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 safer to more speculative stocks when sentiment increases. Exploiting these cross-sectional patterns and changes in share ownership, we find, in contrast to theoretical assumptions and common perceptions, that sentiment metrics capture institutional rather than individual investors' demand shocks. Additional tests suggest a confluence of factors contribute to this relation including institutions' risk management, herding, momentum trading, reputational concerns, attempting to ride bubbles, preferred habitats, and underlying investors' flows. If the commonly used sentiment metrics truly capture investor sentiment, then institutional investors are the sentiment traders whose demand shocks drive prices from value.

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For nearly 70 years the investor sentiment literature has made a near universal assumption that irrational individual investors are the source of sentiment-based demand shocks that drive prices from value. For instance, the earliest work we could identify that considers the impact of investor sentiment on stock prices uses odd-lot trading to identify the demand shocks attributed to "public psychology" relative to the more rational views of "New York Stock Exchange members" (Drew, Gaubis, Fitzgerald, and Livingston (1950)). The assumption that individual investors are responsible for sentiment-induced mispricing is explicitly repeated in the time since, e.g., a small sample of studies expressing this view include Zweig (1973), Shleifer and Summers (1990), Lee, Shleifer, and Thaler (1991), Neal and Wheatley (1998), Nagel (2005), Baker and Wurgler (henceforth BW) (2006, 2007), Barberis and Xiong (2012), Lemmon and Portniaguina (2012), Stambaugh (2014), and Da, Engelberg, and Gao (2015). In fact, traditional proxies for investor sentiment (e.g., closed-end fund discounts, mutual fund flows, odd-lot transactions) are selected precisely because they attempt to capture the behavior of individual investors.

Our study focuses on examining the assumption that irrational individual investors are the source of sentiment-based demand shocks captured by sentiment metrics while institutions are smart-money rational investors. Our primary result is demonstrating that commonly-used measures of investor sentiment capture the demand shocks of institutional investors (in aggregate) rather than individual investors. If these metrics capture investor sentiment, then in aggregate, institutional investors, rather than individual investors, are the traders who drive sentiment-induced mispricings.

There is an extensive literature examining investor sentiment. Most of this work focus on two types of tests: (1) examining the correlation between *changes* in sentiment and contemporaneous returns (i.e., evidence that sentiment traders' demand shocks impact prices), and/or (2) examining the relation between sentiment *levels* and subsequent returns (i.e., evidence that sentiment traders' previous demand shocks have driven prices from value). Moreover, both sets of tests have been examined at the market level (e.g., do high sentiment levels forecast lower market returns?) and with the cross-section of security returns. In the latter case, most (pre-BW) work suggests that small stocks should be more sensitive to the vagaries of sentiment because individual investors (the presumed sentiment traders) own a larger fraction of the outstanding shares of small stocks. Thus, for example, previous work tests if small stocks have larger sentiment betas than large stocks. Unfortunately, as we detail in the Appendix, pre-BW empirical support for the investor sentiment hypothesis is, at best, mixed. For instance, focusing just one sentiment metric—closed-end fund discounts—and cross-sectional tests, Lee Shleifer, and Thaler (1991) report that small stocks have larger sentiment betas while Qui and Welch (2006) argue they do not. Similarly, Neal and Wheatly (1994) find closed-end fund discount levels predict the size premium, while Brown and Cliff (2005) find no evidence that closed-end fund discounts are related to the subsequent size premium.

BW generate four important extensions to the investor sentiment hypothesis and, in contrast to previous work (taken as a whole), find robust evidence that investor sentiment materially impacts asset prices. Their work has led to a renewed focus on investor sentiment in general, and the BW sentiment metric in particular (Google Scholar reports the BW studies have been cited more than 3,500 times).[1] First, BW point out that because any individual sentiment proxy will contain both a sentiment component and an idiosyncratic component, extracting the common component from a set of proxies will better capture sentiment than individual proxies (Brown and Cliff (2004) take a similar approach). This may help explain why earlier sentiment tests often yield conflicting

[1] For example, recent research using the BW metric includes Antoniou, Doukas, and Subrahmanyam (2013), Rosch, Subrahmanyam, and van Dijk (2014), Moskowitz, Ooi, and Pedersen (2012), Karolyi, Lee, and van Dijk (2012), Ramadorai (2012), Hribar and McInnis (2012), McLean and Zhao (2012), Novy-Marx (2014), Stambaugh, Yu, and Yuan (2012, 2014), Baker, Wurgler, and Yuan (2012), and Yu and Yuan (2011).

conclusions. Second, BW emphasize that the 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") combined with finite demand and supply elasticities.[2] Third, BW propose that changes in sentiment impact which securities sentiment traders buy and sell. Specifically, sentiment traders will shift from safe securities to speculative securities when sentiment increases and from speculative securities to safe securities when sentiment declines and it is these sentiment-induced demand shocks that drive the mispricing.[3] Moreover, BW point out that these cross-sectional implications mean that the relation between sentiment and market returns may be weak (even if the cross-sectional relations are strong).[4] As BW point out, their evidence of positive sentiment betas for speculative stocks and negative sentiment betas for safe stocks is consistent with this interpretation. Fourth, BW emphasize that their results—demonstrating speculative stocks tend to have lower future returns than safe stocks when sentiment levels are high—appears inconsistent with rational asset pricing and serves as (2007, p. 135), "…a powerful confirmation of the sentiment-driven mispricing view."

BW's hypotheses provide a unique framework to examine which traders are captured by sentiment metrics. Specifically, the sentiment hypothesis requires net buying or selling by sentiment traders resulting in *changes* in both sentiment traders' ownership levels and security prices (assuming, as the sentiment literature requires, sentiment-induced demand shocks impact prices). However, 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 susceptible to the changes in

[2] 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 sentiment-induced mispricing (see, for example, Miller (1977), DeLong, Shleifer, Summers, and Waldmann (1990a), and Shleifer and Vishney (1997)).
[3] BW propose that greater limits to arbitrage for speculative stocks (relative to safe stocks) also contribute to speculative stocks' larger sentiment betas. We discuss this point in greater detail below.
[4] For example, BW (2007, p. 133) note, "Such episodes may, controlling for any changes in fundamentals, reduce the prices of speculative stocks and at the same time increase the prices of bond-like stocks. In this case, the effect of sentiment on aggregate returns will be muted because stocks are not all moving in the same direction.

sentiment. For ease of exposition, we denote these latter traders as "liquidity" traders.[5] It is this insight from their work that allows us to generate the first test that identifies the traders captured by sentiment metrics via these cross-sectional implications. Specifically, *changes* in sentiment will be positively related to *changes* in sentiment traders' demand (i.e., demand shocks) for speculative stocks and inversely related to their demand shocks for safe stocks. An increase in sentiment, for example, causes sentiment traders to *increase* their demand for risky stocks and *decrease* their demand for safe stocks, i.e., their buying and selling—their demand shocks—are what drives the mispricing in the sentiment literature.

Importantly, given the market clearing condition requires a buyer for every seller, both institutions and individuals (in aggregate) cannot be the sentiment traders. That is, all investors are either individuals or institutions—an increase in the fraction of a company's shares held by institutions requires an equivelent decline in the fraction of the company's shares held by individual investors. If institutional and individual investors' sentiments are positively correlated and sentiment proxies capture sentiment, our results may be interpreted as which group of investors—institutions or individuals—are more subject to sentiment.

Our primary tests demonstrate that, despite the near universal assumption that (as a group) irrational individual investors are the source of sentiment-based demand shocks captured by sentiment metrics, commonly-used measures of investor sentiment capture the demand shocks of institutional, rather than individual, investors. That is, an increase in sentiment is associated with an increase in institutional investors' demand for risky stocks and, by definition, an associated decline in individual investors' demand for speculative stocks. Although our central focus is on examining *changes* in sentiment and institutional versus individual investors' demand shocks (i.e., *changes* in

[5] 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.

institutional ownership levels), we further investigate the hypothesis that sentiment metrics capture institutional investors' behavior by examining the relation between investor sentiment levels and institutional versus individual investors' ownership levels.[6] If the sentiment metrics capture institutional investor demand as our first results suggest, then we should find that their proportional ownership *levels* of speculative stocks, relative to their proportional ownership levels of safe stocks, are higher when sentiment *levels* are higher. Equivalently, high sentiment levels should be associated with (relatively) lower aggregate individual investor ownership levels of speculative stocks. Our results, which are consistent with these expectations, provide further support for the hypothesis that the BW sentiment metric captures institutional, rather than individual, investors' demand.

We also consider a test that exploits the fact that one of the components of the BW sentiment metric—the dividend premium—is computed from the cross-section of securities and therefore is unique from the other components in that it has direct implications for demand shocks in the cross-section of securities. Specifically, 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 premium investors are willing to pay for dividend paying stock (i.e., the "dividend premium"). The direct implication, therefore, is that sentiment traders' demand shocks for dividend-paying stocks relative to their demand shocks for non-dividend paying stocks will positively covary with changes in the dividend premium. We find evidence consistent with this implication—the dividend premium increases when institutions buy dividend paying stocks from individual investors and sell non-dividend paying stocks to

[6] We focus on institutional and individual investors' demand shocks and changes in sentiment because both institutional investors' ownership levels and sentiment levels are persistent, which can lead to problems in inference (see Yule (1926), Granger and Newbold (1974), Ferson, Sarkissian, and Simin (2003), and Novy-Marx (2014)). Our tests based on changes in sentiment (and changes in institutional/individual investor ownership) largely avoid this issue.

individual investors. If sentiment-induced demand shocks drive changes in the dividend premium then, once again, the results suggest that institutions are the sentiment traders.

Because our tests generate the surprising result that sentiment metrics capture institutional, rather than individual, investors' behavior, the balance of our study focuses on understanding why. We first consider the possibility that individual investors' trading is not captured by the inverse of 13(f)-inferred institutional demand shocks. Inconsistent with this explanation, using individual investors' trading data from a large retail broker (i.e., Terry Odean's data), we find that individual investors' demand shocks are strongly related to the inverse of 13(f)-inferred institutional demand shocks.

Second, we consider the possibility that the BW metric is somehow unique in capturing institutional demand shocks by examining 16 alternative investor sentiment metrics—the six individual components of BW metric, three measures of mutual fund flows, two consumer sentiment measures, one survey-based measure of individual investors' sentiment, two measures of venture capital flows as proxies for sophisticated investors' sentiment, and two measures of aggregate economic activity or stress. We find that none of the 17 measures (the BW metric and the 16 alternatives) capture individual investors' demand shocks. In contrast, 10 of the 17 measures appear meaningfully related to institutional investors' demand shocks. Moreover, the ability of sentiment metrics to predict cross-sectional return patterns is limited *only* to those metrics that capture institutional investors' demand shocks. In short, the relations between sentiment metrics, contemporaneous returns, subsequent returns, and institutional demand shocks are pervasive.

Third, we consider the possibility that the relations between sentiment metrics, returns, and institutional demand shocks reflects time-series variation in risk premia and may be related to trading between institutional and individual investors. Although this scenario is impossible to reject (due to the joint hypothesis problem), BW point out that the relation between their metric and subsequent returns is inconsistent with standard conditional asset pricing theory. That is, although the expected risk premium between speculative and safe stocks may vary over time, the sign should remain positive. We, too, find little support for the hypothesis that the patterns in returns and ownership changes can be fully accounted for by time-varying required returns.

Fourth, we examine the hypothesis that institutional investors' sentiment trading derives from underlying investors' flows, e.g., when sentiment increases, underlying investors shift funds from conservative managers to more aggressive managers. There are two important considerations of the underlying investors' flows explanation. First, underlying investors' flows cannot resurrect the hypothesis that individual investors—at least as captured by non-13(f) demand shocks—sentiment trade. For example, if an increase in sentiment causes underlying investors to shift from managers that focus on utilities to managers that focus on technology stocks, someone still has to offset those trades (i.e., someone else has to buy utilities and sell technology). In aggregate, individual investors (as captured by non-13(f) demand shocks) provide the liquidity that allows sentiment traders to sentiment trade. In addition, although we can estimate the impact of flows on trades by assuming institutions invest/divest flows into their existing portfolios, it is possible that flows themselves impact manager's decisions, e.g., a manager with outflows in late 2008 may choose to sell riskier (or safer) stocks rather than proportionately liquidate her portfolio.

