause underlying investors to shift funds from more conservative institutions to more aggressive institutions and, as a result, institutions, in aggregate, sell safe stocks and purchase risky stocks.

To explore this possibility, we follow the method in Griffin, Harris, Shu, and Topaloglu (2011) and estimate three components (details are given in Appendix B) of institutional demand shocks: trades that result from investor flows (*NBFlows*), trades that result from manager's decisions (*Net Active Buying*), and trades that result from reinvested dividends (*Passive*). Specifically, denoting the change in the fraction of security *i*'s shares held by institutions in quarter *t* as $\Delta Inst_{i,t}$:

$$\Delta Inst_{i,t} = \sum_{k=1}^{K} \Delta Inst_{i,k,t} = \sum_{k=1}^{K} NBFlows_{i,k,t} + \sum_{k=1}^{K} Net\ Active\ Buying_{i,k,t} + \sum_{k=1}^{K} Passive_{i,k,t}, \tag{1}$$

where *K* is the number of institutions trading security *i* in quarter *t*. Because covariances are linear in the arguments and aggregate institutional demand is the sum of the three components, the time-series correlation between institutions' attraction to volatile stocks (as captured by the cross-sectional correlation between institutional investors demand shocks and volatility) and changes in sentiment (i.e., the correlation reported in Panel B of Table 4) can be partitioned into three components (see Appendix B for proof)—the portion due to flow induced demand shocks, the portion due to net active buying, and the portion due to passive trades. Recognize, however, that because 13(f) data are aggregated across a given manager's portfolios (e.g., Janus files one 13(f) report for all Janus funds), our estimate of 13(f) flow induced trades are effectively intermanager flows (e.g., flows from Janus to Blackrock) rather than intramanager flows (e.g., flows from one Janus fund to a different Janus fund).

The first column of Panel A in Table 8 reports the correlation between time-series variation in institutions' demand for risky stocks and orthogonal changes in sentiment, i.e., the 36.69% figure reported in Panel B of Table 4. The last three columns in Panel A report the portion of the correlation due to investor flows (net buying flows), manager decisions (net active buying), and reinvested dividends (passive). The *p*-values reported in the last three columns are based on bootstrapped estimates with 10,000 iterations (see Appendix B for details). The results in Panel A reveal little evidence that intermanager flows play a meaningful role in driving the relation between institutional demand shocks and changes in sentiment. Rather, the results reveal that manager's decisions (i.e., net active buying) drive the relation between institutional demand shocks and sentiment accounting for 96% of the time-series correlation reported in the first column (i.e., 0.3514/0.3669).[28]

[Insert Table 8 about here]

Because our measure of 13(f) flows is based on each institutions' aggregate portfolio, it is possible that a given institution's net active buying reflects intramanager flows. Assume, for example, Janus fund "A" holds 100% of their portfolio in Apple and Janus fund "B" holds 50% of their portfolio in GM and 50% in Apple. An investor then moves $100 from Janus fund B to Janus fund A. If both managers do not change portfolio weights (i.e., manager B sells $50 of Apple and $50 of GM; manager A purchases $100 of Apple), Janus' aggregate portfolio weight for GM will decline and their aggregate weight for Apple will increase. As a result, the net active buying (computed at the 13(f) level) may reflect, at least in part, intramanager flows within an institution.

To investigate this possibility, we recalculate aggregate institutional demand shocks using only entry and exit trades. That is, institutional demand shocks computed only from those

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[28] In Appendix A, we repeat these tests by 13(f) investor type. For mutual funds and independent investment advisors (i.e., the two investor types with a meaningful correlations in the first column), the relation between time-series variation in their demand shocks for risky stocks and changes in sentiment is driven by managers' decisions (statistically significant at the 1% level in both cases) and not intermanager flows.

manager/stock/quarter observations where a manager enters a security they did not hold at the beginning of the quarter or completely liquidates a position in a security they held at the beginning of the quarter. By definition, these entry/exit trades are due to manager decisions (e.g., an entry trade cannot arise from a fund investing intramanager flows into their existing portfolio). Specifically, for each security quarter we compute the net fraction of shares purchased by institutional entry and exit trades. Next, analogous to the figures reported in Panel A of Table 4, we compute the cross-sectional correlation between aggregate institutional entry/exit demand shocks and securities' return volatility each quarter (these figures average 0.98% and range from -12.75% to 14.62%). We then calculate the time-series correlation between institutions' demand for risky stocks (as captured by their entry/exit trades) and orthogonal changes in sentiment. Panel B in Table 8 reveals the correlation is 47.89% (statistically significant at the 1% level). The results provide further evidence that managers' decisions play an important role in driving the relation between time-series variation in institutions' demand shocks for volatile stocks and changes in sentiment and are inconsistent with the hypothesis that the relation between institutions and sentiment can be fully explained by intramanager flows.

As a final test, we use the merged Thomson Financial/CRSP data and partition each mutual fund's demand into three components—flow induced demand shocks, net active buying, and passive demand (see Appendix B for details). Because we use the mutual fund data, these estimates are at the fund level and therefore capture flows between funds in the same family. Panel C in Table 8 reports the correlation between changes in sentiment and time-series variation in mutual fund demand shocks for volatile stocks (as captured by the cross-sectional correlation between mutual fund demand shocks and stock volatility) is 33.18% (statistically significant at the 1% level).[29] Thus,

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[29] For consistency, we limit the sample to stocks that are held by at least five mutual funds at the beginning and end of the quarter. The sample size averages 2,052 stocks per quarter.

consistent with our results based on 13(f) data, mutual funds buy risky stocks/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 and reveal that although manager's decisions account for the largest share of the correlation (statistically significant at the 5% level based on bootstrapped p-values), investor flows to mutual funds account for a large component of the correlation (approximately 44%=0.1445/0.3318) and is marginally statistically significant (based on bootstrapped p-values) at the 10% level. In sum, the results in Panel C suggest that intramanager mutual fund flows account for some of the relation between time-series variation in mutual funds' attraction to volatile stocks and changes in sentiment.[30]

Taken together, the "flows" evidence suggests that although managers' decisions appear to be the primary factor driving the relation between institutions and sentiment, investor flows also contribute to the relation. These flow induced demand shocks, however, are primarily within a complex, e.g., flows from one Janus fund to another Janus fund. In interpreting this evidence, it is important to reiterate that not everyone can be a sentiment trader, e.g., every sentiment induced purchase must be offset by the sale from an investor less subject to sentiment. Thus, assuming non-13(f) demand adequately proxies for individual investors' direct trading (which moves inversely with sentiment), the relation between mutual fund flows and sentiment suggests that (in aggregate) individual investors that invest via mutual funds differ from those that invest directly. One possible

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[30] To further examine the role of intramanager flows, we use the CRSP fund family identification data staring in March 1999 (the first quarter with at least 100 fund families identified that have more than one fund; CRSP begins to populate the family identifier data in December 1997) to compute the three components of mutual fund demand (flows, decisions, passive) for both individual funds and at the family level. We estimate the components at the family level as if we were unable to view the components at the fund level, i.e., analogous to the 13(f) data. The correlation between time-series variation in this sample of mutual funds' demand shocks for volatile stocks (as captured by the cross-sectional correlation between their demand shocks and volatility) is 0.424 (statistically significant at the 1% level). Using the fund-level decomposition, 25% of the correlation (0.106 of 0.424) is attributed to flows. Using the family level decomposition, 13% of the correlation (0.054 of the 0.424) is attributed to flows. Thus, the results support the hypothesis that intrafamily flows contribute to the correlation between changes in sentiment and institutional investors attraction to volatile stocks. The results also support the explanation that most of the relation between institutions and sentiment is due to mutual fund managers' decisions.

explanation is that mutual fund flows are also influenced by investment professionals. For example, the Investment Company Institute (2013) estimates that 82% of individual investors who hold mutual funds (outside of workplace retirement plans) purchased the fund with "the help of an investment professional."

C. Do most institutions trade on sentiment?

If sentiment metrics capture (at least partially) "investor sentiment" and institutions are the sentiment traders, we expect most institutions will trade on sentiment (i.e., it should be, in some sense, systematic). Nonetheless, every sentiment induced trade must be offset by an investor less subject to sentiment and recent work suggests that institutional investors account for most trading (recent estimates range from 70-96% of trading volume). As a result, it is likely that although institutions, in aggregate, appear to be the sentiment traders identified by common sentiment metrics, some institutions trade with sentiment while others provide at least some of the offsetting liquidity. Thus, in this section, we classify all institutions into two groups—sentiment traders and liquidity providers—to examine (1) the breadth of institutional sentiment trading and (2) whether some institutions help offset aggregate institutional sentiment trading.

Because covariances are linear in the arguments and aggregate institutional demand shocks are simply the sum of demand shocks across institutions (see Eq. (1)), we can decompose the aggregate correlation into the contribution by each individual institution (see Appendix B for proof).[31] Thus, we begin by computing each manager's contribution to the time-series correlation between changes in orthogonalized sentiment and the cross-sectional correlation between aggregate institutional

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[31] A manager's total contribution will depend on both their cross-sectional contribution (i.e., the extent that their demand shocks across securities relate to return volatility) and their time-series contribution (i.e., the extent that their proclivity to buy high volatility stocks varies with changes in sentiment). Because this is a decomposition of aggregate institutional demand shocks, larger managers will have larger impacts, holding everything else constant. Similarly, a manager's contribution will depend on how long they survive in the sample, e.g., a manager that exists for a few years will only contribute to the correlation in a few periods. The sign of their contribution, however, should be independent of their size and the time they are in the sample.

demand shocks and return volatility reported in Table 4 Panel B (i.e., the 36.69% figure). Those

managers that contribute positively to the correlation (i.e., those institutions that tend to buy volatile

stocks and sell safe stocks when sentiment increases) are denoted sentiment traders. Those managers

that contribute negatively to the correlation (i.e., those institutions that tend to sell volatile stocks

and buy safe stocks when sentiment increases) are denoted liquidity traders.

Table 9 reports the number of institutions in our sample (first column), the fraction of

institutions classified as sentiment traders, and the fraction of institutions classified as liquidity

traders. The last column reports a binomial z-score of the null hypothesis that the fraction of

institutions classified as sentiment traders does not differ meaningfully from 0.5. The remaining

rows repeat the analysis by manager type.

[Insert Table 9 about here]

The results in Table 9 demonstrate that although most (57%) institutions are classified as

sentiment traders, 43% of institutions are classified as liquidity traders, i.e., 43% of institutions tend

to sell volatile stocks and purchase safe stocks when sentiment increases. Although most institutions

are sentiment traders (i.e., the last column indicates the fraction that are sentiment traders is

meaningfully greater than 50%), institutional sentiment trading is far from universal. The remaining

rows reveal the same pattern for each type of institution. In every case, we can reject the null (at the

1% level) that the fraction of institutions classified as sentiment traders does not differ from 50%.

Nonetheless, there is some variation across manager types. Mutual funds exhibit the greatest

propensity for sentiment trading, followed by independent institutions. Even in the case of mutual

funds, however, approximately one-third of mutual fund companies are classified as liquidity traders.

D. Institutional sentiment trading and turnover

Baker and Stein (2004) note that high sentiment induces sentiment traders to trade. Moreover, sentiment traders may be overconfident (Daniel, Hirshleifer, and Subrahmanyam (1998)) and overconfidence leads to excessive trading (e.g. Odean (1998)). Alternatively, managers may trade excessively in an attempt to signal clients that they are informed (e.g., Trueman, (1988)). As a result, we expect sentiment traders to exhibit higher turnover than non-sentiment traders. To examine this possibility, we compute the time-series average of the each manager's turnover percentile.[32] We then partition institutions into three groups—strong sentiment traders (the top quartile of institutions that contribute the most to our aggregate correlation metric, i.e., the 36.69% correlation reported in Table 4), strong liquidity traders (bottom quartile contribution institutions), and passive institutions (institutions in the middle two quartiles). Table 10 reports the cross-sectional mean turnover percentile for each manager group. The last column reports a *t*-statistic of the null hypothesis that the mean turnover percentile for sentiment traders does not differ from that of liquidity traders.