Nonetheless, we find strong evidence that flows impact aggregate institutional demand shocks, e.g., stocks held by managers with large outflows exhibit a large decline in institutional ownership. A series of tests, however, reveal little evidence that underlying investor flows drive aggregate institutional sentiment trading. Most of our tests focus on aggregate institutional demand shocks as measured by 13(f) filings. Because these filings are at the institution level, however, they capture intermanager flows (e.g., flows from Fidelity to Janus). We use mutual fund data to measure intra-manager flows for a subset of institutions (i.e., mutual funds) and find some evidence that intramanger flows (e.g., flows from one Janus fund to a different Janus fund) contribute to institutional sentiment trading. Nonetheless, manager's decisions (whether at the 13(f) level or the mutual fund level) appear to play the dominate role in institutional sentiment trading.

Fifth, we investigate the possibility that several well-known institutional behaviors contribute to institutional sentiment trading. Specifically, previous work suggests institutions: (1) are reluctant to deviate from benchmarks due to risk management or reputational concerns, (2) tend to buy stocks that institutions previously purchased (institutional herding), and (3) are attracted to stocks that have recently outperformed (institutional momentum trading). Consistent with this hypothesis, our estimates suggest that these factors account for 25%-40% of the institutional sentiment trading.

Sixth, we investigate patterns across different types of institutional investors to help understand what drives institutional sentiment trading. We demonstrate that some types of institutions (banks, insurance companies, pensions, and unclassified institutions) tend to avoid holding and trading risky stocks while other types of institutions (mutual funds, independent advisors, and hedge funds) are much more willing to trade in risky stocks. Thus, we hypothesize the former group will contribute little to aggregate institutional sentiment trading due to their preferred habitat of more conservative securities. However, we also show that flows to both mutual funds and independent advisors are sensitive to their lag performance. Thus, if reputational concerns influence institutions' sentiment trading, we also expect mutual funds and independent advisors to contribute relatively more to aggregate institutional sentiment trading. Last, we expect hedge funds are the most likely type of institution to attempt to "ride bubbles." As with flows, however, the bubble riding story cannot resurrect the explanation than individual investors are the sentiment traders because individuals are providing the liquidity for sentiment traders (i.e., individual investors moving in the "opposite" direction as sentiment).

Consistent with preferred habitats, reputational concerns, and bubble ridding, we find that the latter group of institutions—mutual funds, independent advisors, and hedge funds—play a disproportionately large role in driving aggregate institutional sentiment trading. Specifically, although these three investor types account for 50% of the institutional ownership (on average), they account for 89% of our measure of aggregate institutional sentiment trading.

Although our tests suggest that sentiment metrics capture institutional investors' *aggregate* demand shocks, most trades are between institutions (rather than between institutions and individual investors) as institutions account for the vast majority of trading.[7] Because every sentiment induced trade must be offset by a trader less subject to sentiment, it follows that while some institutions trade with sentiment, other institutions provide much of the necessary liquidity to offset their demand, even if institutions, in aggregate, trade with sentiment. Thus, we next investigate factors that influence an individual institution's decision to sentiment trade. These tests yield two key insights. First, consistent with risk management and reputational concerns, managers underweight risky stocks tend to subsequently purchase risky stocks (i.e., managers tend to move toward the market portfolio) regardless of changes in sentiment. Thus, when sentiment increases, managers underweight (overweight) risky stocks tend to be sentiment (liquidity) traders. Analogously, when sentiment declines, managers overweight (underweight) risky stocks tend to be sentiment (liquidity) traders. Second, we find that transient institutions—those institutions with high turnover and relatively small positions—are much more likely to trade on sentiment than non-transient institutions.

Our last set of tests focus on understanding the roles of: (1) the extent that a manager already tilts their portfolio toward risky stocks (i.e., holdings at the beginning of the quarter) and (2) how

[7] Estimates suggest that institutional investors have long accounted for 70-96% of trading volume (e.g., Schwartz and Shapiro (1992), Jones and Lipson (2005)).

managers change that tilt (i.e., trading over the quarter) impacts the manager's returns and flows. We show a manager's beginning of quarter tilt toward risky stocks is much more important than their shift toward risky stocks over the quarter in explaining their portfolio return. Thus, a manager's "risk" in sentiment trading is that she holds a portfolio tilted toward risky stocks when risky stocks underperform. Managers, however, do not appear to face a cost in flows (on average) from bearing this risk. Specifically, managers with high exposure to risky stocks tend to garner greater inflows than other managers when sentiment increases, but do not suffer greater outflows when sentiment declines. This may help explain why managers are willing to shift toward riskier stocks when sentiment increases.

In sum, our results demonstrate that institutional investors (in aggregate), rather than individual investors, are the traders captured by the BW sentiment metric. If, as the sentiment literature suggests, sentiment induced demand shocks drive mispricing, then institutional investors, not individual investors, are the traders behind these sentiment-induced demand shocks. Moreover, our analysis suggests a confluence of factors contribute to aggregate institutional sentiment trading and influence which institutions sentiment trade and which institutions help offset these trades. Our results have implications not only for understanding investor sentiment, institutional investors, and individual investors, but also for interpreting a large body of work that uses these metrics as explanatory variables in other tests.

I. Data

A. Investor Sentiment

BW define their investor sentiment measure as the first principal component of six commonly employed investor sentiment proxies: the level of closed-end fund discounts, NYSE share turnover, the number of IPOs, the average first day return of IPOs, the share of equity issues in total debt and equity issues, and the dividend premium (the difference between the average market-to-book ratios for dividend payers versus nonpayers). BW also compute "orthogonalized sentiment" as the first principal component of the residuals from regressions of each of the six sentiment proxies on a set of business cycle variables: 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.[8] 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.[9]

B. *Stock, Institutional Ownership, and Mutual Fund Data*

We limit the sample to ordinary securities (CRSP share code 10 or 11) and, as suggested by BW (2007), use return volatility as the measure of a stock's speculative nature.[10] 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. We measure institutional ownership levels for a stock as the number of shares held by institutional investors divided by the number of shares outstanding. We measure the institutional demand shock as the change in the number of shares held by institutions over the quarter divided by the number of

[8] Because BW measure changes in sentiment as the first principal component of changes in the proxies rather than the change in the first principal component of the proxies, the BW change-in-sentiment measure is not equal to the changes in their sentiment levels index (see BW (2007) footnote 6 for additional detail).
[9] In untabluated analysis, we repeat our primary tests based on quarterly changes in sentiment computed from the first principal component of the quarterly changes in the six underlying series. Our conclusions remain unchanged.
[10] 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.

shares outstanding.[11] We assume that 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 (those with 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.[12]

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

We merge (using WRDs MFlinks) Thomson Financial N-30D and CRSP mutual fund data to form the mutual fund sample. Our mutual fund sample construction (details given in Appendix A) follows Griffin, Harris, Shu, and Topaloglu (2011) and Ben-David, Franzoni, and Moussawi (2012).

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[11] Many firms have changes in the number of shares outstanding with no change in the CRSP share adjustment factor, e.g., if an employee exercises an option within the quarter, the number of outstanding shares will increase (Core, Guay, and Kothari (2002)). Thus, for example, if an employee exercises a stock option, and there is a small increase in the number of outstanding shares but no institutional trading, the change in the fraction of shares held by institutions would decline. To ensure our results are not driven by such events, we measure institutional demand shocks by directly examining institutional trading. Specifically, the institutional demand shock is the (split-adjusted) change in the number of shares held by institutions divided by end of quarter shares outstanding (rather than the change in the fraction of shares held by institutions at the beginning and end of the quarter). Nonetheless, as a robustness test, we repeat our primary tests based on institutional demand shocks measured as the difference between the fraction of outstanding shares held by institutions at the end of the quarter and the fraction of outstanding shares held by institutions at the beginning of the quarter. Our results remain, effectively, identical. In addition, as discussed in the Section IV (and detailed in Appendix A), we extend our analysis to directly consider the net supply of shares from companies and insiders in addition to individual investors in offsetting net institutional demand. We exclude observations where reported institutional ownership exceeds 100% of shares outstanding (about 1% of observations) following Yan and Zhang (2009).

[12] Figures from Agarwal, Jiang, Tang, and Yang's (2013) Table I shows that confidential filings account for less than 1% of all institutional stock positions.

Analogous to institutional demand shocks, we define the aggregate mutual fund demand shock for security *i* in quarter *t* as the change in the number of shares held by mutual funds divided by the number of shares outstanding.

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.[13] The number of securities in our sample averages 3,945 stocks each quarter between June 1980 and December 2010 (*n*=123 quarters). Table I 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 "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*.[14]

[Insert Table I about here]

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

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)

[13] Because institutions are not required to report holdings less than 10,000 shares and $200,000, we cannot be certain that 13(f) data adequately proxy for institutional ownership levels/demand shocks for stocks with very low levels of institutional ownership. Firms with less than five institutional shareholders account for, on average, less than 0.07% of market capitalization.

[14] This also accounts for seasonality in the filing of 13(f) reports, e.g., once meeting a $100M hurdle at the end of any month, requires the manager to file the first report in December of that year (see Lemke and Lins (1987)). In addition, 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 are not impacted by this de-meaning.

sentiment levels, hold for our quarterly data from 1980-2010.[15] Following BW, 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 return and the (raw or orthogonalized) 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.[16] Appendix A also confirms that sentiment levels are inversely related to the subsequent return differences for high and low volatility stocks, e.g., high volatility stocks meaningfully 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 those of 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, each quarter, the cross-sectional mean

[15] Because the 13(f) data are only available beginning in December 1979, we cannot include the earlier BW sample years in our sample.

[16] As noted earlier, BW point out that speculative stocks also have greater sensitivity to changes in sentiment because they are harder 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 increasing their demand for high volatility and decreasing their demand for low volatility stocks. That is, the different signs on 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.

institutional demand shock 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 securities within each volatility portfolio.[17]

The results, reported in Table II, reveal the pattern in institutional investor demand shocks and contemporaneous returns matches the pattern in changes in sentiment and 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 orthogonalized sentiment is 31.5%) 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 orthogonalized sentiment is -28.7%). As shown in the last column of Table II, the correlation between the difference in institutional demand shocks for high and low volatility stocks and changes in sentiment is meaningfully positive (statistically significant at the 1% level) using either raw or orthogonalized changes in sentiment.

[Insert Table II]

In sum, institutional investors' demand shocks move with, and individual investors' demand shocks move counter to, changes in sentiment for high volatility stocks. Further, just as is the case for returns, the relation is reversed for low volatility stocks. The results reveal that the BW metric captures institutional, rather than individual, investors' aggregate demand shocks.

[17] Because the sentiment hypothesis requires that sentiment traders' demand for speculative securities relative to their demand for safe stocks increases when sentiment increases, we focus directly on the question of which investor groups demand for volatile (and safe) stocks increases when sentiment increases. In Section III, we focus on understanding *why* sentiment metrics capture institutional investors' demand shocks including the possibility that other non-sentiment factors, such as institutional momentum trading, may help explain why sentiment metrics capture institutional investors' demand shocks.

B. Sentiment Levels and Institutional/Individual Investor Ownership Levels

If sentiment metrics capture the demand of institutional rather than individual investors (as Table II suggests), 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. Because institutional ownership grows substantially throughout this period (see, for example, Dasgupta, Prat, and Verardo (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.[18]

Table III reports the time-series mean of the cross-sectional average detrended institutional ownership levels for stocks within each volatility decile during high (above median) and low (below median) sentiment periods (Panel A) or high and low orthogonalized sentiment periods (Panel B). 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.[19] The tests reported in the final column of the table show that detrended institutional ownership levels for high volatility stocks relative to their ownership levels for low volatility stocks 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 III) is consistent with the demand shock analysis (Table II). Both tests support the hypothesis that if the BW metric captures investor sentiment, then institutions, rather than individual, investors are the sentiment traders.

[Insert Table III about here]

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

[19] The sum is not exactly zero because our sample contains an odd number of quarters (123). Specifically, given 61 low sentiment quarters and 62 high sentiment quarters, 61/123*(low sentiment value) + 62/123*(high sentiment value) = 0.

C. An Alternative Test—Time-Series Variation in Institutional Demand for Volatile Stocks and Sentiment

Although the above tests support the argument that institutional (rather than individual) investors' demand shocks are encapsulated by the BW sentiment metric, 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 the full sample of securities. In addition, this metric provides a framework for our subsequent tests. We begin by computing the cross-sectional correlation (across all securities in our sample), each quarter, between institutional demand shocks and securities' return volatility.[20] By construction, this is the correlation between a level (stock volatility) and a change (the change in the fraction of shares held by institutions).[21] That is, each quarter, we measure the extent to which institutions are *buying* volatile stocks from individual investors (cross-sectional correlation greater than zero) or individual investors are buying volatile stocks from institutional investors (cross-sectional correlation less than zero).

Panel A in Table IV reports the time-series descriptive statistics. The cross-sectional correlation varies substantially over time—falling as low as -16.87% and rising as high as 17.65%. Thus, institutions sometimes strongly move toward volatile stocks (e.g., the quarter when the correlation between stock volatility and institutional demand shocks is 17.65%) and, at other times, strongly move away from volatile stocks (e.g., the quarter when the correlation is -16.87%).

[Insert Table IV about here]

Panel B in Table IV reports the correlation between changes in sentiment and time-series variation in institutional demand shocks for risky stocks—as measured by time-series variation in the

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[20] Following BW (2006), volatility is measured over the previous 12 months and winsorized at the 0.5% and 99.5% levels each quarter. To account for skewness, we use the natural logarithm of 1 plus the return standard deviation (measured in percent).

[21] That is, by design, the cross-sectional correlation measures the institutional demand *shock* for speculative stocks. In the words BW (2007, p. 131), "For example, suppose one thinks about investor sentiment as the propensity to speculate by the marginal investor, akin to a propensity to play the lottery; then sentiment almost by definition is a *higher* (emphasis added) demand for more speculative securities. So when sentiment increases, we expect such 'speculative' stocks to have contemporaneously higher returns."

cross-sectional correlation between institutional demand shocks and return volatility (i.e., the cross-sectional correlations summarized in Panel A). That is, we test whether institutional investors *increase* their preference for risky stocks when sentiment *increases*. Consistent with our earlier tests indicating that changes in sentiment capture institutional investors' demand shocks, the results reveal the correlation between time-series variation in institutions' attraction to volatile stocks and changes in sentiment is 37.34% based on changes in raw sentiment and 37.27% based on changes in orthogonalized sentiment (statistically significant at the 1% level in both cases). Equivalently, the correlation between changes in orthogonalized sentiment and time-series variation in individual investors' attraction to volatile stocks is -37.27%.

D. *Institutional Demand and the Dividend Premium*

BW use changes in the dividend premium as one of the components for their change in sentiment metric based upon the hypothesis 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.

The dividend premium is unique from the other components of the BW sentiment metric in that it is computed directly from the cross-section of securities and therefore allows us to directly examine whose demand shocks are captured by changes in this sentiment metric. That is, instead of testing whether the change in the dividend premium (that, according to the sentiment hypothesis, is driven by sentiment-induced demand shocks) is associated with institutional demand shocks for volatile stocks versus safe stocks, we can *directly* test whether an increase in this sentiment metric (-1*the dividend premium) is associated with institutions buying non-dividend paying stocks and selling dividend paying stocks.[22]

To examine whether changes in the dividend premium capture institutional or individual investors' demand shocks, 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.[23] We then compute the time-series correlation between quarterly changes in the dividend premium and the difference in institutional investors' demand shocks for dividend paying and non-dividend paying stocks—the correlation is 40.28% and statistically significant at the 1% level. In short, the dividend premium increases when institutional investors buy dividend paying stocks from, and sell non-dividend paying stocks to, individual investors. If sentiment traders' demand shocks drive time-series variation in the dividend premium (i.e., the dividend premium is a sentiment metric), then institutional investors, rather than individual investors, are the sentiment traders.

III. What Drives the Relation Between Institutions and BW Sentiment?

The balance of our study focuses on better understanding why, contrary to conventional wisdom, the BW sentiment metric captures institutional, rather than individual investors', demand shocks. Specifically, (1) we investigate the possibility that non-13(f) institutional demand shocks do not capture individual investors' direct trading, (2) we examine if the BW metric is unique in

[22] Because non-dividend paying stocks tend to be more volatile than dividend paying stocks, changes in the dividend premium are correlated with changes in the relative valuations of risky and safe stocks. That is, by design, BW (2006) use the dividend premium as both a sentiment indicator and a salient characteristic to sort stocks into groups based on their speculative nature. Note that our test (in this section) focuses on the straightforward question of whose demand shocks for dividend-paying versus non-dividend paying stocks are positively correlated with changes in the dividend premium.
[23] 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.

capturing institutional investor demand shocks by considering 16 additional sentiment metrics, (3) we consider the possibility that the relations between sentiment, returns, and institutions derives from time-varying risk premia, (4) we consider several tests of the role of underlying investors' flows in explaining the results, (5) we consider role of other factors known to influence aggregate institutional demand shocks (risk management, herding, and momentum trading) in explaining the results, (6) we examine variation across institutional investor types to investigate the roles of preferred habitats, reputational concerns, and bubble riding in explaining the patterns, (7) we investigate manager characteristics to better understand why some managers appear to trade on sentiment while other institutions (partially) offset their demand shocks, and (8) we investigate the role of portfolio tilts and sentiment trading to better understand how institutions' portfolio choices impact underlying investors' flows.

A. Are Individuals Captured by Non-13(f) Demand Shocks?

One potential interpretation of our results is that the inverse of 13(f) investors' demand shocks do not capture individual investors' demand shocks. As noted above, for example, institutions are not required to report small positions, small institutions need not file 13(f) reports, and managers are sometimes given exemptions from timely 13(f) filings. Moreover, non-13(f) demand shocks can capture insider trading (see Sias and Whidbee (2010)) and there is some double counting in 13(f) reports due to short sales.[24] These limitations mean that non-13(f) demand shocks may not capture retail investors' trades. Of course, this possibility does not change the fact that the BW sentiment metric *does* capture the aggregate demand shocks of those institutions filing 13(f) reports.

[24] If an institution lends its shares, the institution still reports the position in its 13(f)). We discuss these issues in greater length in the final section and investigate them directly in the Appendix.

To investigate the relation between 13(f) demand shocks and individual investors' direct trades, we compute quarterly estimates of individual investors' demand shocks from a sample of more 1.9 million trades from over 66,000 households at a large discount broker (i.e., Terry Odean's data) between January 1991 and November 1996 (*n*=24 quarters).[25] Specifically, we compute the net fraction of outstanding shares purchased by the sample of individual investors (in the discount broker dataset) for each stock quarter. We then compute the cross-sectional correlation between individual investor demand shocks (from the discount broker data) and institutional demand shocks (from the 13(f) data)—both overall and by institutional investor type. Following Barber, Odean, and Zhu (2009), we limit the sample to securities with at least ten individual investors trading over the quarter to ensure a meaningful proxy for aggregate individual investor demand shocks. Table V reports the time-series mean cross-sectional correlation between individual investors' direct demand shocks and institutional demand shocks. Although the discount broker data represents only a small fraction of individual investors' aggregate trades, we find a strong inverse relation between institutional and individual investors' demand shocks—across the 24 quarters in the overlapping sample period, the cross-sectional correlation averages -22% (*t*-statistic=-19.59). The analysis by 13(f) manager type reveals that individual investors' demand shocks from the discount broker data are inversely related (and the relation is statistically significant) to demand shocks by insurance companies, banks, mutual funds, independent advisors, and hedge funds. In contrast, individual investors' demand shocks (from the discount broker data) are positively related to pension funds' demand shocks (and largely independent from unclassified institutions' demand shocks).

[Insert Table V about here]

The results reveal that despite the fact that mutual funds primarily trade on behalf of individual investors, individual investors' direct trading serves, on average, as the counterparty to mutual funds'

[25] See Barber and Odean (2000, 2001, 2002) for additional description of the data.

trades. In fact, retail investors' direct trading exhibits the strongest (negative) correlation with mutual funds' demand shocks (-26%, *t*-statistic=-17.66) based on the 13(f) mutual funds trades. For robustness, we also compute the correlation based on aggregate demand shocks of mutual funds in the CRSP/Thomson mutual fund sample. Panel B reveals that the cross-sectional correlation averages -17% (*t*-statistic=-11.20). In short, the analysis in Table V provides strong support for the hypothesis that individual investors' direct trading is captured by the inverse of the 13(f) demand shocks.[26]

B. Is the BW Metric Unique in Capturing Institutional Demand Shocks?

As noted in the introduction, BW point out that because individual sentiment proxies contain both a sentiment component and an idiosyncratic non-sentiment component, the first principal component of changes in the six sentiment proxies that underlie their measure should better capture changes in investor sentiment than innovations in the individual components. Nonetheless, we may gain insights into why the BW sentiment metric captures institutional demand shocks by examining the individual components. One may expect, for example, that some components (e.g., changes in closed end fund discounts) may better capture individual investor demand shocks while other components may better capture institutional investor demand shocks. For instance, Aggarwal, Prabhala, and Puri (2002) find that first day IPO returns are positively related to the fraction of the IPO allocated to institutional investors.

[26] Although we lose more than 80% of our sample period (i.e., n=24 quarters of the Odean data), we also examine whether individual investors' time-series variation in their attraction to volatile stocks (as captured by the Odean data) positively covaries with changes in the BW sentiment metric or any of the other potential sentiment metrics reported in Table VI (we exclude the venture capital measures because they overlap with the Odean data for only seven quarters). We find no evidence the BW or any of the other measures are meaningfully (statistically significant at the 5% level or better) related to individual investors' demand shocks. In fact, the point estimates of the correlation between time-series variation in individual investors' attraction to volatile stocks and changes in sentiment (i.e., analogous to the last column in Table VI) suggests individual investors are the liquidity (rather than sentiment) traders—it is negative for 9 of the 15 change in sentiment metrics.

In addition, although the BW sentiment metric is ubiquitous in recent research, there are a number of alternative proxies for investor sentiment. It is possible that proxies other than the BW metric, better capture individual investors' demand shocks. Thus, we consider three sets of alternative proxies for individual investor sentiment—mutual fund flows, consumer confidence, and a survey-based measure of individual investor sentiment. BW (2007, p. 142) note that mutual fund flows are another potential sentiment metric because these flows reflect the decisions of "a large set of investors who are, on average, less sophisticated and more likely to display sentiment." We closely follow the method in BW (2007) to compute the first and second principal components of changes in mutual fund flows across seven mutual fund categories (aggressive growth, growth, balanced, growth and income, sector, income equity, and income mixed) over the 1984-2010 period with adequate Investment Company Institute (ICI) flow data. Consistent with BW, we find the first principal component loads positively on all fund categories while the second principal component loads positively on the more aggressive categories (e.g., the factor has the largest positive loading on aggressive growth flows and the largest negative loading on income mixed flows). Thus, following BW, we denote the first principal component as a "general demand" effect and the second principal component as a "speculative demand" effect. In addition, Ben-Rephael, Kandel, and Wohl (2012) propose that net exchanges from bond and money market funds to equity funds better captures investor sentiment than mutual fund flows because net exchanges directly reflect mutual fund investors' asset allocation decisions (in contrast to sales and redemptions that reflect savings and withdrawal decisions).[27] Thus, we also use their measure of net exchanges into equity funds.