[Insert Table 10 about here]

The results reveal that strong sentiment traders average turnover in the 58th percentile versus the 56th percentile for strong liquidity traders and the 50th percentile for passive institutions.[33] We also find (last column) a meaningful difference in the mean turnover percentiles for strong sentiment traders versus strong liquidity traders.[34] Assuming sentiment traders tend to engage in higher turnover, the results are consistent with the hypothesis that institutional investors (or at least a large subset of institutions) trade on sentiment.

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[32] We calculate turnover as the minimum of the dollar value of a managers' buys and sells normalized by the average of the managers' portfolio size at the beginning and end of the quarter.

[33] Because the values reported in Table 10 are computed from the average across institutions and institutions appear in the sample for different numbers of quarters, the mean percentile need not equal 50% (i.e., for our sample, high turnover institutions tend to appear in the sample for shorter periods).

[34] We also find (untabulated) that strong sentiment institutions average meaningfully higher turnover than passive institutions.

4. **Discussion and conclusions**

A. Discussion

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 sentiment induced individual investor demand shocks drive prices from fundamental value. If sentiment metrics capture "investor sentiment" and the return patterns documented by BW are due to sentiment induced demand shocks, then institutions, rather than individual investors, are the sentiment traders.

There are, however, several alternative interpretations. First, perhaps institutional investors are short-term momentum traders and they simply chase lag returns. For instance, when volatile stocks outperform safe stocks, institutions, in aggregate, sell safe stocks and buy volatile stocks, but their demand shocks do not impact prices. Although plausible, such an explanation is clearly inconsistent with the sentiment hypothesis because the sentiment hypothesis *requires* that demand shocks from those investors trading with changes in sentiment impact prices. That is, we cannot argue that individual investors' demand shocks drive speculative stock prices too high when sentiment increases if individual investors, in aggregate, sell speculative stocks to institutional investors when sentiment increases.

Another possibility is that non-13(f) demand does not, somehow, capture individual investor demand. As noted in our discussion of the data, positions less than 10,000 shares and $200,000 (both conditions must be met), may be excluded from 13(f) reports, institutions managing less than $100 million are not required to file 13(f) reports, and some managers are sometimes given an exemption from timely 13(f) filings. Thus, it is possible (although arguably improbable), that individual investors do trade with sentiment, but that small institutions' positions, small managers, and the few manager-quarter-stocks that receive 13(f) exemptions, trade so strongly against

sentiment, that they dominate individual investors' demand shocks. Moreover, this would not change the fact that institutions' aggregate demand (at the least the portion we can identify via 13(f) reports) moves with sentiment.

One may fairly propose that our results are not surprising given previous studies (e.g., Sias, Starks, and Titman (2006)) reveal that, on average, there is a positive cross-sectional relation between changes in the fraction of shares held by institutions and contemporaneous returns. That, however, does not change the fact that a large literature has assumed that sentiment induced individual investor demand shocks impact prices. Our results are clearly inconsistent with this assumption. If sentiment induced demand shocks drive mispricing, volatile stocks have larger sentiment betas, and the metrics we examine capture investor sentiment, then individual investors, who sell risky stocks to institutions and buy safe stocks from institutions when sentiment increases, cannot be the sentiment traders driving mispricing.

It is also possible that sentiment metrics (even when "orthogonalized") capture economic fundamentals. This explanation, however, seems hard to reconcile with negative sentiment beta for low volatility stocks (see BW (2007) and Appendix A). That is, if an increase in sentiment reflects improving economic fundamentals, all stock prices should rise (albeit they may rise more for speculative stocks). More important, under this interpretation, our main conclusion remains intact— we find no evidence that investment sentiment metrics capture individual investors' demand shocks. In short, if cross-sectional return patterns are driven by demand shocks, then sentiment metrics capture institutional investors' demand shocks.

Last, as noted in the introductory quote, Friedman (1984) argues that perhaps we should expect institutions to be more prone to sentiment. Specifically, Friedman points out four factors (some of which are related to the issues discussed in Section 3) that suggest institutions will more likely pay attention to "fads and fashions" than individual investors. First, at least relative to individual

investors, institutional investors are a close-knit community with (p. 508) "constant communication and mutual exposure." Second, institutional investors' performance is typically judged relative to other institutions rather than in absolutes. Third, institutions suffer from asymmetry of incentives—the potential rewards for overperformance may not be worth the cost if wrong. Finally, if sentiment does impact prices, smart managers would pay attention to sentiment.

B. *Summary*

A burgeoning literature focuses on the role of investor sentiment in driving asset prices. This work nearly uniformly assumes that individual investors' aggregate sentiment induced demand shocks drive mispricing. Recent work reveals (and we confirm) that speculative stocks exhibit positive sentiment betas while conservative stocks exhibit negative sentiment betas. Given the sentiment literature's assumption that sentiment traders' demand shocks drive the relation between changes in sentiment and contemporaneous stock returns (i.e., the sentiment betas are due to sentiment-induced demand shocks) and that sentiment traders' demand shocks must be offset by liquidity traders' supply shocks, we examine changes in ownership to identify whose demand shocks are capture by changes in sentiment. For instance, an increase in sentiment will cause sentiment traders to sell safe stocks to, and buy risky stocks from, liquidity traders.

Inconsistent with conventional wisdom, we find that sentiment metrics captures institutional investors' demand—an increase in sentiment is associated with institutions buying risky stocks from, and selling safe stocks to, individual investors. Moreover, high sentiment levels are associated with higher institutional ownership levels for risky stocks relative to their ownership levels for safe stocks. In short, we find no evidence that investor sentiment metrics capture direct trading by individual investors. Rather, if sentiment metrics capture irrational sentiment-based demand shocks then institutional investors, rather than individual investors, are the sentiment traders.

Our analysis by institutional type reveals some support for the hypothesis that institutional sentiment trading arises, at least in part, from institutions' reputational concerns but no evidence it primarily results from institutions attempting to ride bubbles. In addition, although we find some evidence that flows within an institutional family may play a role in driving the relation between institutions and sentiment, our results suggest that managers' decisions play the dominate role.

Our results have implications not only for understanding investor sentiment, but also for any study that uses these metrics as explanatory variables in other tests (see, for example, many of the studies cited in the introduction that use the BW metric).

REFERENCES

Abreu, Dilip, and Markus K. Brunnermeier, 2003, Bubbles and crashes, *Econometrica* 71, 173-204.

Allen, Franklin, and Gary Gorton, 1993, Churning bubbles, *The Review of Economic Studies* 60, 813-836.

Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2013, Uncovering hedge fund skill from the portfolio holdings they hide, *Journal of Finance*, forthcoming.

Antoniou, Constantinos, John A. Doukas, and Avanidhas Subrahmanyam, 2013, Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.

Baker, Malcolm, and Jeremy C. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271- 299.

Baker, Malcolm, and Jeffrey Wurgler, 2004, A catering theory of dividends, *Journal of Finance* 59, 1125-1165.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–152.

Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272–287.

Barberis, Nicholas, and Wei Xiong, 2012, Realization utility, *Journal of Financial Economics* 104, 251-271.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge funds stock trading during the financial crisis of 2007-2009, *Review of Financial Studies* 25, 1-54.

Bergman, Nittai K., and Sugata Roychowdhury, 2008, Investor sentiment and corporate disclosure, *Journal of Accounting Research* 46, 1057-1083.

Blume, Marshall E., and Donald B. Keim, 2011, Changing institutional preferences for stocks: Direct and indirect evidence, Working paper, The University of Pennsylvania.

Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013-2040.

Choi, Nicole, and Richard W. Sias, 2012, Why does financial strength forecast stock returns? Evidence from subsequent demand by institutional investors, *Review of Financial Studies* 25, 1550-1587.

Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics* 66, 409-462.

Cornell, Bradford, Wayne R. Landsman, and Stephen Stubben, 2011, Do institutional investors and security analysts mitigate the effects of investor sentiment? Working paper, California Institute of Technology.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839-1886.

Dasgupta, Amil, Andrea Prat, and Michela Verardo, 2011a, The price impact of institutional herding, *Review of Financial Studies* 24, 892-925.

Dasgupta, Amil, Andrea Prat, and Michela Verardo, 2011b, Institutional trade persistence and long-term equity returns, *Journal of Finance* 66, 635-653.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990a, Noise trader risk in financial markets, *The Journal of Political Economy* 98, 703-738.

De Long, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.

Del Guercio, Diane, and Paula A. Tkac, 2002, The determinants of the flow of funds of managed portfolios: Mutual fund vs. pension funds, *Journal of Financial and Quantitative Analysis* 37, 523-557.

Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: Is there a connection? *Journal of Finance* 52, 1087-1129.

Ferson, Wayne, Timothy Simin, and Sergei Sarkissian, 2003, Spurious regressions in financial economics? *Journal of Finance* 58, 1393-1414.

Fisher, Kenneth L., and Meir Statman, 2003, Consumer confidence and stock returns, *Journal of Portfolio Management* 30, 115-127.

Friedman, Benjamin M., 1984, A comment: Stock prices and social dynamics, *Brooking Papers on Economic Activity* 2, 504-508.

Gibson, Scott, Assem Safieddine, and Ramana Sonti, 2004, Smart investments by smart money: Evidence from seasoned equity offerings, *Journal of Financial Economics* 72, 581-604.

Goetzmann, William N. and Nadav Peles, 1997, Cognitive dissonance and mutual fund investors, *Journal of Financial Research* 20, 145-158.

Goyal, Amit, and Sunil Wahal, 2008, The selection and termination of investment management firms by plan sponsors, *Journal of Finance* 63, 1805-1847.

Graham, John R., 1999, Herding among investment newsletters: Theory and evidence, *Journal of Finance* 54,169-182.

Granger, Clive W.J, and Paul Newbold, 1974, Spurious regressions in econometrics, *Journal of Econometrics* 2, 111-120.

Grantham, Jeremy, 2012, My sister's pension assets and agency problems, GMO quarterly letter.

Griffin, John M., Jeffrey H. Harris, Tao Shu, and Selim Topaloglu, 2011, Who drove and burst the tech bubble? *Journal of Finance* 66, 1251-1290.

Gompers, Paul A., and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229-260.

Heisler, Jeffrey, Christopher R. Knittel, John J. Neumann, and Scott D. Stewart, 2009, Absence of value: An analysis of investment allocation decisions by institutional plan sponsors, *Financial Analysts Journal* 65, 34-51.

Hribar, Paul, and John McInnis, 2012, Investor sentiment and analysts' earnings forecast errors, *Management Science* 58, 308-319.

Investment Company Institute, 2013, 2013 Investment Company Fact Book, www.icifactbook.org.

Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45-70.

Jones, Charles M., and Mark Lipson, 2005, Are retail orders different, Working paper, Columbia University.

Karolyi, G. Andrew, Kuan-Hui Lee, and Mathijs A. van Dijk, 2012, Understanding commonality in liquidity around the world, *Journal of Financial Economics* 105, 82-112.

Lee, Charles M.C., Andrei Shleifer, and Richard Thaler, 2001, Investor sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75-109.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer confidence and assets prices: Some empirical evidence, *Review of Financial Studies* 19, 1499-1529.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.

McLean, R. David, and Mengxin Zhao, 2012, The business cycle, investor sentiment, and costly external finance, *Journal of Finance*, forthcoming.

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228-250.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277-309.

Nofsinger, John, and Richard W. Sias, 1999, Herding and feedback trading by institutional and individual investors, *Journal of Finance* 54, 2263-2295.

Novy-Marx, Robert, 2012, Pseudo-predictability in conditional asset pricing tests: Explaining anomaly performance with politics, the weather, global warming, sunspots, and the stars, Working paper, University of Rochester and NBER.

Odean, Terrance, 1998, Volume, volatility, price, and profit when all traders are above average, *Journal of Finance* 53, 1887-1934.

Ramadorai, Tarun, 2012, The secondary market for hedge funds and the closed hedge fund premium, *Journal of Finance* 67, 479-512.

Reca, Blerina Bela, Richard W. Sias, Harry J. Turtle, 2013, Hedge fund crowds and mispricing, Working paper, University of Toledo.

Rosch, Dominik, Avanidhar Subrahmanyam, and Mathijs A. van Dijk, 2013, Is there systematic variation in market efficiency? Working paper, Rotterdam School of Management and UCLA.

San, Granit, 2010, Who gains more by trading--institutions or individuals? Working paper, Hebrew University of Jerusalem.

Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465-479.

Schmeling, Maik, 2009, Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16, 394-408.

Schwartz, Robert, and James Shapiro, 1992, The challenge of institutionalization for the equity markets, *Recent Developments in Finance*, 31-45.

Shiller, Robert J., 2000, Irrational exuberance, Princeton, NJ: Princeton University Press.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589-1622.

Sias, Richard W., 2004, Institutional herding, *Review of financial studies* 17, 165-206.

Sias, Richard W., Laura T. Starks, and Sheridan Titman, 2006, Changes in institutional ownership and stock returns: Assessment and methodology, *Journal of Business* 79, 2869-2910.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012a, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012b, The long of it: Odds that investor sentiment spuriously predicts anomaly returns, Working paper, The University of Pennsylvania.

Trueman, Brett, 1988, A theory of noise trading in securities markets, *Journal of Finance* 43, 83-96.

Yan, Xuemin, and Zhe Zhang, 2009, Institutional investors and equity returns: Are short-term institutions better informed, *Review of Financial Studies* 22, 893-924.

Yu, Jianfeng, and Yu Yuan, 2011, Investor sentiment and the mean-variance relation, *Journal of Financial Economics* 100, 367-381.

Yule, G. Udny, 1926, Why do we sometimes get nonsense-correlations between time-series?--A study in sampling and the nature of time-series, *Journal of the royal statistical* society 89, 1-63.

Table 1
Descriptive Statistics

This table reports time-series averages of the cross-sectional descriptive statistics for the sample securities. An institutional demand shock is defined as the raw change in the fraction of shares held by institutions less the cross-sectional average change in the same quarter. The sample period is June 1980 through December 2010 (n=123 quarters). On average, there are 3,953 securities in the sample each quarter.

Time-series descriptive statistics				
	Mean	Median	10th percentile	90th percentile
%shares held by institutions	35.90%	33.79%	6.52%	68.61%
Raw Δ(%shares held by institutions)	0.64%	0.31%	-3.02%	4.61%
Institutional demand shock	0.00%	-0.33%	-3.66%	3.97%
Number of institutions trading	66.62	31.98	4.29	168.17
σ(monthly return$_{t=-1 \text{ to } -12}$)	13.38%	11.45%	5.8%	22.76%

Table 2
Time-series correlation between mean institutional investor demand shocks and changes in sentiment by volatility decile

This table reports the time-series correlation between the quarterly changes in sentiment and the cross-sectional average institutional investor demand shock for stocks within each volatility decile (volatility is measured based on monthly returns over the previous 12 months). The last column reports the correlation for the difference in mean institutional demand shocks for high and low volatility stocks and changes in sentiment. Panel A reports results based on the change in investor sentiment and Panel B reports results based on the orthogonalized change in investor sentiment. *P*-values are reported parenthetically.

	Low volatility	2	3	4	5	6	7	8	9	High volatility	High-low (*t*-statistic)
	Panel A: Change in investor sentiment										
$\rho_t(\overline{\Delta Inst_{i,t}}, \Delta Sent_t)$	-0.245	-0.274	-0.335	-0.257	-0.134	-0.135	-0.160	0.149	0.251	0.237	0.273
(*p*-value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.14)	(0.14)	(0.08)	(0.10)	(0.01)	(0.01)	(0.01)
	Panel B: Orthogonalized change in investor sentiment										
$\rho_t(\overline{\Delta Inst_{i,t}}, \Delta Sent_t^{\perp})$	-0.291	-0.302	-0.377	-0.276	-0.234	-0.151	-0.102	0.086	0.202	0.318	0.343
(*p*-value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.27)	(0.35)	(0.03)	(0.01)	(0.01)

Table 3
Institutional ownership levels and sentiment levels

We sort the 123 quarters (June 1990-December 2010) into high (above median) and low sentiment periods and report the time-series mean of the cross-sectional average detrended institutional ownership level (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). Panels A and B reports results based on raw and orthogonalized sentiment levels, respectively. Detrended levels are the residuals from regressions for each volatility sorted portfolio of cross-sectional mean institutional ownership levels on time. The final column reports the difference in institutional ownership levels for the high volatility portfolio and the low volatility portfolio. The third row reports the difference and associated t-statistics (based on a t-test for difference in means).

Period	Low volatility	2	3	4	5	6	7	8	9	High volatility	High-low (t-statistic)
Panel A: Detrended fraction of shares held by institutional investors (%) for high and low sentiment level periods											
High sentiment	-0.84	-0.20	-0.36	0.05	-0.11	0.10	0.25	0.53	0.53	1.03	1.88
Low sentiment	0.86	0.20	0.37	-0.05	0.11	-0.10	-0.25	-0.53	-0.54	-1.05	-1.91
High-low sent.	-1.70	-0.40	-0.73	0.11	-0.22	0.21	0.50	1.06	1.08	2.08	3.78 (4.79)***
Panel B: Detrended fraction of shares held by institutional investors (%) for high and low orthogonal sentiment level periods											
High sentiment⊥	-0.50	-0.09	-0.17	0.25	-0.01	0.47	0.65	0.85	0.86	1.39	1.89
Low sentiment⊥	0.51	0.09	0.17	-0.26	0.01	-0.48	-0.66	-0.86	-0.88	-1.41	-1.92
High-low sent.⊥	-1.01	-0.18	-0.33	0.51	-0.01	0.94	1.31	1.71	1.74	2.80	3.81 (4.83)***

Table 4
Institutional demand for volatile stocks and sentiment

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between institutional demand shocks and security return volatility for all stocks in the sample. Volatility is based on monthly returns over the previous 12 months. Panel A reports the time-series mean, standard deviation, minimum, and maximum 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 institutional demand shocks for 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.

Panel A: Descriptive statistics for cross-sectional correlation between institutional demand shocks and volatility			
	Mean (*t*-statistic)	Standard deviation	Minimum	Maximum
$\rho_t\left(\Delta Inst_{i,t}, \sigma_{i,t}\right)$	2.15% (4.46)***	5.35%	-15.19%	17.99%

Panel B: Time-series correlation between changes in sentiment and institutional demand shocks for volatile stocks (*n*=123 quarters)		
	ΔSentiment (*p*-value)	Orthogonalized Δsentiment (*p*-value)
$\rho\left(\rho_t\left(\Delta Inst_{i,t}, \sigma_{i,t}\right), \Delta Sent_t\right)$	37.81% (0.01)	36.69% (0.01)

Table 5
Institutional demand for volatile stocks and consumer confidence

Panel A reports the time-series correlation (n=123 quarters) between Baker and Wurgler's (2006, 2007) quarterly changes in sentiment metrics (raw and orthogonalized) and contemporaneous quarterly changes in two measures of consumer confidence (University of Michigan measure and the Conference Board measure). Panel B reports the correlation between Baker and Wurgler's sentiment levels and the two measures of consumer confidence levels (n=123 quarters). Panel C reports consumer confidence "sentiment betas" computed from time-series regressions (n=123 quarters) of the returns for stocks in the top volatility decile, stocks in the bottom volatility decile, and their difference, on contemporaneous market returns and contemporaneous (standardized) changes in consumer confidence. Panel D reports the coefficient associated with consumer confidence from a time-series regression of the difference in the quarterly returns for the high and low volatility portfolios on beginning of quarter consumer confidence levels. Panel E reports the time-series correlation between institutional demand shocks for volatile stocks (i.e., the cross-sectional correlation between volatility and changes in the fraction of shares held by institutions summarized in Panel A of Table 4) and changes in consumer confidence.

Panel A: Correlation between the Baker and Wurgler changes in sentiment metric and changes in consumer confidence (p-values)		
	ΔMichigan$_t$	ΔConference$_t$
$\rho_t(\Delta Sent_t, \Delta X_t)$	34.50%	26.96%
	(0.01)	(0.01)
$\rho_t(\Delta Sent_t^{\perp}, \Delta X_t)$	19.53%	24.85%
	(0.03)	(0.01)
Panel B: Correlation between Baker and Wurgler's sentiment levels metric and consumer confidence levels (p-values)		
	Michigan$_t$	Conference$_t$
$\rho_t(Sent_t, X_t)$	14.87%	23.41%
	(0.10)	(0.01)
$\rho_t(Sent_t^{\perp}, X_t)$	0.40%	12.24%
	(0.97)	(0.18)
Panel C: Consumer confidence "sentiment" betas (t-statistics)		
	ΔMichigan$_t$	ΔConference$_t$
High σ return$_t$	0.040	0.017
Low σ return$_t$	0.003	-0.002
High σ – Low σ	0.038	0.018
	(3.06)***	(1.44)
Panel D: Does consumer confidence levels predict returns? (t-statistics)		
	Michigan$_{t-1}$	Conference$_{t-1}$
High σ return$_t$ – Low σ return$_t$	-0.044	-0.047
	(-2.86)***	(-3.14)***
Panel E: Time-series correlation between changes in consumer confidence and institutional demand shocks for volatile stocks (n=123 quarters)		
	ΔMichigan$_t$ (p-value)	ΔConference$_t$ (p-value)
$\rho(\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta X_t)$	0.181	0.257
	(0.05)	(0.01)

Table 6
Institutional demand for dividend paying stocks and sentiment

Each quarter (between June 1980 and December 2010) we compute the cross-sectional average institutional demand shock in dividend paying and non-dividend paying stocks. This table reports the time-series correlation between the change in the dividend premium and the contemporaneous difference in institutional demand shocks for dividend paying and non-dividend paying stocks. The dividend premium is computed as the natural logarithm of the difference in the average market-to-book ratio for dividend paying stocks and the market-to-book ratio for non-dividend paying stocks. We also report the figure for the change in the dividend premium orthogonalized with respect to growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator.

Time-series correlation between the difference in institutional demand shocks for dividend payers and non-payers and the changes in the dividend premium		
	ΔDividend premium (*p*-value)	Orthogonalized Δdividend premium (*p*-value)
$\rho_t\left(\overline{\Delta Inst\, DivPayer_t} - \overline{\Delta Inst\, NonDivPayer_t}, \Delta DivPrem_t\right)$	41.73% (0.01)	41.40% (0.01)

Table 7
Time series variation in institutional demand for volatile stocks by investor type and changes in sentiment

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between security return volatility and demand shocks by hedge funds, mutual funds, independent investment advisors, and other institutional investors. Volatility is based on returns over the previous 12 months. Panel A reports the time-series mean, standard deviation, minimum, and maximum cross-sectional correlation and associated t-statistics (in parentheses) computed from the time-series of cross-sectional correlations. Panel B reports the time-series correlation between each type of institutions' demand shocks for volatile stocks (i.e., the cross-sectional correlation between volatility and the changes in the fraction of shares held by each type of institution summarized in Panel A) and changes in investor sentiment or orthogonalized changes in investor sentiment.

Panel A: Descriptive statistics for cross-sectional correlation between institutional demand shocks (by type) and volatility				
$\rho_t(\Delta Inst_{i,t}, \sigma_{i,t})$	Mean (t-statistic)	Standard deviation	Minimum	Maximum
ΔHedge funds	4.68%	10.29%	-20.43%	42.37%
(n=90 quarters)	(4.31)***			
ΔMutual funds	3.00%	7.85%	-20.87%	27.94%
(n=123 quarters)	(4.24)***			
ΔIndep. advisors	2.65%	5.51%	-12.02%	18.63%
(n=123 quarters)	(5.32)***			
ΔOthers institutions	1.58%	4.62%	-11.58%	15.21%
(n=123 quarters)	(3.79)***			

Panel B: Time-series correlation between changes in sentiment and institutional demand shocks (by type) for volatile stocks		
$\rho[\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta Sent_t]$	ΔSentiment (p-value)	Orthogonalized Δsentiment (p-value)
ΔHedge funds	11.54%	9.48%
(n=90 quarters)	(0.28)	(0.38)
ΔMutual funds	39.92%	35.14%
(n=123 quarters)	(0.01)	(0.01)
ΔIndep. advisors	43.44%	31.54%
(n=123 quarters)	(0.01)	(0.01)
ΔOthers institutions	13.98%	14.62%
(n=123 quarters)	(0.13)	(0.11)

Table 8
Flow induced demand, net active buying, and passive demand for volatile stocks and changes in sentiment

Each quarter (between June 1980 and December 2010, $n=123$ quarters) we compute the cross-sectional correlation 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 time-series correlation (and associated p-values) between aggregate institutional demand shocks for volatile stocks and orthogonalized changes in investor sentiment. We then decompose the correlation into the portion attributed to demand shocks from investor flows (Net buying flows), managers' decisions (Net active buying), and reinvested dividend (Passive). 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 Appendix B 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.