[27] Appendix A provides details regarding the mutual fund flow data and computation of the BW principal components and Ben_Rephael, Kandel, and Wohl (2012) net exchange measures. As discussed in Appendix A, we differ from BW because (1) our mutual fund flow data sample spans 27 years (1984-2010) versus Baker and Wurgler's 16 year sample (1990-2005) and (2) we exclude asset allocation funds (to increase our sample period) from the principal component analysis. As shown in Appendix A, however, exclusion of asset allocation funds from the analysis yields, essentially, no difference in the estimation of the principal components and the conclusions remain intact if including asset allocation funds (and, as a result, shortening the sample period).

We examine two measures of consumer confidence (the University of Michigan Survey of Consumer Expectations and the Conference Board Consumer Confidence Index) used as sentiment proxies in previous work.[28] Last, we use the American Association of Individual Investors (AAII) survey as a proxy for individual investors' sentiment. Following previous work, we compute individual investors' AAII sentiment as the difference between the fraction of individual investors who forecast the market to increase in the next six months less the fraction that forecast the market to decline in the next six months.[29]

As a further test of whether the BW metric captures time-series variation in institutional investors' views, we also consider a new measure of sophisticated investors' sentiment—venture capital "flows." Specifically, we assume venture capitalists are sophisticated (relative to individual investors) and compute: (1) the percent change in the dollar value of "cash-for-equity investments by the professional venture capital community in private emerging companies in the US" and (2) the change in the number of venture capital deals. The venture capital data are from PWC/National Venture Capital Association.

Although we focus on the BW metric that is "orthogonalized" to economic conditions, the BW metric likely still captures, to some extent, changes in economic conditions assuming the regression used to control for changing economic conditions is less than perfectly specified. Moreover, as Qiu and Welch (2006) point out, sentiment *should* be related to economic conditions, e.g., sentiment traders are more likely to view prospects more favorably when unemployment falls or GDP growth increases. Thus, we also consider two measures of changes in economic conditions—changes in the Chicago Fed's National Activity Index (the first principal component of 85 economic series that

[28] See, for example, Fisher and Statman (2003) and Lemmon and Portniaguina (2006). See Lemmon and Portniaguina for discussion of the similarities and differences between the Baker and Wurgler (2006, 2007) metric and the consumer confidence metrics. Both consumer confidence measures are based on monthly surveys (over our sample period) to households asking for their views on current and future economic conditions.
[29] See Brown and Cliff (2004) for details regarding the AAII survey.

capture economic growth) and changes in the St. Louis Fed's Financial Stress Index (the first principal component of 18 variables that capture financial stress).

The first column in Table VI reports the time-series correlation between the BW orthoganlized change in sentiment metric and each of the other 16 change in sentiment metrics. Because changes in closed end fund discounts, the dividend premium, and the stress index are theoretically inversely related to changes in sentiment, we multiple these three metrics by -1 such that the expected signs are consistent across all 17 measures we evaluate. Because changes in BW sentiment is the first principle component of changes in the six components reported in Panel B, it is not surprising that the BW metric tends to be positively related to these measures. Nonetheless, there is variation across the components—innovations in the BW metric are largely independent of changes in closed-end fund discounts and turnover, but strongly related to the changes in the number of IPOs, changes in IPO returns, changes in equity share of new offerings, and changes in the dividend premium.

[Insert Table VI about here]

The results in Panel C reveal little evidence that BW change in sentiment metric captures shifts in mutual fund investors' demand for speculative stocks. Specifically, although the BW change sentiment metric is largely independent of the BW measure of mutual fund investors' speculative demand shocks and mutual fund investors' shift from bond funds to equity funds ("Net Exchanges to Equity Funds"), it is weakly positively related to the first principal component of mutual fund flows ("General Demand").[30] The results in Panels D and E reveal that the BW change in sentiment metric is also meaningfully related to changes in consumer confidence and weakly related (marginally significant at the 10% level) to shifts in individual investor sentiment as captured by the AAII surveys. Nonetheless, Panel F reveals that the BW change in sentiment metric appears strongly

[30] Ben-Rephael, Kandel, and Wohl (2012) also find that their net exchange into equity funds measure is independent of the BW metric.

related to shifts in *sophisticated* investors' sentiment as captured by changes in venture capital investments or changes in the number of venture deals completed and Panel G demonstrates that changes in the BW metric are strongly related to changes in the two measures of economic conditions.

Following the method in BW (2007), we next compute the sentiment beta from a time-series regression of returns on the market portfolio and the standardized (i.e., unit variance) change in the sentiment metric. The second column in Table VI reports the sentiment beta for the portfolio long the high volatility stocks (top decile) and short low volatility stocks (bottom decile). Consistent with BW, the results in Panel A reveal that a one standard deviation increase in sentiment is associated with risky stocks outperforming safe stocks by 5.7% the contemporaneous quarter. Evaluation across the remaining panels reveal that 12 of the 16 measures exhibit the expected positive point estimate (matching Panel A) and five of the 12 differ meaningfully from zero (at the 10% level or better). In contrast, none of four negative estimates differs meaningfully from zero.

We next examine whether high volatility securities underperform low volatility securities following high sentiment *levels* (these tests are directly analogous to Table V in BW (2006) and Table 7 in Baker, Wurgler, and Yuan (2012)). Specifically, the third column reports the coefficient (and associated *t*-statistic) from a regression of the quarterly return difference for the portfolio of high volatility stocks and the portfolio of low volatility stocks on sentiment levels at the beginning of the quarter.[31] Consistent with BW, the estimates in Panel A show that a one standard deviation increase in the BW sentiment level is associated with high volatility stocks underperforming low volatility stocks by 4.3% the following quarter (on average). Consistent with the BW metric, 13 of the 16

[31] Following BW (e.g., see footnote 5 in BW (2007)), we use the beginning of quarter *t* value for closed-end fund discount, the equity share, and IPO volume, and the lag beginning of quarter value (i.e., beginning of quarter *t*-1) for IPO returns, turnover, and the dividend premium. Nonetheless, we find similar results when using beginning of quarter *t* values for these variables as well.

alternative measures are negative and the relation is statistically significant at the 5% level or better for five of the estimates. In contrast, none of the three positive point estimates in the third column differ meaningfully from zero. Notably, none of the mutual fund flow metrics appear to be meaningfully related to the subsequent return difference for risky and safe stocks. As discussed in the extended literature review in the Appendix, this result is consistent with most previous examinations of mutual fund flows (e.g., Brown and Cliff (2005), Ben-Rephael, Kandel, and Wohl (2012)).

In sum, the results in the first three columns are largely consistent with hypothesis that the BW metric captures investor sentiment. That is, signs are generally in the expected direction, and we find no cases where signs are in opposite direction and differ meaningfully from zero. The fact that some of the coefficients reported in the second and third columns do not differ meaningfully from zero mean that either: (1) the metric does not capture investor sentiment, (2) sentiment traders' demand shocks do not drive return differences between risky and safe stocks, or (3) the measure is simply too noisy, i.e., as BW point out, because sentiment is unobservable, any sentiment proxy contains both a sentiment component and an idiosyncratic component.

Our central question, however, is whether the BW metric is unique from the other measures in capturing institutional investors' demand shocks. The last column in Table VI reports the correlation between time-series variation in institutional investors' demand shocks for risky stocks (i.e., the cross-sectional correlations between institutional demand shocks and security volatility summarized in Panel A of Table IV) and quarterly changes in each of the sentiment metrics. A positive (negative) value in the last column indicates that institutions (individual investors) tend to increase their demand for risky stocks when sentiment increases, i.e., institutional (individual) investors are the sentiment traders. Once again, Panel A reports the value for the BW change in sentiment metric (i.e., is identical to the value reported in Panel B of Table IV). The remaining panels demonstrate that alternative measures of sentiment also tend to capture institutional, rather than individual, investors' demand shocks. Specifically, 12 of the 16 metrics are positive and eight of the 12 positive correlations differ meaningfully from zero at the 5% level or better (and a ninth is marginally significant at the 10% level). Institutions tend to buy risky stocks from, and sell safe stocks to, individual investors when the number or IPOs increase, when the equity share of new issues increases, when the dividend premium declines (Panel B), when consumer confidence measure increases (Panel D), when venture capital flows increase (Panel F), and when economic indicators get stronger (Panel G). Interestingly, only those sentiment metrics that are meaningfully related to institutional demand shocks (last column) are meaningfully related to subsequent returns (third column). In sum, the results in Panel VI reveal no evidence that *any* of the 17 metrics (the BW metric and the 16 additional metrics) capture individual investors' demand shocks. Thus, to the extent that changes in sentiment capture time-series variation in sentiment traders' attraction to speculative stocks, the results uniformly indicate that the metrics capture institutional, rather than individual, investors' demand shocks.

C. Economic Activity, Sentiment, and Time-varying Risk Premia

As pointed out above, it is not surprising that economic activity is related to sentiment. Nonetheless, the fact that broad economic indicators (Panel G) exhibit the same pattern as the BW sentiment metric (Panel A) raises the possibility that time-varying risk premia lead to changes in the relative valuation of risky and safe stocks and shifts in institutional and individual investors' demand for risky stocks. BW point out, however, the return patterns they document (and we confirm in the second and third columns of Table V) are inconsistent with traditional models of risk-based asset pricing. Specifically, BW note that there are two manners in which the risk premium between speculative and safe stocks may vary over time: (1) stock betas are fixed but the market risk premium varies over time, or (2) stocks' betas vary over time and this variation is related to their sentiment proxy. In the former case, the difference in expected returns between volatile and safe stocks varies over time, but the sign is constant inconsistent with the evidence that volatile stocks tend to outperform safe stocks following low sentiment levels but underperform safe stocks following high sentiment levels. We follow the method in BW (2006) and formally examine the second scenario (time-varying factor loadings related to beginning of quarter sentiment levels) by regressing the difference in returns for volatile and safe stocks on beginning of the quarter sentiment levels, the excess market return, and the excess market return interacted with beginning of quarter sentiment levels (untabulated). Consistent with BW (2006, Table VII), and inconsistent with the time-varying beta explanation, we find no evidence the interaction term differs meaningfully from zero (*p*-value=0.37) while beginning of quarter sentiment levels remain highly significant. In sum, as BW point out, it hard to reconcile the predictive power of the sentiment metric with a non-sentiment explanation because it would require that less speculative stocks require a risk premium over more speculative stocks when sentiment levels are high.[32]

It is possible that the relation between economic conditions and institutional ownership is related to time-varying risk premia for several reasons. First, some authors propose that institutional ownership itself reduces a stock's risk premia through, for example, increased liquidity or better diversification (see Edelen, Ince, and Kadlec (2015) for a brief summary). Previous studies, however, tend to find the opposite pattern between returns and ownership levels by institutions (e.g.,

[32] The economic indicators do not subsume the role of sentiment in predicting subsequent returns. Specifically, we also estimated regressions including both the economic indicators and sentiment levels in the same regression to predict the difference in risky and safe stocks returns (i.e., analogous to the coefficients reported in the third column of Table VI). In a model with all three variables (the two economic indicators and sentiment), only sentiment remains meaningfully related to subsequent returns. In a model including only sentiment and each of economic indicators individually, sentiment remains statistically significant in both cases. (And one of the economic indicators (national activity indicator) also remains statistically significant).

Gompers and Metrick (2001)) or mutual funds (e.g., Wermers (2000)) inconsistent with the hypothesis that high institutional ownership levels are associated with lower expected returns.