	$\rho\left[\rho_t\left(\Delta X_{i,t},\sigma_{i,t}\right),\Delta Sent_t^\perp\right]$	Contribution to $\rho\left[\rho_t\left(\Delta X_{i,t},\sigma_{i,t}\right),\Delta Sent_t^\perp\right]$ due to:		
		Net buying flows	Net active buying	Passive
Panel A: All 13(f) institutions				
All 13(f) institutions	36.69%	0.74%	35.14%	0.81%
	(0.01)	(0.78)	(0.01)	(0.61)
Panel B: All 13(f) institutions – Demand due to entry and exit trades only				
All 13(f) entries and exits	47.89%			
	(0.01)			
Panel C: CRSP/TFN mutual fund data				
ΔCRSP/TFN Mutual funds	33.18%	14.44%	19.68%	-0.01%
	(0.01)	(0.07)	(0.05)	(0.59)

Table 9
Institutional sentiment trading and liquidity trading

We compute each institution's contribution (see Appendix B) to the correlation between changes in orthogonalized sentiment and time-series variation in aggregate institutional demand shocks for volatile stocks reported in Panel B of Table 4 (i.e., 36.69%). Each institution is then classified as a sentiment trader (contribution to the correlation is greater than zero) or a liquidity trader (contribution to the correlation is less than zero). The first three columns report the number of institutions, the fraction that are classified as sentiment traders, the fraction that are classified as liquidity traders, respectively. The last column reports a z-statistic associated with the null hypothesis that the fraction classified as sentiment traders does not differ meaningfully from 50%.

	Number of institutions	%Sentiment traders	%Liquidity traders	z-statistic (Ho: %Sent=0.5)
All	5,368	57.30%	42.70%	20.69***
Hedge funds	966	55.18%	44.82%	3.19***
Mutual funds	139	67.63%	32.37%	4.07***
Indep. advisors	2,883	58.07%	41.94%	8.64***
Other institutions	1,380	56.16%	43.84%	4.55***

Table 10
Institutional sentiment trading and turnover

We compute each institution's contribution (see Appendix B) to the correlation between changes in orthogonalized sentiment and time-series variation in aggregate institutional demand shocks for volatile stocks reported in Panel B of Table 4 (i.e., 36.69%). We then partition institutions into three groups—the top quartile (denoted "strong sentiment institutions"), the middle two quartiles (denoted "passive institutions"), and the bottom quartile (denoted "strong liquidity institutions"). We then compute the time-series average of each institution's turnover percentile. This table reports the cross-sectional average turnover percentile for institutions within each group. The last column reports the difference in turnover for strong sentiment institutions and strong liquidity institutions and the associated t-statistic associated with the null hypothesis that these two groups exhibit equal turnover.

Strong sentiment institutions (t-statistic)	Passive institutions (t-statistic)	Strong liquidity institutions (t-statistic)	Strong Sent. – Strong liq. (t-statistic)
58.32%	50.12%	55.71%	2.61%
(7.90)***	(-6.89)***	(3.45)***	(3.03)***

Appendix A: Robustness Tests

This appendix: (1) confirms that the Baker and Wurgler (2006, 2007, henceforth BW) and Baker, Wurgler, and Yuan (2012) results (based on monthly or annual data over different periods) holds for our quarterly data from 1980-2010, and (2) presents a number of robustness tests for our main results.

A.1 Quarterly sentiment betas in the 1980-2010 sample period

We begin by confirming the BW (2007) finding (based on monthly data from 1966-2005) that high volatility stocks exhibit larger "sentiment betas" than low volatility stocks holds for our quarterly data from 1980-2010. Specifically, we form volatility deciles (based on NYSE breakpoints) at the beginning of each quarter and compute the equal-weighted return for securities within each volatility decile portfolio. We then estimate time-series regressions of quarterly portfolio returns on the value-weighted market portfolio and the quarterly orthogonalized sentiment change index (results are nearly identical based on the raw sentiment change index). Further, we re-scale sentiment changes over our sample period to zero mean and unit standard deviation such that the resulting coefficient reflects the impact of a one standard deviation change in orthogonalized sentiment on quarterly returns (in percent).

Figure A-1 reveals that the sentiment betas increase monotonically across the volatility-sorted portfolios. Controlling for market returns, a one standard deviation increase in quarterly orthogonalized sentiment is associated with a 4.1% higher quarterly return for stocks in the most volatile decile and a -1.7% quarterly return for stocks in the least volatile decile.[35] The coefficients for the high and low volatility portfolios differ significantly at the 1% level (untabulated). Consistent

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[35] Because we examine quarterly returns and quarterly changes in sentiment, our estimates are approximately three times those reported by Baker and Wurgler (2007). In untabulated analysis, we also included size, value, and momentum factors in the model. The analysis continues to reveal that high volatility stocks have larger sentiment betas than low volatility stocks (statistically significant at the 1% level).

with BW (2007, Figure 4B), the results suggest that an increase in sentiment causes sentiment traders to sell safe stocks and buy risky stocks and these sentiment induced demand shocks impact prices.

[Insert Figure A-1 about here]

A.2 Sentiment levels and subsequent high and low volatility portfolio returns in the 1980-2010 sample period

BW point out that there are other possible explanations for the patterns in Figure A-1. Perhaps, for instance, "sentiment" traders chase returns rather than impact returns or the change-in-sentiment metric proxies for changes in economic fundamentals. The authors propose that the sentiment explanation differs from other explanations because it results in temporary mispricing causing a negative relation between sentiment levels and future returns that similarly varies across security returns. That is, if sentiment traders' demand shocks cause mispricing and high volatility stocks have larger sentiment betas, then high volatility stocks will underperform low volatility stocks *following* high sentiment *levels* and outperform low volatility stocks *following* low sentiment *levels*. BW document this property for U.S. equities and Baker, Wurgler, and Yuan (2012) find the same pattern for the five countries they investigate outside the U.S.

Following BW and Baker, Wurgler, and Yuan (2012), we partition our sample period into high (above median) and low sentiment periods using the beginning of quarter orthogonalized sentiment level. Figure A-2 plots the mean market-adjusted quarterly return for stocks within each volatility decile following both low and high sentiment levels. The figure is nearly identical to Figure 5 in BW (2007)—on average, stocks in the top volatility decile underperform stocks in the low volatility decile by 3.97% in quarters following high sentiment levels, but outperform stocks in the low volatility decile by 4.96% in quarters following low sentiment levels. The difference between the high and low volatility portfolio returns following high and low sentiment is statistically significant at the 1% level (untabulated, based on *t*-test for difference in means).

[Insert Figure A-2 about here]

Further following BW (2006), we regress subsequent quarterly returns for the highest volatility portfolio, the lowest volatility portfolio, and their difference, on beginning of the quarter sentiment levels. We estimate the regressions using beginning of quarter sentiment level (raw or orthogonalized) as the only independent variable and also including the contemporaneous quarter excess market return, and size, value, and momentum factors.[36] The estimated coefficients, reported in Table A-1, reveal that the return difference between high volatility stocks and low volatility stocks is inversely related to beginning of the quarter sentiment levels (statistically significant at the 1% level in all four cases) even when controlling for standard asset pricing variables. In sum, although based on a different sample period and periodicity, Table A-1 and Figures A-1 and A-2 are fully consistent with BW and Baker, Wurgler, and Yuan (2012).

[Insert Table A-1 about here]

A.3 Alternative measures of a stock's susceptibility to sentiment

Following BW (2007), we use return volatility as the measure of a stock's susceptibility to sentiment. In their earlier paper (BW (2006)), the authors examine a number of alternative characteristics to measure a stock's susceptibility to sentiment induced demand shocks. In this section we focus on four additional metrics that BW (2006, Table V) find generate the same monotonic pattern in returns following high and low sentiment levels: firm size, firm age, companies with positive earnings versus companies with negative earnings, and dividend paying versus non-dividend paying stocks.[37]

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[36] Market, size, value, and momentum factors are from Ken French's website.

[37] In addition to the five metrics we examine (return volatility, size, age, profitability, and dividends), BW (2007) also examine two measures of tangibility (fixed assets to assets and research and development to assets) and three measures of "growth opportunities and distress" (book to market, external finance to assets, and sales growth decile). The authors,

Following BW (2006) using NYSE breakpoints, we partition stocks into three groups by market capitalization (measured at the beginning of each quarter): firms in the top three deciles are denoted large, firms in the middle four deciles are classified as medium, and firms in the bottom three deciles are denoted small. We analogously define three portfolios based on firm age (number of months since first appearing on CRSP). We define dividend paying firms as firms that paid a dividend (CRSP variable DIVAMT) in the 12 months preceding the start of the quarter and define profitable firms as firms that had positive cumulative income (Compustat IBQ) in the 12 months preceding the start of the quarter.

The first two columns of Table A-2 report the estimated sentiment betas (based on changes in sentiment and orthogonalized changes in sentiment, respectively) for each portfolio formed by size, age, profitability, and dividend payments. Specifically, these are the coefficients from time-series regressions of equal-weighted portfolio returns on the market portfolio and standardized changes in sentiment (i.e., analogous to the sentiment betas reported in BW (2007) and our Figure A-1). The bottom row in each panel reports the sentiment beta for the portfolio long speculative stocks and short conservative stocks (and associated *t*-statistic). Consistent with the results based on the volatility sorted portfolios, small stocks, younger firms, unprofitable companies, and non-dividend paying companies are all meaningfully more sensitive to changes in sentiment than their more conservative counterparts.

[Insert Table A-2]

We next examine the relation between changes in sentiment and institutional/individual investor demand shocks for each of the portfolios discussed above. Specifically (analogous to Table 2), we compute the cross-sectional mean institutional demand shock (i.e., the change in the fraction of shares held by institutions for stock *i* less the mean change across all stocks in quarter *t*) for

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however, fail to find a meaningful monotonic relation between the tangibility and growth/distress metrics and sentiment levels. As a result, we focus on the first five metrics.

securities within each size, age, profitability, and dividend portfolio. We then calculate the time-series correlation between changes in sentiment and the contemporaneous quarterly cross-sectional average institutional demand shocks (or, equivalently, individual investors' supply shocks) for each portfolio.

The results, reported in the last two columns of Table A-2, reveal the pattern in institutional investor demand shocks matches the pattern in contemporaneous returns. When sentiment increases, institutions buy small stocks, young stocks, unprofitable companies, and non-dividend paying companies from individual investors (i.e., the correlations reported in the top row of each panel are positive) and sell large stocks, more mature stocks, profitable companies, and dividend paying companies to individual investors (i.e., the correlation reported in the bottom row of each panel are negative). As shown in the bottom row of each panel in Table A-2, the correlations between the differences in institutional demand shocks for speculative and more conservative stocks and changes in sentiment are positive (and statistically significant at the 5% level or better in every case using either raw or orthogonal sentiment). In short, these results confirm that institutions buy speculative stocks from, and sell safe stocks to, individual investors when sentiment increases.

A.4 Raw institutional ownership levels and sentiment levels

In this section, we examine the relation between sentiment levels and institutional ownership levels of volatile and safe stocks, i.e., we repeat the tests in Table 4, but use raw, rather than detrended, institutional ownership levels. Specifically, we compute the mean institutional ownership level (i.e., the fraction of shares held by institutions) across stocks within each volatility decile at the beginning of each quarter. We then partition the sample into low (below median) and high beginning of quarter sentiment level periods and compute the time-series mean of the cross-

sectional average institutional ownership levels for stocks within each volatility decile during high and low sentiment periods.