Second, perhaps the trading between institutions and individual investors results from the changes in risk and differences in their risk bearing abilities. Specifically, as pointed out by Ben-Rephael, Kandel, and Wohl (2012), if investors' relative risk aversion is decreasing in wealth, an increase in risk will result in poorer investors selling riskier stocks to wealthier investors. Barber and Odean (2009) report that the average individual investor in their dataset holds only 4.3 stocks worth $47,000. Thus, to the extent that these are investors may be representative of the larger population of individual investors and assuming a decline in sentiment reflects an increase in risk (i.e., see Panel G of Table VI), this argument would appear to suggest that individual investors should sell riskier assets to wealthier institutions when sentiment declines (and buy riskier assets from institutions when sentiment increases), i.e., opposite of what we find in the data. Similarly, given that individual investors are grossly underdiversified (e.g., 4.3 stocks), it would seem that institutions—with large well diversified portfolios—would be better suited to bear the risk associated with high volatility stocks when economic conditions worsen.

Regardless, if sentiment metrics are related to time-varying risk premium, our main conclusion remains intact—investor sentiment metrics capture institutional investors' demand shocks, not those of individual investors. In short, our results our inconsistent with the hypothesis that irrational individual investors' sentiment-induced demand shocks drives mispricing and the returns patterns documented in the literature.

D. Underlying Investors Flows

Perhaps the simplest explanation institutional sentiment trading is that it simply reflects underlying investor flows, e.g., underlying investors shifting funds from conservative managers to more aggressive managers when sentiment increases. As noted in the introduction, however, underlying investors flows cannot resurrect the hypothesis that individual investors—at least as captured by non-13(f) demand shocks—sentiment trade, i.e., our tests demonstrate that individual investors' direct trading offsets the institutional sentiment trading.

Our initial investigation into underlying investors' flows contribution to sentiment trading uses the Griffin, Harris, Shu, and Topaloglu (2011) method to estimate three components (details are given in Appendix A) of institutional demand shocks: trades that result from investor flows (*Net Buying Flows*), trades that result from managers' decisions (*Net Active Buying*), and trades that result from reinvested dividends (*Passive*). This method assumes that flows are used to purchase and sell existing securities held by the manager and in direct proportion to the manager's portfolio weights.[33] Therefore, the method defines net active buying to be any trade that causes deviations from existing portfolio weights regardless of whether managers' decisions are influenced by flows (e.g., a manager receiving flows in late 2008 may invest in more conservative securities than her existing portfolio).

Specifically, the institutional demand shock for security i in quarter t ($\Delta Inst_{i,t}$) can be written:

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

where K is the number of institutions trading security i in quarter t. Because covariances are linear in the arguments and the aggregate institutional demand shock 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 IV) can be partitioned into three

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

components (see Appendix A 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 institution's portfolios (e.g., Janus files one 13(f) report for all Janus funds), our estimate of 13(f) flow induced trades are intermanager flows (e.g., flows from Janus or 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 VII reports the correlation between time-series variation in institutions' demand for risky stocks and changes in orthogonalized sentiment, i.e., the 37.27% figure reported in Panel B of Table IV. 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 A for details). The results in Panel A provide little evidence that managers' investing net flows into their existing portfolios play a meaningful role in driving the relation between institutional demand shocks and changes in sentiment. Rather, the results show that managers' decisions (i.e., net active buying) strongly drive the relation between institutional demand shocks and sentiment, accounting for 97% of the time-series correlation reported in the first column (i.e., 0.3615/0.3727).

[Insert Table VII 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. To examine whether intramanager flows can fully explain institutional sentiment trading, we recalculate aggregate institutional demand shocks using only entry and exit trades—that is, institutional demand shocks computed only from those manager-stock-quarter observations where managers enter a security they did not hold at the beginning of the quarter or completely liquidate a position in a security they held at the beginning of the quarter. Edelen, Ince, and Kadlec (2015) take the same approach to identifying non-flow induced institutional demand shocks. By definition, these entry/exit trades are due to manager decisions (e.g., an entry trade cannot arise from a fund investing flows into their existing portfolio).[34] Accordingly, we compute the cross-sectional correlation between aggregate institutional entry/exit demand shocks and securities' return volatility each quarter (these untabulated correlations average 0.94% and range from -14.48% to 14.29%). We then calculate the time-series correlation between institutions' entry/exit demand shocks for risky stocks and changes in orthogonalized sentiment (analogous to the figures reported in Panel B of Table IV). Panel B in Table VII reveals the correlation is 48.58% (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.

We next repeat the analyses using the mutual fund data. Specifically, 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 A 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 VII reports the correlation between changes in sentiment and time-series variation in mutual funds' attraction to volatile stocks (as captured by the cross-sectional correlation between mutual fund demand shocks and stock volatility) is 35.67% (statistically significant at the 1% level).[35] Thus, consistent with our results based on 13(f) data, mutual funds buy risky stocks and sell safe stocks when sentiment increases.

[34] A portion of the exit trade could be attributed to outflows. By definition, however, a portion of the exit trade must also be due to the manager's decision.

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

The next three columns in Panel C partition the Thomson Financial/CRSP mutual fund correlation into the three components and reveal that, although managers' decisions (net active buying) account for the largest share of the correlation (statistically significant at the 1% level based on bootstrapped *p*-values), investor flows to mutual funds account for a substantial component of the correlation (approximately 43%=0.1536/0.3567) and are also statistically significant (based on bootstrapped *p*-values) at the 1% level. In sum, the results in Panel C suggest that although managers' decisions play the largest role, 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. As a final test, we examine mutual funds' entry and exit trades. Panel D reports the correlation is 42.81% (statistically significant at the 1% level), which demonstrates that mutual fund managers' decisions play an important role in driving the relation between time-series variation in mutual funds' demand shocks for volatile stocks and changes in sentiment.

Taken together, the evidence in this section suggests that managers' investing/divesting flows into their existing portfolios is not the primary factor driving the relation between aggregate institutional demand shocks and changes in sentiment. Nonetheless, we find some evidence that investor flows meaningfully 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. Moreover, the analysis of entry/exit trades shows that managers' decisions, for both 13(f) institutions and mutual funds, play a meaningful role in sentiment trading. 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 shocks adequately proxy for individual investors' direct trading (which moves inversely with sentiment), the relation between mutual fund flows and changes in sentiment suggests that (in aggregate) individual investors who invest via mutual funds differ from those who invest directly consistent with the evidence in Table V. One possible 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."

E. Explaining Institutional Demand Shocks Across Stock-Quarters

Our tests demonstrate that sentiment metrics capture institutional, rather than individual, investors' demand shocks. It is possible, however, that other factors drive the relation between sentiment and institutions. For instance, if high volatility stocks tend outperform low volatility stocks *prior* to an increase in sentiment, then sentiment metrics may capture institutional demand shocks because institutions (in aggregate) are momentum traders and individual investors (in aggregate) are contrarian traders (see Sias, Starks, and Titman (2006)). Although it is possible that other factors may explain why sentiment metrics capture institutional demand shocks, it would not change the interpretation that sentiment metrics capture institutional investors' demand shocks and individual investors are *not* the sentiment traders. That is, we cannot argue that individual investors are the sentiment traders if individuals sell volatile stocks to institutions when sentiment increases.

In this section, we jointly consider four factors that may help explain why sentiment metrics capture institutional investors' demand shocks: underlying investors' flows, institutional herding, institutional momentum trading, and risk-management/reputation concerns. As in the previous section, we estimate flow-induced demand shocks for each manager-stock-quarter observation and then sum those figures across managers for each stock-quarter to generate the expected flow-induced demand shock for each observation. As discussed above, this method assumes that institutions invest flows in their current portfolio. Thus, we expect that this assumption will better hold for outflows than inflows as an institution with outflows has no choice but to sell existing holdings (although not necessarily in direct proportion to portfolio weights). Thus, we estimate, for each stock-quarter, expected flow induced demand shocks by managers experiencing inflows and expected flow induced demand shocks by managers experiencing outflows.[36]

Previous work (Sias (2004)) demonstrates that institutional demand shocks are positively related to both lag institutional demand shocks (i.e., institutional herding) and lag returns (i.e., institutional momentum trading). Sias (Panel B in Table 4) also demonstrates that institutional demand shocks are hard to predict—herding and momentum trading account for only 4% of the cross-sectional variation in institutional demand shocks. Nonetheless, in untabulated analysis, we find that high volatility stocks tend to have higher institutional demand and higher returns (than low volatility stocks) in the quarter *prior* to an increase in sentiment (differences are statistically significant at the 5% level). High volatility stocks also average lower returns than low volatility stocks in the quarter prior to a large decline in sentiment (marginally significant at the 10% level). The patterns are consistent with the hypothesis that institutional herding and momentum trading are related to their sentiment trading. Thus, following Sias, we measure lag return as the stock's return in quarter t-1 and lag institutional demand shock as the ratio of the number of institutions buying the stock in quarter t-1 to the number of institutions trading the stock in quarter t-1.

A number of previous studies suggest that institutional investors are reluctant to deviate from their benchmarks due to both risk-management constraints and reputational concerns.[37] Thus, we generate two measures of the aggregate institutional portfolio's deviation from the market portfolio. First, we measure the aggregate institutional active weight at the beginning of the quarter, i.e., the difference between the stock's weight in aggregate institutional portfolio and the stock's weight in

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[36] In untabulated tests we repeat these regressions pooling inflow and outflow demand shocks into aggregate flow demand shocks and find nearly identical results.

[37] For instance, see Cao, Han, and Wang (2015), Almazan, Brown, Carlson, and Chapman (2004), Maug and Naik (2011), Arnott (2003), and Cohen Gompers, and Vuolteenaho (2002).

the market portfolio. We expect, everything else equal, that institutions will shift toward (away from) underweighted (overweighted) stocks. We also consider the impact of returns and initial weighting. If institutions are underweighted a given stock at the beginning of quarter *t* and the stock outperforms the market in quarter *t*, then, absent trading, institutions will be even more underweighted at the end of the quarter *t*. Thus, as a second measure, we compute the expected end of quarter *t* active weight (assuming no trading) less the beginning of quarter active weight.[38] We expect negative coefficients associated with both beginning of quarter active weight and the expected change in active weight absent trading.

To evaluate the importance of flows, herding, momentum trading, and risk management in explaining institutional sentiment trading, we partition our 123 quarters of data into quintiles based on the extent of institutional sentiment trading. Specifically, we define the 24 quarters (top quintile) that contribute the most to the correlation between changes in sentiment and time-series variation in institutional demand for high volatility stocks (i.e., the 37.27% correlation reported in Panel B of Table IV) because sentiment increases and institutions shift from safe to speculative stocks as extreme "up sentiment" quarters. Analogously, we define the 24 quarters that contribute the most to the correlation because sentiment decreases and institutions shift from volatile to safe stocks as extreme "down sentiment" quarters.

We begin by estimating a panel regression of institutional demand shocks on stock volatility and stock volatility interacted with up-sentiment quarters and down-sentiment quarters (standard errors are clustered at the stock level). To allow for variation over time, we standardize both the dependent variable (the institutional demand shock) and the independent variables each quarter.[39] Consistent

[38] Assume, for example, a stock is 20% of the market portfolio and 10% of the aggregate institutional portfolio. Thus, the beginning of quarter active weight is -10%. If the market return is 0% and the stock return is 50%, the aggregate institutional active weight declines to -13% by the end of the quarter if institutions do not trade the security.
[39] Subtracting the mean each quarter is identical to adding quarterly fixed effects in the panel. Because institutional ownership grows dramatically over our sample period, we also divided by the standard deviation each quarter.

with Table IV, the results in the first column of Table VIII reveal that, on average, institutions shift toward volatile stocks over our sample period (i.e., the coefficient associated with stock volatility is positive and significant). Further consistent with our earlier tests, the next two rows in the first column demonstrate that institutions' attraction to volatile stocks is much stronger in the extreme up sentiment quarters, and reverses for the extreme down sentiment quarters. Our strategy in this set of tests is to examine how the values in the second and third rows (i.e., "abnormal" institutional demand shocks associated with extreme up and down sentiment quarters) change once accounting for flows, herding, momentum trading, and risk management.

We next add expected inflow and outflow induced demand shocks (second column) to the panel. Consistent with the hypothesis that investor flows impact institutional demand shocks, we find a strong positive relation between flows to managers holding a stock and institutional demand shocks. We also find, consistent with expectations, that the impact of outflows is greater than the impact of inflows. Although an important component in explaining which stocks institutions buy from individual investors, flows have only a minor impact on the coefficients associated with stock volatility in up sentiment or down sentiment periods, e.g., the coefficient in the second row falls from 0.072 to 0.071 and the coefficient in the third row "falls" from -0.052 to -0.050.

The third column in Table VIII adds lag institutional demand, lag return, beginning of quarter active weight, and the expected change in active weight. All coefficients have the expected sign—institutional demand shocks are positively related to lag institutional demand (institutional herding) and lag returns (institutional momentum trading) and inversely related to the aggregate institutional active weight and the expected change in active weight (consistent with the constraints hypothesis). Moreover, adding these variables to the regression results in a substantial reduction in the magnitude of the coefficients associated with extreme up and down sentiment periods—the coefficient associated with extreme up sentiment falls by 25% and the coefficient associated with extreme down sentiment periods falls by 40%.[40] In sum, the results in Table VIII suggest that institutional herding, institutional momentum trading, and institutional constraints meaningfully contribute to institutional sentiment trading.

F. *Evidence from Institution Types*

Although institutions are distinct from individuals, there is substantial heterogeneity across different types of institutions (e.g., Del Guercio (1996), Bennett, Sias, and Starks (2003)). Thus, we begin the analysis of manager type by examining the role of low- (bottom decile), mid- (middle eight deciles), and high- (top decile) volatility stocks in institutions' portfolios. Given we use NYSE volatility breakpoints (following BW), and volatile stocks are more likely to be small, we find (untabulated) that safe stocks (bottom decile) account for 7% of stocks, but 17% of market capitalization while the decile of the riskiest stocks accounts for 24% of stocks, but less than 5% of total market capitalization (on average).

Panels A and B in Table IX report time-series averages of the cross-sectional mean fraction of positions and fraction of portfolio held in low-, mid-, and high-volatility stocks by institutional investors, both overall and by institution type. For instance, the first column reports that the average institution holds 12.3% of their positions in low volatility stocks that account for 14.5% of their total portfolio value versus 9.4% of their position in high volatility stocks that account for 6.3% of their total portfolio value. The remaining columns report figures by institution type and reveal substantial variation across investor types. The average bank, for example, has only 5.1% of their positions in high volatility stocks that account for 1.7% of their portfolio value, versus 11.3% of positions accounting for 6.7% of portfolio value for the average mutual fund.

[Insert Table IX about here]

[40] We repeat these tests using Fama-MacBeth (1973) regressions and find nearly identical results.

We also compute the time-series standard deviation of the exposure to securities in the most volatile decile for the aggregate institutional portfolio, for each type of institution, and for the first four types of institutions (insurance companies, pensions, banks, and unclassified institutions) and the last three types of institutions (mutual funds, independent advisors, and hedge funds). As shown in second column of Panel C, for example, the time-series standard deviation of insurance companies' aggregate weight in the decile of most volatile stocks is 1.7%. The results reveal that mutual funds, independent advisors, and hedge funds have substantially greater variation in their exposure to risky stocks over time than the other institution types. Tests (untabluated) reveal the difference in standard deviations reported in the last two columns are statistically significant at the 1% level.

Institutions may trade on sentiment for reputational concerns given that institutional investors ultimately invest on behalf of individuals and therefore must answer to those who delegate portfolio management to them such as pension fund boards, foundation boards, individual investors, and the consultants responsible for selecting and retaining their services. If the perceptions of the individuals to whom institutional investors answer are influenced by sentiment, a rational institution will act accordingly, or face the risk of termination and declining revenue.[41] Thus, we next examine whether lag returns and lag flows explain cross-sectional variation in flows to managers. (As before flows are estimated following the method in Griffin, Harris, Shu, and Topaloglu (2011) scaled by portfolio values.) We estimate each manager's quarterly return as the return on the portfolio of securities held at the beginning of the quarter. For ease of comparison, all values are standardized to unit variance and zero mean each quarter. Panel D in Table IX reports the time-series mean coefficient and

[41] Consistent with this reputation effect, in 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."

associated t-statistic (with standard errors computed from the time-series of coefficients) from the regressions. Consistent with previous work, flows are positively related to both lag flows and lag returns across the sample of all institutions.[42] Once again, however, we find substantial variation across investor types—mutual funds and independent investment advisors primarily drive the relation between lag returns and flows.

The analysis in Panels A through D motivates tests of three potential explanations of aggregate institutional sentiment trading. First, the results suggest that insurance companies, pension funds, banks, and unclassified institutions: (1) tend to avoid risky stocks (Panels A and B) and (2), are less willing make adjustments to their exposure to risky stocks (Panel C). Because these investors play a *relatively* minor role in holding and trading of high volatility securities, we predict that they will play a relatively small role (versus the role of mutual funds, independent advisors, and hedge funds) in accounting for time-series variation in the aggregate institutional investor shifts between low and high volatility securities (the "preferred habitat hypothesis").

Second, previous work (e.g., Sias (2004) and Dasgupta, Prat, and Verardo (2011b)) and the results in Panel D suggest that mutual funds and independent investment advisors are the institution types most concerned about reputations. Thus, if reputational concerns contribute to institutional sentiment trading, we expect that these two investor groups will play a disproportionally large role in driving aggregate institutional sentiment trading. Note that the implications of the reputational concerns hypothesis is identical to the preferred habitat hypothesis—both predict that insurance companies, pensions, banks, and unclassified institutions will tend to contribute less to aggregate sentiment trading than mutual funds and independent advisors.

Third, it is possible some institutions attempt to ride bubbles to exploit less sophisticated investors. Although the idea of profitably riding a bubble appears, at least initially, straightforward

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[42] See, for example, Coval and Stafford (2007) and Qi, Goldstein, and Wang (2010).

(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 offsets these trades. That is, if both sentiment traders and rational speculators (attempting to ride bubbles) buy speculative stocks, some third group of traders must sell speculative stocks.[43] Thus, as with the underlying investor flows explanation, this hypothesis cannot resurrect the explanation that non-13(f) investors are the sentiment traders (in aggregate). That is, 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 even if some subset of institutions attempted to ride bubbles.[44] Previous work (e.g., Brunnermeier and Nagel (2004)) suggests that hedge funds are more likely to attempt to ride bubbles than other types of institutions. Thus, if such behavior contributes meaningfully to the relation between institutions and sentiment, we expect hedge funds will also play a disproportionally large role in contributing to aggregate institutional sentiment trading.

To examine contributions by manager type, we begin by calculating the fraction of the aggregate institutional equity portfolio accounted for by each manager type at the beginning of each quarter. The first row in Panel E reports the time-series average (across the 123 quarters) of the fraction of the aggregate institutional portfolio accounted for by each investor type. As shown in the last two columns, insurance companies, pensions, banks, and unclassified institutions account for, on

[43] The theoretical literature takes different approaches to resolving 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 frictions.

[44] Our results suggest that if some institutions are attempting to exploit sentiment traders, they are attempting to exploit, in aggregate, other institutions (rather than individuals directly).

average, almost exactly half of the total institutional ownership, while mutual funds, independent advisors, and hedge funds account for the other half.[45] Because covariances are linear in the arguments and the change in aggregate institutional ownership is simply the sum of the changes across investor types, the correlation between changes in sentiment and time-series variation in institutions' attraction to volatile stocks (i.e., the 37.27% figure in Panel B of Table IV) can be decomposed into the contribution by each type of institution (see Appendix A for proof). The second row in Panel E reports the fraction of the total contribution attributed to each manager type, e.g., insurance companies account for 2.7% (=0.0100/0.3727) of the correlation between changes in sentiment and time-series variation in aggregate institutional investors' attraction to volatile stocks. Bold figures indicate the manager type's average quarterly contribution differs meaningfully from zero at the 5% level.[46] The third row in Panel E reports the ratio of the manager type's percentage contribution to aggregate institutional sentiment trading (second row) to their average percentage of the total institutional portfolio value (first row), i.e., values greater (less) than one indicate that the manager type's contribution to aggregate institutional sentiment trading is greater (less) than the manager's expected value if the likelihood of sentiment trading was independent of manager type.

Consistent with hypotheses that preferred habitats, reputational concerns, and bubble riding contribute to institutional sentiment trading, mutual funds, independent advisors, and hedge funds account for a disproportionately large share of the aggregate institutional sentiment trading. As shown in the last two columns, for example, these three investor groups account for (on average)

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[45] There is, of course, time-series variation in ownership levels by each type over time. As an alternative to the simple averaging of ownership over time, we compute the average of each manager type's ownership, weighting each observation by that quarter's contribution to the aggregate sentiment trading metric (i.e., that quarter's contribution to the 37.27% figure reported in Table IV). As a result, the "weighted" average more closely reflects average ownership levels in periods when sentiment trading is large. The results (untabulated), however, remain essentially unchanged.

[46] Each quarter we compute each type of institution's contribution to the correlation between orthogonal changes in sentiment and time-series variation in institutional demand for risky stocks. We test whether the manager type contributes meaningfully to the aggregate measure by testing if the average of 123 quarterly contributions for each manager type differ meaningfully from zero via a standard *t*-test.

approximately half the institutional ownership, but 89% of the aggregate institutional sentiment trading. Hedge funds, in particular, play an outsized role in the contribution to sentiment trading—accounting for, on average, under 2% of aggregate institutional ownership but more than 13% of the aggregate institutional sentiment trading. Note also that the only type of institution with a negative point estimate for contribution (pensions) is also the only type of institution that appears to trade in the same direction as individual investors (Table V).

Although mutual funds, independent advisors, and hedge funds disproportionally contribute to aggregate institutional sentiment trading, other institutional investor types (insurance companies, pension funds, banks, and unclassified) may also contribute to sentiment trading (e.g., if they too have reputational concerns or are, themselves, somehow influenced by sentiment) even if their contribution to *aggregate* institutional sentiment trading is relatively small (due to, for example, their preferred habitat). Thus, to estimate the "breadth" of institutional sentiment trading, we compute the fraction of managers who contribute positively to the correlation between changes in sentiment and time-series variation in institutions' demand for volatile stocks. Specifically, because the aggregate institutional demand shock is the the sum of the demand shocks by each institution, we can partition the correlation in Panel B of Table IV into the contribution by each individual institution (see Appendix A for proof). Panel F reports the number of institutions (overall and by type) and the fraction of those institutions that contribute positively to the sentiment-trading metric. Bold values in the last row indicate the value differs meaningfully from 0.5 (at the 5% level).

Although insurance companies, pension funds, banks, and unclassified institutions account for relatively little of the aggregate institutional sentiment trading (Panel E), most contribute positively to aggregate institutional sentiment trading. Differences between total contributions (Panel E) and the fraction of investors contributing positively (Panel F) reflect the relatively intensity of the sentiment trading, e.g., while more banks may increase, rather than decrease, their exposure to high volatility stocks when sentiment increases, the increase in aggregate institutional ownership in high volatility stocks due to banks' trading remains small relative to mutual funds' contribution. Consistent with the hypothesis that because institutions account for the vast majority of trading, and therefore likely provide much of the offsetting liquidity for sentiment-trading institutions, the results in Panel F reveal that 42% (i.e., 1-58%) of institutions, on average, offset sentiment trading.[47]

G. *Evidence from Variation Across Institutions*

In this section, we investigate differences across individual institutional investors to help understand both why institutions in aggregate sentiment trade and why the behavior varies across individual institutions (as show in Panel F of Table IX). Because our focus is on understanding variation in sentiment trading across institutions and time, we focus on a measure of sentiment trading at the manager-quarter level—the extent that their trading shifts *their own* portfolio toward risky stocks within a given quarter.