Panels A and B in Table A-3 report the results based on sentiment levels and orthogonalized sentiment levels, respectively. The last column reports the difference in mean institutional ownership levels for high and low volatility stocks. Regardless of sentiment levels, institutional ownership of low volatility stocks is, on average, higher than their ownership of high volatility stocks (although institutional ownership levels are highest for stocks in the middle volatility deciles), i.e., differences reported in the last column of the first two rows in Panels A and B are negative. Nonetheless, contrary to the hypothesis that individual investors are the sentiment traders, institutional investors' preference for risky stocks relative to their preference for safe stocks is larger when sentiment is high, i.e., the differences reported in the third row of the last column in Panels A and B are positive and statistically significant (at the 1% level), which means that individual investors' direct ownership preferences are the reverse.[38] In sum, consistent with the de-trended analysis, the results indicate that institutional ownership levels for volatile stocks are higher (and individual investors' ownership levels are lower) when sentiment is higher inconsistent with the hypothesis that sentiment metrics captures individual investors' demand.

[Insert Table A-3 about here]

A.5 Flows, net active buying, and passive trades by 13(f) investor type

In this section, analogous to Panel A of Table 8, we partition the correlations between time-series variation in each investor types' attraction to volatile stocks and changes in orthogonal sentiment (i.e., the correlations reported in the last column of Table 7) into the portion due to

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[38] Institutional ownership levels across all portfolios are higher when sentiment is lower, i.e., the differences in the third row of Panels A and B are negative for all the volatility deciles. This occurs because there are more high sentiment periods in the earlier half of our sample and institutional ownership levels increase over time (see, for example, Blume and Keim (2011)). Thus, the detrended ownership level results are more appropriate.

investor flows (net buying flows), manager decisions (net active buying), and reinvested dividends (passive). The *p*-values reported in the last three columns are based on bootstrapped estimates with 10,000 iterations (see Appendix C for details). For mutual funds and independent investment advisors (i.e., the two investor types with a meaningful correlations in the first column), the relation between time-series variation in their demand shocks for risky stocks and changes in sentiment is driven by managers' decisions (statistically significant at the 1% level in both cases) and not intermanager flows.

Table A-1
Regression of subsequent quarterly high and low volatility portfolio returns on sentiment levels

The first two rows report the results of time-series regressions (June 1980-December 2010) of the quarter t return for the portfolio of the top decile of risky stocks and the portfolio of the bottom decile of risky stocks (where risk is measured as the standard deviation of monthly returns over the previous 12 months), respectively, on sentiment levels at the beginning of the quarter (i.e., end of quarter t-1). The first column reports the coefficient on beginning of quarter sentiment, when sentiment is included as the only explanatory variable. The second column reports the coefficient on beginning of quarter sentiment when including contemporaneous market excess returns and size, value, and momentum factors. The last two columns are analogously defined using beginning of quarter orthogonalized sentiment levels (denoted $\perp$). The third row reports the difference between the first two rows and associated t-statistics.

Dependent variable	$Sentiment_{t-1}$	$Sentiment_{t-1}$ (controlling for market, size, value, and momentum factors)	$Sentiment^{\perp}_{t-1}$	$Sentiment^{\perp}_{t-1}$ (controlling for market, size, value, and momentum factors)
High σ portfolio return$_t$	-0.028	-0.016	-0.022	-0.015
Low σ portfolio return$_t$	0.020	0.009	0.021	0.09
High σ return$_t$ – Low σ return$_t$	-0.049	-0.025	-0.043	-0.024
	(-3.19)***	(-2.86)***	(-2.84)***	(-2.75)***

Table A-2
Alternative characteristics for risky and safe stocks

Each quarter we sort stocks into three portfolios based on beginning of quarter market capitalization and NYSE breakpoints (small=bottom three deciles, medium=middle four deciles, and large=top three deciles). The first two columns report sentiment betas (based on either raw or orthogonalized change in sentiment), estimated from time-series regressions of equal-weighted portfolio returns on the market return and standardized changes in sentiment. The last row in the first two columns report the sentiment beta for the portfolio long in speculative stocks and short in conservative stocks (and associated t-statistics). The last two columns report the time-series correlation between the cross-sectional mean institutional demand shock for securities in that portfolio and changes in sentiment. The last row reports the time-series correlation between the difference in institutional demand shocks for speculative and conservative stocks and changes in sentiment (and associated p-values).

	Sentiment beta (t-statistics)		Correlation between institutional demand shock and changes in sentiment (p-value)	
	$\Delta Sent_t$ (t-statistic)	$\Delta Sent_t^{\perp}$ (t-statistic)	$\rho\left(\overline{\Delta Inst_t}, \Delta Sent_t\right)$ (p-value)	$\rho\left(\overline{\Delta Inst_t}, \Delta Sent_t^{\perp}\right)$ (p-value)
Panel A: Capitalization				
Small	2.19%	1.58%	8.86%	10.30%
Medium	0.50%	-0.07%	1.93%	2.99%
Large	0.31%	-0.19%	-12.26%	-22.18%
Small-Large	2.50%	1.76%	11.87%	19.88%
	(3.39)***	(2.38)**	(0.20)	(0.03)
Panel B: Age				
Young	2.61%	1.91%	31.94%	26.34%
Medium	0.45%	0.31%	-25.09%	-11.14%
Old	-1.67%	-1.44%	-28.21%	-34.35%
Young-Old	4.28%	3.35%	31.19%	34.09%
	(8.50)***	(6.16)***	(0.01)	(0.01)
Panel C: Profitable and unprofitable firms				
Earnings<0	4.40%	3.85%	18.75%	27.28%
Earnings>0	-0.08%	-0.44%	-15.75%	-20.95%
<0 - >0	4.48%	4.30%	18.51%	26.33%
	(5.44)***	(5.30)***	(0.05)	(0.01)
Panel D: Dividend payers and non-dividend payers				
Dividends=0	3.70%	2.65%	33.90%	21.56%
Dividends>0	-1.32%	-1.62%	-31.60%	-30.66%
=0 - >0	5.02%	-4.27%	-37.32%	-29.87%
	(8.02)***	(6.55)***	(0.01)	(0.01)

Table A-3
Institutional ownership levels and sentiment levels

We sort the 123 quarters (June 1990-December 2010) into high (above median) and low sentiment periods and report the time-series mean of the cross-sectional average institutional ownership level (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). Panels A and B reports raw ownership levels for high and low sentiment and orthogonal sentiment periods, respectively. The final column reports the difference in institutional ownership levels for the high volatility portfolio and the low volatility portfolio. The third row reports the difference and associated t-statistics (based on a t-test for difference in means).

Period	Low volatility	2	3	4	5	6	7	8	9	High volatility	High-low (t-value)
Panel A: Fraction of shares held by institutional investors (%) for high and low sentiment level periods											
High sentiment	29.81	36.74	38.62%	39.88	39.54	38.98	37.53	35.53	32.11	24.69	-5.13
Low sentiment	35.97	41.89	44.44%	45.43	46.00	45.23	43.54	41.21	37.42	27.62	-8.35
High-low sent.	-6.16	-5.16	-5.82	-5.56	-6.46	-6.26	-6.01	-5.67	-5.31	-2.93	3.23 (3.91)***
Panel B: Fraction of shares held by institutional investors (%) for high and low orthogonal sentiment level periods											
High sentiment⊥	30.04	36.72	38.68	39.93	39.48	39.17	37.77	35.68	32.27	24.91	-5.12
Low sentiment⊥	35.75	41.91	44.38	45.38	46.06	45.03	43.31	41.06	37.26	27.40	-8.35
High-low sent.⊥	-5.71	-5.19	-5.69	-5.45	-6.59	-5.86	-5.54	-5.38	-4.98	-2.48	3.23 (3.91)***

Table A-4
Flow induced demand, net active buying, and passive demand for volatile stocks and changes in sentiment by investor type

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between security return volatility and demand shocks by each 13(f) institution type. Volatility is based on returns over the previous 12 months. The first column in Panel A reports the time-series correlation (and associated p-values) between institutional demand shocks for volatile stocks and orthogonalized changes in investor sentiment (i.e., the values reported in Panel B of Table 8). We then decompose the correlation into the portion attributed to demand shocks from investor flows (Net buying flows), managers' decisions (Net active buying), and reinvested dividend (Passive). 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 Appendix B for details). The hedge fund sample is limited to the final 90 quarters.

	$\rho[\rho_t(\Delta X_{i,t}, \sigma_{i,t}), \Delta Sent_t]$ (p-value)	Contribution to $\rho[\rho_t(\Delta X_{i,t}, \sigma_{i,t}), \Delta Sent_t]$ due to: (p-value)		
		Net buying flows	Net active buying	Passive
ΔHedge funds	9.48%	9.99%	5.38%	-5.89%
(*n*=90 quarters)	(0.38)	(0.04)	(0.97)	(0.16)
ΔMutual funds	35.14%	1.77%	34.72%	-1.35%
(*n*=123 quarters)	(0.01)	(0.42)	(0.01)	(0.12)
ΔIndep. Advisors	31.54%	-0.01%	32.07%	-0.52%
(*n*=123 quarters)	(0.01)	(0.99)	(0.01)	(0.64)
ΔOther institutions	14.62%	2.17%	10.78%	1.68%
(*n*=123 quarters)	(0.11)	(0.51)	(0.23)	(0.34)

Figure A-1. Sentiment betas for volatility sorted portfolios
We regress the time series of quarterly portfolio returns for volatility sorted portfolios on the value-weighted market portfolio and the quarterly orthogonalized change-in-sentiment index. The quarterly orthogonalized change-in-sentiment is re-scaled to mean zero and unit variance. The bars represent the impact of a one standard deviation increase in quarterly orthogonalized sentiment on quarterly returns, in percent.

Figure A-2. Sentiment levels and future returns
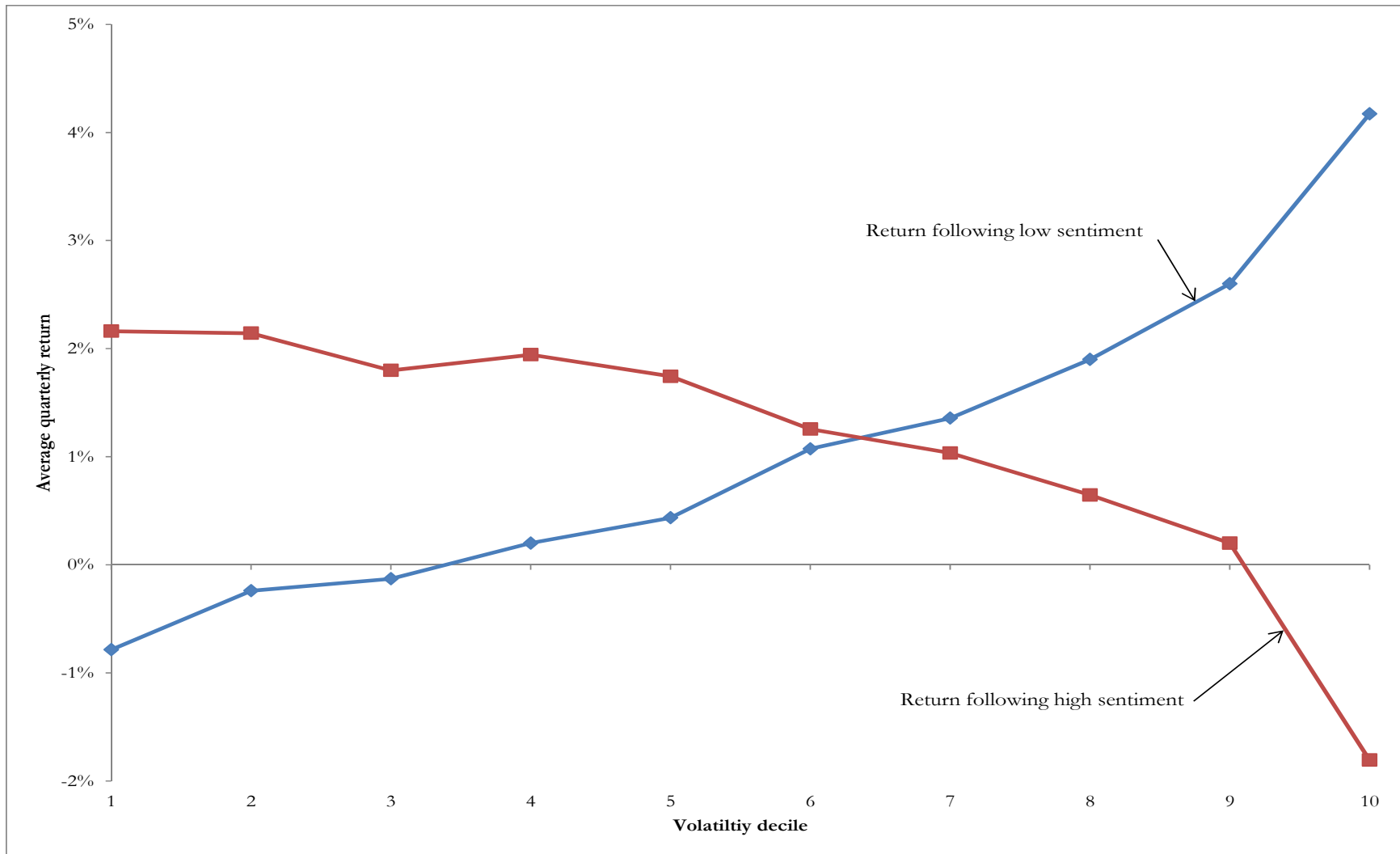The figure plots the average market-adjusted quarterly return for stocks within each volatility decile following both high (red line) and low (blue line) sentiment periods. The returns for the volatility weighted portfolios are equal weighted each period. High (low) sentiment is defined as a period with above (below) median sentiment.