Analogous to our examination of variation across stocks and time (Table VIII), we estimate a panel regression of the extent that each manager shifts their portfolio toward high volatility stocks on manager characteristics and those characteristics interacted with dummy variables for the quintiles of extreme up sentiment quarters and extreme down sentiment quarters (as defined previously). Our dependent variable is the extent that the managers shifts her portfolio toward risky stocks and is calculated as the sum (over the manager's stocks) of the product of stock volatility measured at the beginning of quarter t and changes in the manger's portfolio weight due to trading in quarter t. Our initial panel includes five independent variables: (1) the extent that the manager's portfolio is "tilted" toward volatile stocks at the beginning of the quarter (computed as the sum of

[47] A given institution may sometime contribute to sentiment trading and other times help provide offsetting liquidity. These figures are based on the sign of their contribution over all quarters for which they are included in the sample.

product of the manager's beginning of quarter weights and security return volatility), (2) a dummy variable for transient institutions, (3) a dummy variable for non-transient institutions, (4) manager flows the previous quarter, and (5) manager size at the beginning of the quarter.[48]

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

We hypothesize that, due to risk management/reputation concerns, a managers' beginning of quarter tilt toward volatile stocks will be inversely related to the extent that they shift their portfolio toward risky stocks over the quarter. For instance, a manager already overweight risky stocks relative to their peers will be more likely than their peers to reduce their exposure than increase it. Thus, managers underweight risky stocks will be more likely to sentiment trade when sentiment increases (and sentiment traders shift toward risky stocks) and managers overweight risky stocks will be more likely to sentiment trade when sentiment declines (and sentiment traders shift away from risky stocks). Moreover, given risky stocks tend to outperform safe stocks when sentiment increases, we expect the impact of initial tilt to be increased in up sentiment quarters (e.g., a manager underweight volatile stocks will be even more underweight when sentiment increases and risky stocks outperform other stocks). In contrast, we expect the impact to be muted in sentiment decrease quarters (e.g., a manager overweight risky stocks will tend to become less overweight in a period when risky stocks

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

perform poorly relative to other stocks). In sum, the risk management/reputation explanation suggests a negative coefficient associated with initial weight, a negative coefficient associated with the interaction with up sentiment quarters, and a positive coefficient associated with the interaction with down sentiment quarters.

Second, we expect that institutions with a short-term focus are more likely to trade on sentient. Specifically, we use Brian Bushee's data to identify transient institutions (those with high portfolio turnover and relatively small stakes in the companies they hold). We expect the coefficient on transient to be positive for up sentiment quarters (i.e., transient institutions will tend to shift to riskier stocks) and negative for down sentiment quarters (i.e., transient institutions will tend to shift to safe stocks). If non-transient institutions help offset the trades of transient institutions, then the signs will be opposite for non-transient institutions. We use manager's lag flows (flows in quarter *t*-1 scaled by portfolio value at the beginning of quarter *t*-1) and lag size (natural logarithm of total equity portfolio value at the beginning of quarter *t*) to proxy for managers with strong reputational concerns. We expect that managers who recently suffered outflows and small managers will be more concerned about reputation than other managers. As a result, we expect negative coefficients associated with lag flows and size in the up sentiment quarters (i.e., small managers and managers with recent outflows will be more likely to shift toward riskier stocks when sentiment increases) and positive coefficients associated with the down sentiment indicator (i.e., small managers and managers with recent outflows will be more likely to shift away from riskier stocks when sentiment declines).

The panel regression results are reported in Table X (standard errors are clustered at the manager level). The coefficient reported in the first column of the first row is consistent with the hypothesis that managers' risk management/reputation concerns impact their decision to shift toward or away from risky stocks. A manager with a one standard deviation larger tilt toward risky stocks at the beginning of the quarter averages a -0.12 standard deviation shift away from risky stocks over the quarter. The next two columns reveal, however, that the impact of exposure to risky stocks at the beginning of the quarter does not increase in up sentiment quarters or decrease in down sentiment quarters. In fact, the coefficient associated with up sentiment quarters is positive and marginally significant—managers overweight risky stocks are slightly more reluctant (i.e., the sum of the first and second columns) to sell them to managers underweight risky stocks when sentiment increases.

[Insert Table X about here]

The results in the second and third rows are consistent with the hypothesis that transient institutions are more likely to sentiment trade and non-transient institutions are more likely to at least partially offset transient institutions' sentiment trading. In general, transient institutions are more likely to shift toward riskier stocks than other institutions (first column). This effect is even greater when sentiment increases (i.e., the sum of the first and second columns). In contrast, transient institutions are more likely to shift away from risky stocks (i.e., the sum of the first and third columns of the third row) when sentiment declines (although not reported in the Table, the sum of the first and third columns differs meaningfully from zero at the 1% level).

The results for lag flows and manager size reveal some evidence that mangers with larger flows and larger managers shift toward risky stocks (first column). We find little support for the reputation hypothesis, however, as lag flows and portfolio size do not appear to impact institutions' sentiment trading (second and third columns).

In sum, the results in Table X demonstrate that manger with low exposure to risky stocks are more likely to buy risky stocks, and to a much lesser extent, managers with high flows and large managers are more likely to buy risky stocks. These patterns, however, are not exacerbated in extreme up or down sentiment quarters. As a result, managers underweight risky stocks are more likely to sentiment trade when sentiment increases and managers overweight risky stocks are more likely to sentiment trade when sentiment declines. In addition, transient institutions are more likely to sentiment trade than other institution—when sentiment increases (declines), transient institution are more likely to purchase (sell) risky stocks from (to) other investors.[49]

H. Flows, Tilts, and Sentiment Trading

It is possible that even the clients of the most sophisticated invstors may be subject to sentiment and, as a result, institutional sentiment trading results, at least in part, from their concerns regarding retaining or attracting clients. For instance, Brunnermeier and Nagel (2004) point out that hedge funds that traded with (against) the technology bubble had net inflows (outflows). To better understand the relation between flows, tilts, returns, and sentiment trading, we estimate a panel regression of quarter *t* portfolio returns on the extent that the manager's beginning of quarter portfolio tilts toward risky stocks, the extent that the manager trades toward risky stocks, the manager's lag trading toward risky stocks, the manager's lag portfolio return, and the manager's lag flows (lag values are all quarter *t*-1). As with Table X all variables are: (1) measured relative to the same type managers each quarter, and (2) rescaled to zero mean and unit variance each quarter. We interact manager tilts, trading toward riskier stocks, and lag trading toward riskier stocks with extreme up and down sentiment indicators.

The results in the first three columns of Table XI demonstrate that the extent that a manager's portfolio is *already* tilted toward high volatility stocks has a much more important role than the *shift* toward or away from risky stocks in explaining variation in portfolio performance in up and down sentiment periods. For instance, a manager with a one standard deviation greater tilt toward riskier stocks has a 28% standard deviation larger return in an up sentiment quarter. In contrast, a manager

[49] We repeat these tests using Fama-MacBeth (1973) regressions and find nearly identical results.

with a one standard deviation shift toward risky stocks has a 1.8% standard deviation higher return in an up sentiment quarter. Although the manager tilt is measured at the beginning of the quarter, the manager shift is measured over the same quarter as return. Thus, we cannot be certain if managers shifting toward risky stocks when sentiment increases experience larger returns or if managers with larger returns tend to shift toward risky stocks. The results in the third column, however, provide evidence consistent with the latter interpretation. In extreme down sentiment quarters (when volatile stocks tend to underperform safe stocks), larger returns are still associated with a shift toward risky stocks.

[Insert Table XI about here]

Because a manager's initial exposure to risky stocks is much more important than their shift in exposures in determining performance, the "risk" of trading on sentiment is that the manager has higher exposure to risky stocks when sentiment levels fall (or a lower exposure to risky stocks when sentiment increases). The results in the last three columns of Table XI provide some evidence to support the hypothesis that institutional sentiment trading may attract flows. Specifically, managers with high exposure to sentiment (i.e., managers with a large tilt toward risky stocks at the beginning of the quarter) have larger flows when sentiment increases (first row). When sentiment falls, however, these managers do not experience a meaningful negative outflow (i.e., the sum of the fourth and sixth columns of the first row).[50] Consistent with the evidence in Table IX, we find that managers with high lag flows and lag returns also experience large flows. We also document a weak positive relation between changes in sentiment and the extent that managers shift toward volatile stocks—although given the contemporaneous relation the results suggest that either mangers with flows tend to shift toward riskier stocks, or managers shifting toward riskier stocks have larger flows.

[50] In untabulated tests we estimate these regressions for the two groups of institutional investors (see Table IX) and find that the relation between tilt and flows is driven by the latter group (mutual funds, independent advisors, and hedge funds).

Note also that even when a manager correctly *forecasts* a change in sentiment (i.e., shifts their portfolio toward riskier stocks the quarter prior to an increase in sentiment or away from riskier stocks prior to a decrease in sentiment), they do not experience abnormal flows (last two columns of last row in Regression 2).[51]

IV. Discussion and Conclusions

A. Discussion

When sentiment increases, institutions, in aggregate, buy volatile stocks from, and sell safe stocks to, individual investors. If sentiment metrics capture investor sentiment and the cross-sectional return patterns documented by BW are due to sentiment-induced demand shocks, then institutions, rather than individual investors, are the sentiment traders. The results are inconsistent with the hypothesis that individual investors' sentiment-induced demand shocks drive prices from fundamental value.

There are, however, several possible alternative interpretations of our results. First, perhaps institutional investors are short-term (intraquarter) momentum traders that simply chase lag returns and their demand shocks do not impact prices. Although this explanation could explain why institutions buy volatile stocks from, and sell safe stocks to, individual investors when sentiment increases, it would not change our primary conclusion that sentiment metrics do not capture individual investors' demand shocks. Further, the intraquarter institutional momentum trading explanation is inconsistent with the sentiment hypothesis because the sentiment hypothesis *requires* that demand shocks from those investors that are buying speculative stocks (and selling safe stocks) when sentiment increases is what *causes* the misvaluation.

[51] In untabulated tests we also examine whether flows in quarter t+1 are impacted by sentiment trading in quarter t for the extreme up and down sentiment quarters (defined at time t). Again, we find no evidence that sentiment trading, itself, impacts flows.

Related, although we define the traders who offset aggregate institutional investors' demand shocks as individual investors, this offsetting volume could instead arise, at least in part, from insiders or the company itself (e.g., share buybacks).[52] In Appendix A, we further investigate this issue by partitioning the institutional demand shock into the portions offset by changes in company shares outstanding, insider trades, and individual investors' demand shocks (i.e., the residual). Given our focus on institutional demand shocks (and to conserve space), we do not report test results in the paper. Detailed results provided in Appendix A, however, reveal that although both companies and insiders appear to trade against sentiment, individual investors account for the vast majority (>75%) of the offsetting demand.

B. Conclusions

A burgeoning literature posits investor sentiment impacts equity prices and has important implications for both asset pricing and corporate finance. 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 sentiment traders' demand shocks must be offset by liquidity traders' supply and the sentiment literature's assumption that sentiment traders' demand shocks drive the relation between changes in sentiment and contemporaneous stock returns (i.e., differences in sentiment betas for high and low volatility portfolios are due to sentiment-induced demand shocks), we examine the relation between changes in ownership and changes in sentiment to identify whose demand shocks are captured by changes in sentiment.

[52] Because we closely follow BW and require stocks have at least nine monthly returns prior to the quarter to compute volatility, our sample does not include IPOs.