Appendix B: Proofs and estimation details

B.1 Decomposing 13(f) demand into flows, decisions, and passive trades

We follow the method in Griffin, Harris, Shu, and Topaloglu (2011) to partition 13(f) demand shocks into three components—changes in holdings due to net flows, net active buying by each institution, and passive changes in ownership (reinvested dividends). We begin by computing the flow ratio for each institution k in quarter t (identical to Griffin, Harris, Shu, and Topaloglu's Equation (IA.4)):

$$FlowRatio_{k,t} = \frac{\sum_{i=1}^{N_t} P_{i,t} H_{i,k,t}}{\sum_{i=1}^{N_t} P_{i,t-1} H_{i,k,t-1}(1+R_{i,t})} \, , \tag{B.1}$$

where $P_{i,t}$ is the price of security i at the end of quarter t, $H_{i,k,t}$ is the numbers of shares of security i held by investor k at the end of quarter t, $R_{i,t}$ is security i's quarter t return, and there are N_t securities in the market in quarter t. Following Griffin, Harris, Shu, and Topaloglu, we Winsorize the flow ratio at the 5th and 95th percentile for the 13(f) data.[39]

The fraction of outstanding shares of security i purchased by institution k in quarter t due to flows is given by (Griffin, Harris, Shu, and Topaloglu's (2011) Equation (IA.5)):

$$NBFlows_{i,k,t} = \frac{(P_{i,t-1} H_{i,k,t-1}) \times (1+R_{i,t}) \times (FlowRatio_{k,t} - 1)}{P_{i,t} S_{i,t}} \, , \tag{B.2}$$

where $S_{i,t}$ is the number of shares outstanding for security i in quarter t. Equation (B.2) can be re-written:

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[39]As Griffin, Harris, Shu, and Topaloglu (2011) point out, outliers can occur in the 13(f) data if an institution moves from non-equity holdings to equity holdings.

$$NBFlows_{i,k,t} = \frac{\left(\dfrac{P_{i,t-1}H_{i,k,t-1}(1+R_{i,t})}{\displaystyle\sum_{i=1}^{N}P_{i,t-1}H_{i,k,t-1}(1+R_{i,t})}\right)\left(\displaystyle\sum_{i=1}^{N_t}P_{i,t}H_{i,k,t}-P_{i,t-1}H_{i,k,t-1}\left(1+R_{i,t}\right)\right)}{P_{i,t}S_{i,t}}.\qquad(B.3)$$

Note that the numerator in Equation (B.3) is manager k's weight in stock i at the end of the quarter t assuming the manager traded no securities (first term) times the estimated net flows to institution k in quarter t (second term). Dividing this value by price yields the estimated number of shares of security i purchased by institution k in quarter t due to investor flows. Further dividing by security i's shares outstanding yields the fraction of shares of security i purchased by institution k in quarter t due to investor flows. Following Griffin, Harris, Shu, and Topaloglu, we Winsorize flow induced net buying at the 99.9% level.

Net Active Buying for institution k over quarter t in security i is given by (Griffin, Harris, Shu, and Topaloglu's (2011) Equation (IA.6)):

$$Net\ Active\ Buying_{i,k,t} = \frac{P_{i,t}H_{i,k,t}-\left(\left(P_{i,t-1}H_{i,k,t-1}\right)\times\left(1+R_{i,t}\right)\times\left(FlowRatio_{k,t}\right)\right)}{P_{i,t}S_{i,t}}.\qquad(B.4)$$

Substituting in Equation (B.1) and rearranging yields:

$$Net\ Active\ Buying_{i,k,t} = \frac{P_{i,t}H_{i,k,t}-\left(\dfrac{\left(P_{i,t-1}H_{i,k,t-1}\right)\left(1+R_{i,t}\right)}{\displaystyle\sum_{i=1}^{N}P_{i,t-1}H_{i,k,t-1}(1+R_{i,t})}\times\left(\displaystyle\sum_{i=1}^{N}P_{i,t}H_{i,k,t}\right)\right)}{P_{i,t}S_{i,t}}.\qquad(B.5)$$

The numerator of Equation (B.5) is the difference between the dollar value of end of quarter t holdings of security i by manager k and the expected value of manager k's holdings of security i if the manager made no deviations in his portfolio weights and invested all flows at end of quarter portfolio weights. Dividing by price yields the net number of shares purchased by the manager due

to active decisions and further dividing by shares outstanding yields the change in the fraction of

outstanding shares due to manager k's active trades of security i in quarter t.

Following Griffin, Harris, Shu, and Topaloglu (2011), we define manager k's passive changes in

holdings of security i in quarter t as:

$$Passive_{i,k,t} = \frac{\left(P_{i,t-1}H_{i,k,t-1}\right)\times\left(1+R_{i,t}\right)-P_{i,t}H_{i,k,t-1}}{P_{i,t}S_{i,t}} . \tag{B.6}$$

Note that if the security pays no dividend, passive trading is equal to zero (i.e., $P_{i,t} = P_{i,t-1}(1+R_{i,t})$). If

security i pays a dividend, Equation (B.6) assumes institution k reinvests the dividend in security i.

Summing Equations (B.2), (B.4), and (B.6) simply yields the change in the fraction of security i's

shares held by investor k over quarter t:

$$\Delta Inst_{i,k,t} = NBFlows_{i,k,t} + Net\ Active\ Buying_{i,k,t} + Passive_{i,k,t} . \tag{B.7}$$

Summing Equation (B.7) across institutions yields the institutional demand shock and its three

components (flows, decisions, and passive) for security i in quarter t:

$$\Delta Inst_{i,t} = \sum_{k=1}^{K}\Delta Inst_{i,k,t} = \sum_{k=1}^{K}NBFlows_{i,k,t} + \sum_{k=1}^{K}Net\ Active\ Buying_{i,k,t} + \sum_{k=1}^{K}Passive_{i,k,t} . \tag{B.8}$$

Equation (B.8) is effectively identical to Griffin, Harris, Shu, and Topaloglu's (2011) Equation (2).[40]

B.2 Decomposing mutual fund demand into flows, decisions, and passive trades

Our mutual fund demand decomposition also follows Griffin, Harris, Shu and Topaloglu (2011).

We merge Thompson N-30D mutual fund holdings data and CRSP mutual fund data using WRDs

Mutual Fund Links. We delete observations where the difference in shares held from the previous

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[40] Our notation differs slightly from Griffin, Harris, Shu, and Topaloglu (2011). Specifically, the first two terms on the right hand side of their Equation (2) is identical to the negative of our numerator in Equation (A.6) because Griffin, Harris, Shu, and Topaloglu write net active buying as a function of passive and flows (whereas we write institutional demand shock as the sum of the three components). If one moves the right hand side of their Equation (2) to the left-hand side, the equation becomes the dollar value of institutional demand due to net active buying, reinvested dividends (passive), and flows. If estimated at the stock level, dividing by market capitalization yields the net fraction of shares purchased by institutions in security i over quarter t (i.e., our Equation (A.8)). In short, we follow their exact method.

and current report differs from the reported change in shares. We limit the sample to stocks with CRSP share codes 10 and 11 that are listed on NYSE, Amex, or NASDAQ. If a report date does not fall on the last trading day of the month we assume it is equal to the last trading day of the current (previous) month if the report date occurs after (before) the 15th of the month.

Using the CRSP mutual fund data we require funds to have non-missing returns and total net assets data for all share classes. We also require funds to report in consecutive quarters. We calculate quarterly fund returns by computing each share class' quarterly returns and then value weighting the returns using beginning of quarter total net assets.[41] We restrict the sample to domestic equity funds by deleting all funds with Lipper asset codes not equal to 'EQ,' equity codes not equal to 'E,' and funds with common stock investments that make up less than 50% of their portfolio. We also limit the sample to funds with Lipper class codes equal to one of the following: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLVE, SCCE, SCGW, SCVE, or whose Lipper objective code equals one of the following: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, SCG. Finally, we exclude funds whose name contains the word 'Global,' 'International,' 'Europe,' or 'Emerging.'

Analogous to our 13(f) metric, we compute the mutual fund demand shock for security i in quarter t as the net fraction of outstanding stock i shares purchased by mutual funds. We next partition each mutual fund's demand shock for each security into flow-induced shocks, net active buying, and passive components. Because the CRSP mutual fund data includes total net assets, we further follow Griffin, Harris, Shu, and Topaloglu (2011) and define the flow ratio for mutual fund k in quarter t as:

$$FlowRatio_{k,t} = \frac{TNA_{k,t}}{TNA_{k,t-1}(1 + R_{k,t})},$$
(B.9)

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[41] Because most mutual funds only report quarterly total net assets prior to 1992, we differ slightly from Griffin, Harris, Shu, and Topaloglu (2011) in that we value-weight quarterly returns using quarterly total net assets while the authors use monthly total net assets. Our method results in a substantially larger sample size, especially early in our sample period when few funds report monthly return data.

where $TNA_{k,t}$ is the total net assets (the sum of the total net assets for all share classes) as reported by CRSP for mutual fund k at the end of quarter t and $R_{k,t}$ is the return for mutual fund k in quarter t where returns are value weighted across all share classes. Given the mutual fund flow ratio, we use Equations (B.2)-(B.6) to decompose mutual fund demand shocks into flow induced trades, net active buying, and passive trades.

B.3 Decomposing the correlation into flows, decisions, and passive trades

The quarter t cross-sectional correlation between institutional demand shocks for security i and stock return volatility is given by:

$$\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right) = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{\Delta Inst_{i,t} - \overline{\Delta Inst_t}}{\sigma(\Delta Inst_t)}\right)\left(\frac{\sigma(ret_{i,t}) - \overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))}\right), \tag{B.10}$$

where XS denotes cross-sectional, $\Delta Inst_{i,t}$ is the aggregate institutional demand shock (i.e. the change in the fraction of shares held by institutions) for stock i in quarter t, $\overline{\Delta Inst_t}$ is the cross-sectional average institutional demand shock in quarter t, $\sigma(\Delta Inst_t)$ is the cross-sectional standard deviation of institutional demand shocks in quarter t, $\sigma(ret_{i,t})$ is the standard deviation of returns over the previous 12 months for stock i, $\overline{\sigma(ret_t)}$ is the cross-sectional mean return volatility in quarter t, $\sigma_{XS}(\sigma(ret_t))$ is the cross-sectional standard deviation of return volatility in quarter t, and N_t is the number of stocks in our data in quarter t. Because the institutional demand shock is simply the sum of demand shocks across all institutions, we can rewrite Equation (B.10) as:

$$\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right) = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{\sum_{k=1}^{K_{i,t}}\left[\Delta Inst_{i,k,t} - \left(\frac{\overline{\Delta Inst_t}}{K_{i,t}}\right)\right]}{\sigma(\Delta Inst_t)}\right)\left(\frac{\sigma(ret_{i,t}) - \overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))}\right), \tag{B.11}$$

where $K_{i,t}$ is the number of institutions trading stock i in quarter t and $\Delta Inst_{i,k,t}$ is institution k's demand shock for stock i in quarter t (i.e., the quarter t change in the fraction of security i's shares held by institution k). Limiting the sample to a single manager (k) and summing over stocks in quarter t yields manager k's total contribution to the cross-sectional correlation given in Equation (B.10):

$$Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)=\frac{1}{N_t}\sum_{i=1}^{N_t}\left[\left(\frac{\Delta Inst_{i,k,t}-\left(\frac{\overline{\Delta Inst_t}}{K_{i,t}}\right)}{\sigma(\Delta Inst_t)}\right)\left(\frac{\sigma(ret_{i,t})-\overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))}\right)\right]. \tag{B.12}$$

Thus, summing the contributions across institutions in quarter t (i.e., Equation (B.12)) yields the cross-sectional correlation in quarter t (i.e., Equation (B.10)):

$$\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)=\sum_{k=1}^{K}Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right). \tag{B.13}$$

Moreover, as shown in Equation (B.7), each institution's demand shock for each security each quarter is the sum of their net buying due to flows ($NBflows_{i,k,t}$), net active buying ($NAB_{i,k,t}$), and reinvested dividend ($Passive_{i,k,t}$). As a result, Equation (B.12) can be written:

$$Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)=\frac{1}{N_t}\sum_{i=1}^{N_t}\left[\left(\frac{NBFlows_{i,k,t}-\left(\frac{\overline{NBFlows_t}}{K_{i,t}}\right)}{\sigma(\Delta Inst_t)}\right)\left(\frac{\sigma(ret_{i,t})-\overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))}\right)\right]+$$

$$\frac{1}{N_t}\sum_{i=1}^{N_t}\left[\left(\frac{NAB_{i,k,t}-\left(\frac{\overline{NAB_t}}{K_{i,t}}\right)}{\sigma(\Delta Inst_t)}\right)\left(\frac{\sigma(ret_{i,t})-\overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))}\right)\right]+$$

$$\frac{1}{N_t} \sum_{i=1}^{N_t} \left[\left(\frac{Passive_{i,k,t} - \left(\frac{\overline{Passive_t}}{K_{i,t}} \right)}{\sigma(\Delta Inst_t)} \right) \left(\frac{\sigma(ret_{i,t}) - \overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))} \right) \right]. \tag{B.14}$$

That is, the contribution to the cross-sectional correlation due to institution k in quarter t (i.e., Equation (B.12)) can be partitioned into the contributions due to flows, decisions, and reinvested dividends):

$$Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)\right) = NBFlows\ Cont_{k,t} + NAB\ Cont_{k,t} + Passive\ Cont_{k,t}. \tag{B.15}$$

The correlation between time-series variation in institutional investors' attraction to volatile stocks (i.e., the cross-sectional correlation between institutional demand shocks and lag return volatility) and changes in sentiment is given by:

$$\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)\right), \Delta Sent\right) =$$

$$\frac{1}{T} \sum_{t=1}^{T} \left(\frac{\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right) - \overline{\rho_{XS}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)}}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)\right)} \right) \left(\frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right), \tag{B.16}$$

where *TS* denotes time series and *T* is the total number of quarters. Substituting Equation (B.13) into Equation (B.16) yields:

$$\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)\right), \Delta Sent\right) =$$

$$\frac{1}{T} \sum_{t=1}^{T} \left(\frac{\sum_{k=1}^{K} Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)\right) - \overline{\rho_{XS}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)}}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t}, \sigma(ret_{i,t})\right)\right)} \right) \left(\frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right). \tag{B.17}$$

Rearranging yields:

$$\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right),\Delta Sent\right)=$$

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{K_t}\left[\frac{\left[Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)-\dfrac{\overline{\rho_{XS}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)}}{K_t}\right]}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right). \quad \text{(B.18)}$$

Thus, limiting the sample to institution k generates institution k's contribution to the time-series correlation between institutions' attraction to volatile stocks and changes in sentiment:

$$Cont_k\left(\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right),\Delta Sent\right)\right)=$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\frac{\left[Cont_{k,t}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)-\dfrac{\overline{\rho_{XS}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)}}{K_t}\right]}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right). \quad \text{(B.19)}$$

Equation (B.19) allows us to partition institutions into those that contribute positively (i.e., Equation (B.19)>0; "sentiment traders" in Table 9) to the time-series correlation and those that contribute negatively (i.e., Equation (B.19)<0; "liquidity traders" in Table 9). Similarly, managers in the top and bottom quartiles of Equation (B.19) are denoted "strong sentiment institutions" and "strong liquidity institutions" in Table 10. Managers in the middle two quartiles of Equation (B.19) are denoted "passive institutions" in Table 10. Further, summing across institutions' contributions (i.e., Equation (B.19)) yields the correlation reported in Panel B of Table 4 (i.e., Equation (B.17)):

$$\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right),\Delta Sent\right)=\sum_{k=1}^{K}Cont_k\left[\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right),\Delta Sent\right)\right]. \quad \text{(B.20)}$$

Substituting Equation (B.15) into Equation (B.19) and rearranging:

$$Cont_k\left(\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma_{XS}(ret_{i,t})\right)\right),\Delta Sent\right)\right)=$$

$$\frac{1}{T}\sum_{t=1}^{T}\left(\left[\frac{NBFlows\,Cont_{k,t}-\overline{\frac{NBFlows\,Cont}{K_t}}}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right)\right)+$$

$$\frac{1}{T}\sum_{t=1}^{T}\left(\left[\frac{NAB\,Cont_{k,t}-\overline{\frac{NAB\,Cont}{K_t}}}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right)\right)+$$

$$\frac{1}{T}\sum_{t=1}^{T}\left(\left[\frac{Passive\,Cont_{k,t}-\overline{\frac{Passive\,Cont}{K_t}}}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right)\right). \tag{B.21}$$

Thus, each manager's contribution to the time series correlation between changes in sentiment and the cross-sectional correlation between institutional investors' demand shocks and stock volatility is simply the sum of the components due to investor flows, managers' decisions, and reinvested dividends:

$$Cont_k\left(\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma_{XS}(ret_{i,t})\right)\right),\Delta Sent\right)\right)=NBFlowsCont_k+NABCont_k+PassiveCont_k\,. \tag{B.22}$$

Summing over managers yields the portion of the correlation due to flows, decisions, and passive trades (i.e., the values reported in Table 8):

$$\rho_{TS}\left(\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right),\Delta Sent\right)=$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\sum_{k=1}^{K}\left(\left[\frac{NBFlows\,Cont_{k,t}-\overline{\frac{NBFlows\,Cont}{K_t}}}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right]\right)\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right)\right]+$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\sum_{k=1}^{K}\left(\frac{\left[NABCont_{k,t}-\dfrac{\overline{NABCont}}{K_t}\right]}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right)\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right)+$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\sum_{k=1}^{K}\left(\frac{\left[PassiveCont_{k,t}-\dfrac{\overline{PassiveCont}}{K_t}\right]}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right)\right]\left(\frac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right). \tag{B.23}$$

B.4 Bootstrapped p-values

We use a bootstrap procedure to generate *p*-values for contributions due to flows, net active buying, and passive trades reported in Table 8. Specifically, we randomly assign (without replacement) standardized sentiment, i.e., $\left(\dfrac{\Delta Sent_t-\overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)}\right)$ to each term in square braces in Equation (B.23). For example, we assign standardized sentiment from random quarter *x*, to flows in quarter *t*:

$$\left[\sum_{k=1}^{K}\left(\frac{\left[NBFlowsCont_{k,t}-\dfrac{\overline{NBFlowsCont}}{K_t}\right]}{\sigma_{TS}\left(\rho_{XS,t}\left(\Delta Inst_{i,t},\sigma(ret_{i,t})\right)\right)}\right)\right]. \tag{B.24}$$

We then compute the mean value of the product of these two terms over the 123 quarters to calculate the pseudo-contribution to the correlation due to flows, i.e., we calculate the value of the first term on the right-hand side of Equation (B.23) when the term is square braces is assigned to random changes in sentiment. We repeat the procedure 10,000 times to form a distribution of pseudo contributions due to each component. The bootstrapped *p*-values reported in Table 8 are based on two tail tests from these distributions.

Appendix C: The relation between sentiment levels and subsequent institutional demand

Cornell, Landsman, and Stubben (2011) report that institutional investors buy speculative stocks and sell safe stocks following high sentiment levels. Although our papers overlap, we differ both empirically and theoretically. On the theory front, Cornell, Landsman, and Stubben propose there are two possible scenarios: (1) sentiment affects individual investors and rational institutions only partially offset sentiment in speculative stocks, or (2) sentiment is marketwide and there is "…no tendency for institutions to take contrarian positions." That is, consistent with nearly all previous work, Cornell, Landsman, and Stubben assume individual investors, in aggregate, trade on sentiment. In contrast, we propose the possibility that sentiment metrics may actually capture institutional investor demand shocks (and individual investors, in aggregate, offset sentiment induced demand shocks). Given a buyer for every seller and classifying all investors as either institutional or individual investors, both institutions and individual investors cannot, in aggregate, simultaneously trade on sentiment.

Empirically, Cornell, Landsman, and Stubben (2011) focus on the relation between *high sentiment levels* and previous and subsequent institutional demand shocks. Our analysis focuses on *changes* in sentiment and contemporaneous *changes* in ownership (i.e., demand shocks) as well as sentiment *levels* and contemporaneous ownership *levels*. In this appendix, we repeat their tests and add further tests to better understand these relations. There are, however, three complicating factors when examining sentiment *levels* and subsequent institutional demand shocks (i.e., *changes* in institutional demand).

First, as shown in Panel A of Table 4, institutional demand shocks are, on average, positively related to volatility, i.e., unconditional on sentiment levels, institutional demand shocks for high volatility stocks are greater than their demand shocks for low volatility stocks. Thus, in contrast to Cornell, Landsman, and Stubben (2011) who solely focus on institutional demand shocks following

high sentiment levels, we examine whether the relation between subsequent institutional demand shocks and lag return volatility *differs* following high and low sentiment levels.

Second, if sentiment induced demand shocks drive mispricing, then demand shocks (i.e., buying and selling by institutions or individuals) should be related to *changes* in sentiment (e.g., Table 2) and ownership *levels* (i.e., the fraction of shares held by institutions) should be related to sentiment *levels* (e.g., Table 3). If, for instance, sentiment increases this quarter, sentiment traders should buy speculative stocks from (and sell safe stocks to) liquidity traders this quarter. If sentiment does not change next quarter, there should be no systematic change in sentiment traders' or liquidity traders' demand for speculative or safe stocks, i.e., existing holdings should reflect their current preferences. Nonetheless, there are reasonable scenarios that may drive a relation between sentiment levels and subsequent sentiment or liquidity traders' demand shocks. Some rational liquidity traders, for instance, may try to forecast when sentiment will change and adjust their positions with a lag.[42]

Third, even if there is a delayed response to changes in sentiment, it is not clear how one expects a sentiment trader or a liquidity trader to adjust their positions. Specifically, as shown below, sentiment is mean-reverting, i.e., changes in sentiment are inversely related to beginning of quarter sentiment levels. As a result, there are reasonable scenarios where *either* sentiment traders or liquidity traders may move from speculative stocks toward safe stocks following high sentiment levels. First, high beginning of quarter sentiment may encourage slow responding liquidity traders to sell overvalued speculative stocks to, and buy undervalued safe stocks from, sentiment traders. Alternatively, given high sentiment levels forecast a decline in sentiment, it also forecasts a decline in sentiment traders' demand for speculative stocks. That is, regardless of beginning of quarter sentiment levels, the sentiment hypothesis implies that a decrease in sentiment should be associated

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[42] Note, however, that this would also require sentiment traders to respond with a lag. That is, if sentiment is high now, a sentiment trader's current holdings of high volatility stocks will reflect her current demand level for high volatility stocks. To encourage her to hold additional speculative shares (without a change in sentiment), she too must respond with a lag.

with sentiment traders selling risky stocks. Of course, both these scenarios cannot simultaneously be true, i.e., both sentiment and non-sentiment trades cannot, in aggregate, simultaneously decrease their fractional ownership in risky stocks. (Analogous scenarios hold for low beginning of quarter sentiment levels.)

   With these issues in mind, we begin by examining the auto- and cross-correlations in sentiment levels and changes. Panel A in Table C-1 reports the autocorrelation in the quarterly sentiment and change in sentiment series. Consistent with Baker and Wurgler's (2006) Figure 1 and Novy-Marx (2012) Figure 9, sentiment levels (both raw and orthogonalized) are highly autocorrelated. Raw changes in sentiment exhibit much lower, but still meaningful, persistence. The serial correlation in orthogonalized changes in sentiment, however, does not differ meaningfully from zero. Panel B reports the correlation between sentiment *levels* at the end of quarter *t*-1 and *changes* in sentiment over the following quarter. As noted above, quarterly changes in sentiment are inversely related to beginning of quarter sentiment levels (statistically significant at the 5% level or better for both raw and orthogonalized values).[43] This is consistent with the investor sentiment hypothesis in that sentiment should be a mean-reverting process.

<div align="center">[Insert Table C-1 about here]</div>

   We next sort the sample into high and low beginning of quarter sentiment levels and examine both subsequent returns and subsequent institutional demand shocks. Panels A and B in Table C-2 report the time-series means of the cross-sectional average values following high and low sentiment. Panel C reports the difference between Panels A and B. Not surprisingly, given sentiment is mean-reverting, the results in the third column reveal that, on average, sentiment declines following high sentiment levels (Panel A) and increases following low sentiment levels (Panel B). The results in Panel C reveal the difference is statistically meaningful (at the 5% level).

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[43] Because Baker and Wurgler's (2006, 2007) change in sentiment index is not equivalent to changes in sentiment levels (as discussed in the paper), this is not a purely mechanical relation.

[Insert Table C-2 about here]

Consistent with Figure A-2, the fourth column reveals that high volatility stocks tend to underperform low volatility stocks following high sentiment levels (Panel A) and outperform low volatility stocks following low sentiment levels (Panel B). Results in Panel C reveal the difference is statistically meaningful (at the 1% level). Consistent with Cornell, Landsman, and Stubben (2011), the last column in Panel A reveals that, on average, institutional demand shocks for high volatility stocks are greater than their demand shocks for low volatility stocks following high sentiment levels. The results in Panel B reveal, however, that this pattern also holds following low sentiment levels (consistent with Panel A in Table 4). Panel C reveals that institutional investors' demand shocks for high volatility stocks are greater following low sentiment levels and their demand shocks for low volatility stocks are greater following high sentiment levels. As shown in the last row, however, the difference following high and low sentiment levels is not meaningful. In short, we find no evidence that institutional demand *shocks* for volatile and safe stocks are meaningfully related to beginning of quarter sentiment *levels*.

The results in Table C-2 reveal that sentiment levels are related to subsequent returns in the predicted direction. And although the differences are not statistically meaningful, the difference in institutional demand shocks for high and low volatility stocks are greater following low sentiment levels than high sentiment levels. Thus, institutional demand shocks are in the same "direction" as returns, i.e., the signs in the final two columns of Panel C are identical. As discussed above, however, this could reflect both a delayed fundamental trade (e.g., institutional demand shocks for high volatility stocks are lower following high sentiment levels than low sentiment levels because high volatility stocks are overvalued following high sentiment levels) or a sentiment trade (e.g., institutional demand shocks for high volatility stocks is lower following high sentiment levels than

low sentiment levels because sentiment tends to decline following high sentiment levels and institutions trade on sentiment).

To differentiate these explanations, we partition high (and low) sentiment periods into those followed by an increase in sentiment and those followed by a decrease in sentiment. If the institutional demand shock patterns in Table C-2 are driven by institutions trading in the direction of fundamentals, then high sentiment followed by an increase in sentiment should result in even lower institutional demand shocks for high volatility stocks. Alternatively, if the relation is driven by aggregate institutional sentiment trading, then high sentiment followed by an increase in sentiment will cause even greater institutional demand shocks for high volatility stocks. An analogous argument holds for low sentiment periods.

The first two rows of Table C-3 reveal that in 40 of the 62 quarters following high sentiment, changes in sentiment are negative. Thirty-five percent of the time (22/62 quarters), high sentiment is followed by an increase in sentiment. Note that the figures in Table C-2 are simply the weighted averages of the figures in Table C-3. The results in Panel A of Table C-3 reveal that the tendency for safe stocks to outperform risky stocks following high sentiment fully results from those quarters where sentiment is high and then declines (top row in Panel A). When sentiment is high, but the subsequent change in sentiment is positive (second row in Panel A), high volatility stocks outperform low volatility stocks. This is fully consistent with Baker and Wurgler's (2006, 2007) sentiment hypothesis.

[Insert Table C-3 about here]

Inconsistent with the idea that institutional demand shocks for high volatility stocks are lower when sentiment is high because institutions are fundamental traders, high sentiment followed by an increase in sentiment (second row in Panel A) is associated with increased institutional demand for high volatility stocks. In short, matching the return pattern once more, high sentiment followed by

an increase in sentiment (second row in Panel A) results in: (i) higher institutional demand for high volatility stocks and decreased institutional demand for safe stocks and (ii) volatile stocks outperforming safe stocks. In contrast, when high sentiment is followed by a decline in sentiment (first row in Panel A), volatile stocks underperform safe stocks and there is no evidence of a meaningful difference in institutional demand shocks for safe and risky stocks.

Panel B reveals that high volatility stocks tend to outperform low volatility stocks following low sentiment (Table C-2) because low sentiment is usually followed by an increase in sentiment (38 of 61 quarters). In those 23 of 61 quarters where low sentiment is followed by a decline in sentiment (top row of Panel B), we do not find a meaningful difference between high and low volatility stock returns (although the point estimate is negative consistent with Baker and Wurgler's (2006, 2007) sentiment hypothesis). In the low sentiment case (Panel B), however, we find no evidence that institutional demand shocks vary with changes in sentiment (third row of Panel B).

In sum, we find no evidence that institutional demand shocks for volatile and safe stocks differs meaningfully following high and low sentiment levels (Table C-2). When we limit the sample to high beginning of quarter sentiment and further partition the sample into those quarters that subsequently increase sentiment and those that decrease sentiment (Panel A in Table C-3), we find further evidence that institutions are sentiment traders. Specifically, even when sentiment is already high, institutional investors continue to buy risky stocks from, and sell safe stocks to, individual investors when sentiment increases (second row of Panel A in Table C-3). When we limit the sample to low beginning of quarter sentiment and further partition the sample into those quarters that subsequently increase or decrease sentiment, we find no evidence of a meaningful difference in subsequent institutional demand shocks (Panel B of Table C-3). However, because the sample sizes are relatively small (e.g., we only have 22 quarters where high sentiment levels are followed by an increase in sentiment) the results in this appendix should be interpreted with caution.

Table C-1
Descriptive Statistics

Panel A reports the autocorrelation in the Baker and Wurgler (2006, 2007) sentiment levels and change in sentiment metrics. $\perp$ indicates the metric is orthogonalized with respect to growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator. Panel B reports the correlation between beginning of quarter sentiment levels and subsequent changes in sentiment. In Panels A and B, p-values are reported parenthetically.

Panel A: Autocorrelation in sentiment levels and changes in sentiment (n=123 quarters; 198006-201012)			
Sentiment	Sentiment$^\perp$	ΔSentiment	ΔSentiment$^\perp$
0.925	0.923	0.197	0.027
(0.01)	(0.01)	(0.03)	(0.77)

Panel B: Time-series correlation between sentiment levels and the subsequent change in sentiment		
	ΔSentiment$_t$	ΔSentiment$^\perp_t$
Sentiment$_{beg\ of\ quarter\ t}$	-0.209	
	(0.03)	
Sentiment$^\perp_{beg\ of\ quarter\ t}$		-0.182
		(0.05)

Table C-2
Sentiment levels and subsequent institutional demand shocks

We partition the sample into high (Panel A) and low (Panel B) beginning of quarter sentiment periods. The second column reports the mean sentiment level at the beginning of the quarter and the third column reports the mean change in sentiment during the quarter. We also compute the average return and institutional demand shock over the quarter for stocks in the top and bottom volatility deciles. The third row in each panel reports the difference in subsequent returns or institutional demand shocks for high and low volatility stocks and associated t-statistics. Panel C reports the difference between Panels A and B and associated t-statistics.

	N	Beg. of quarter Sent$^\perp$	ΔSent$^\perp$ over quarter	Return over quarter	Institutional demand shock over quarter
Panel A: Returns and demand following high sentiment levels					
	62	0.724	-0.187		
High σ				-0.018	0.111
Low σ				0.022	-0.225
High σ – low σ				-0.040	0.336
				(-2.02)*	(2.79)**
Panel B: Returns and demand following low sentiment levels					
	61	-0.736	0.190		
High σ				0.042	0.142
Low σ				-0.008	-0.363
High σ – low σ				0.050	0.505
				(2.17)**	(4.83)***
Panel C: Differences following high versus low sentiment levels					
		1.461	-0.376		
		(-11.94)***	(2.12)**		
High σ				-0.060	-0.031
Low σ				0.029	0.138
High σ – low σ				-0.089	-0.169
				(-2.96)***	(-1.06)

Table C-3
Sentiment levels and subsequent institutional demand shocks conditional on subsequent changes in sentiment

We partition the sample into high (Panel A) and low (Panel B) sentiment quarters based on beginning of the quarter sentiment levels. We further partition each sample into those quarters that experience a decrease in sentiment or an increase in sentiment. The second column reports the mean sentiment level at the beginning of the quarter and the third column reports the mean change in sentiment during the quarter for the four conditional samples. The next six columns report the mean return or institutional demand shock for the high volatility portfolio, the low volatility portfolio, and their difference for each sample. The third row in each panel reports the difference in returns and demand shocks given a subsequent decline in sentiment or a subsequent increase in sentiment (i.e., the difference between the first and second rows) and associated t-statistics.

	N	Beginning of quarter Sent$^\perp$	ΔSent$^\perp$ over the quarter	Return over quarter			Institutional demand shock over quarter		
				High σ	Low σ	High-low σ	High σ	Low σ	High-low σ
				Panel A: High beginning of quarter sentiment levels					
$\Delta Sentiment^\perp < 0$	40	0.775	-0.794	-0.051	0.042	-0.093 (-4.03)***	-0.004	-0.091	0.087 (0.64)
$\Delta Sentiment^\perp > 0$	22	0.633	0.918	0.041	-0.015	0.057 (2.13)**	0.319	-0.469	0.788 (3.92)***
$\Delta Sent.^\perp < 0 - \Delta Sent.^\perp > 0$			-1.712 (-9.82)**			-0.149 (-4.25)***			-0.701 (-2.89)***
				Panel B: Low beginning of quarter sentiment levels					
$\Delta Sentiment^\perp < 0$	23	-0.684	-0.694	-0.022	0.006	-0.028 (-1.23)	0.118	-0.343	0.461 (2.75)***
$\Delta Sentiment^\perp > 0$	38	-0.768	0.724	0.080	-0.016	0.097 (3.27)***	0.157	-0.375	0.532 (3.93)***
$\Delta Sent.^\perp < 0 - \Delta Sent.^\perp > 0$			-1.418 (-10.38)*			-0.125 (-3.30)***			-0.071 (-0.33)