Inconsistent with conventional wisdom, we find that sentiment metrics capture 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 greater institutional investor ownership levels of risky stocks relative to their ownership levels of safe stocks

Additional tests reject the hypotheses that our results are driven from either: (1) the possibility that the inverse of 13(f) demand shocks does not proxy for individual investors' demand shocks, or (2) there is something unique about the BW metric and institutional demand shocks. Rather, we find evidence that a confluence of factors appear to play a role in aggregate institutional sentiment trading—intramanager flows, risk-management, institutional herding, institutional momentum trading, preferred habitats, reputational concerns, and attempting to ride bubbles. Moreover, several factors help explain which institutions trade on the sentiment including manager type, risk management concerns, and manager style (i.e., transient). Last our results demonstrate that managers' relative performance in extreme sentiment periods is largely determined by their initial portfolio tilt toward risky stocks (rather than the extent they change the tilt over the quarter by sentiment or liquidity trading). A large tilt toward risky stocks does not appear to hurt investors' flows—when sentiment increases, institutions with a tilt toward risky stocks garner larger flows than others; when sentiment falls, managers with a larger tilt toward risky stock do not suffer greater outflows.

We also find evidence that sentiment metrics (even when "orthogonalized") are related to economic conditions. Although impossible to reject (due to the joint hypothesis problem), the patterns in sentiment, returns, and institutional demand do not appear to be consistent with a time-varying risk premium explanation. Regardless, contrary to popular beliefs, sentiment metrics do not capture individual investors' demand shocks. Thus, if sentiment metrics capture sentiment-based demand shocks, institutional investors, rather than individual investors, are the sentiment traders.

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Table I
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 number of shares held by institutions divided by shares outstanding less the cross-sectional average ratio the same quarter. The sample period is June 1980 through December 2010 (*n*=123 quarters). On average, there are 3,945 securities in the sample each quarter.

Time-series Descriptive Statistics

	Mean	Median	10^{th} Percentile	90^{th} Percentile
%Shares held by institutions	35.72%	33.61%	6.49%	68.29%
Raw Δ(%shares held by institutions)	0.63%	0.31%	-3.02%	4.60%
Institutional demand shock	0.00%	-0.33%	-3.65%	3.96%
Number of institutions trading	66.58	31.95	4.28	168.12
σ(Monthly return$_{t=-1 \text{ to } -12}$)	13.37%	11.44%	5.82%	22.76%

Table II
Time-series Correlation between 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 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. Panel B reports results based on the change in orthogonalized investor sentiment. *P*-values are reported parenthetically.

	Low Volatility Stocks	2	3	4	5	6	7	8	9	High Volatility Stocks	High-Low
						Panel A: Change in Investor Sentiment					
$\rho\left(\overline{\Delta Inst_{i,t}}, \Delta Sent_t\right)$	-0.232	-0.260	-0.325	-0.249	-0.127	-0.130	-0.172	0.131	0.251	0.226	0.259
(*p*-value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.17)	(0.16)	(0.06)	(0.15)	(0.01)	(0.02)	(0.01)
						Panel B: Change in Orthogonalized Investor Sentiment					
$\rho\left(\overline{\Delta Inst_{i,t}}, \Delta Sent_t^{\perp}\right)$	-0.287	-0.293	-0.370	-0.272	-0.234	-0.144	-0.112	0.076	0.202	0.315	0.339
(*p*-value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.22)	(0.39)	(0.03)	(0.01)	(0.01)

Table III
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 levels (i.e., fraction of shares held by institutions) for securities within each volatility decile (sentiment levels and ownership levels are measured at the same point in time). Panels A and B report 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 (in percent) 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 between high and low sentiment periods and associated *t*-statistics (based on a *t*-test for difference in means). Statistical significance at the 1% is indicated by ***.

Period	Low Volatility Stocks	2	3	4	5	6	7	8	9	High Volatility Stocks	High-Low (*t*-statistic)
	Panel A: Detrended Fraction of Shares held by Institutional Investors (%) for High and Low Sentiment Level Periods										
High sentiment	-0.81	-0.18	-0.33	0.07	-0.09	0.13	0.24	0.52	0.51	1.01	1.82
Low sentiment	0.83	0.18	0.34	-0.07	0.09	-0.13	-0.25	-0.53	-0.52	-1.03	-1.85
High-low sent.	-1.64	-0.35	-0.67	0.13	-0.18	0.26	0.49	1.05	1.03	2.04	3.68
											(4.67)***
	Panel B: Detrended Fraction of Shares held by Institutional Investors (%) for High and Low Orthogonalized Sentiment Level Periods										
High sentiment$^{\perp}$	-0.45	-0.04	-0.11	0.30	0.04	0.53	0.69	0.87	0.88	1.39	1.84
Low sentiment$^{\perp}$	0.46	0.04	0.11	-0.31	-0.04	-0.54	-0.70	-0.89	-0.90	-1.42	-1.87
High-low sent.$^{\perp}$	-0.90	-0.08	-0.22	0.61	0.09	1.07	1.39	1.76	1.78	2.81	3.71
											(4.72)***

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

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between institutional demand shocks 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 of the cross-sectional correlation and associated *t*-statistics (in parentheses) computed from the time-series of cross-sectional correlations. Panel B reports the correlation between time-series variation in institutional investors' attraction to volatile stocks (i.e., the cross-sectional correlation between volatility and changes in the fraction of shares held by institutions summarized in Panel A) and changes in raw or orthogonalized investor sentiment (and associated *p*-values). Statistical significance at the 1% level is indicated by ***.

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

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

Panel B: Time-series Correlation between Changes in Sentiment and Institutional Demand Shocks for Volatile Stocks (*n*=123 quarters)

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

Table V
Correlation between Individual Investors Demand Shocks and Institutional Investors' Demand Shocks

Each quarter (between 1991 and 1996) we compute the net faction of security's outstanding shares purchased by: (1) individuals investors in Terry Odean's discount broker database, (2) by 13(f) institutions (both in aggregate and by investor type), and (3) CRSP/Thomson mutual funds. The figures report the time-series mean (n=24 quarters) cross-sectional (i.e., across securities) correlation and associated t-statistics (compute from the time-series standard error of the correlations) between individual investors' demand shocks (Odean data) and institutional investors' demand shocks.

	$\overline{\rho_t\left(\Delta Inst_{i,t}, \Delta Indv_{i,t}\right)}$ (*t*-statistic)
Panel A: Mean correlations based on 13(f) data	
All 13(f) institutions	-21.50%
	(-19.59)***
Insurance	-7.50%
	(-5.02)***
Pension	8.60%
	(5.85)***
Banks	-3.34%
	(-5.23)***
Unclassified	-1.84%
	(-1.42)
Mutual funds	-26.39%
	(-17.66)***
Independent advisors	-20.85%
	(-19.32)***
Hedge funds	-14.75%
	(-3.07)***
Panel B: Mean correlation based on CRSP/Thomson mutual fund data	
Mutual funds	-17.43%
	(-11.20)***

Table VI
Examination of Alternative Sentiment Metrics

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

Table VI (continued)
Examination of Alternative Sentiment Metrics

	Correlation with BW metric	Sentiment Beta	Predict Returns?	Capture individual investors' demand?
	$\rho(\Delta X_t, \Delta Sent_t)$	High σ – Low σ (*t*-statistic)	Coefficient on lag levels (*t*-statistic)	$\rho(\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta X_t)$ (*p*-value)
Panel A: BW Sentiment Metric (*n*=123 quarters)				
Sentiment$^{\perp}$	100.00%	0.057	-0.043	37.27%
		(4.82)***	(-2.85)***	(0.01)***
Panel B: BW Sentiment Components (*n*=123 quarters)				
CEF Disc.(*-1)	-5.64%	-0.001	-0.013	0.75%
	(0.54)	(-0.07)	(-0.84)	(0.94)
Turnover	10.97%	0.014	0.021	-2.92%
	(0.23)	(1.19)	(1.36	(0.75)
Num. IPOs	23.91%	-0.001	-0.037	35.75%
	(0.01)***	(-0.10)	(-2.40)**	(0.01)***
IPO Return	50.18%	0.051	-0.010	7.69%
	(0.01)***	(4.41)***	(-0.62)	(0.40)
Eq. Share	22.34%	0.014	-0.019	26.34%
	(0.02)**	(1.15)	(-1.25)	(0.01)***
Div. Prem.(*-1)	70.65%	0.088	-0.065	38.77%
	(0.01)***	(7.77)***	(-4.46)***	(0.01)***
Panel C: Mutual Fund Flows (*n*=106 quarters)				
MF General Demand	16.48%	-0.010	-0.020	-1.27%
	(0.10)*	(-0.63)	(-1.17)	(0.90)
MF Speculative	1.78%	0.008	0.017	8.15%
Demand	(0.86)	(0.60)	(0.99)	(0.41)
Net Exchange to	14.82%	-0.011	-0.011	-0.71%
Equity Funds	(0.13)	(-0.70)	(-0.61)	(0.95)
Panel D: Consumer Confidence (*n*=123 quarters)				
Michigan	19.53%	0.038	-0.043	19.12%
	(0.04)**	(3.06)***	(-2.87)***	(0.04)**
Conference	24.85%	0.018	-0.047	29.87%
	(0.01)***	(1.44)	(-3.14)***	(0.01)***
Panel E: American Association of Individual Investors Sentiment (*n*=93 quarters)				
AAII sentiment	19.33%	0.001	0.005	-12.30%
	(0.07)*	(0.07)	(0.26)	(0.24)
Panel F: Venture Capital Flows (*n*=63 quarters)				
Venture Capital	36.58%	0.015	-0.035	37.64%
	(0.01)***	(0.75)	(-1.37)	(0.01)***
#Venture Deals	40.50%	0.013	-0.034	39.37%
	(0.01)***	(0.63)	(-1.31)	(0.01)***
Panel G: Economic Indicators (sample sizes in first column)				
National Activity	26.15%	0.037	-0.045	28.46%
(*n*=123 quarters)	(0.01)***	(3.28)***	(-3.00)***	(0.01)***
Economic Stress(*-1)	34.38%	0.041	-0.028	20.42%
(*n*=68 quarters)	(0.01)***	(2.11)***	(-1.18)	(0.10)*

Table VII
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 correlation (and associated *p*-value) between time-series variation in institutional investors' attraction to volatile stocks and changes in orthogonalized investor sentiment (and is identical to Panel B of Table IV). 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 A for details). Panel B repeats the analysis when aggregate institutional demand shocks are limited to 13(f) entry and exit trades. Panel C reports the estimates based on the Thomson Financial/CRSP merged mutual fund data where flows are estimated at the fund (rather than the institution) level. Panel D repeats the analysis when demand shocks are limited to Thomson Financial/CRSP mutual funds' entry and exit trades.

	$\rho\left[\rho_t\left(\Delta X_{i,t},\sigma_{i,t}\right),\Delta Sent_t^{\perp}\right]$ (*p*-value)	Contribution to $\rho\left[\rho_t\left(\Delta X_{i,t},\sigma_{i,t}\right),\Delta Sent_t^{\perp}\right]$ due to:		
		Net Buying Flows (*p*-value)	Net Active Buying (*p*-value)	Passive (*p*-value)
Panel A: All 13(f) Institutions				
All 13(f) Institutions	37.27%	0.86%	36.15%	0.26%
	(0.01)	(0.37)	(0.01)	(0.45)
Panel B: All 13(f) Institutions – Demand due to Entry and Exit Trades Only				
13(f) entry/exit trades	48.58%			
	(0.01)			
Panel C: CRSP/TFN Mutual Fund Data				
Δ CRSP/TFN Mutual Funds	35.67%	15.36%	19.64%	0.67%
	(0.01)	(0.01)	(0.01)	(0.77)
Panel D: CRSP/TFN Mutual Fund Data – Demand due to Entry and Exit Trades Only				
Δ CRSP/TFN MF entry/exit trades	42.81%			
	(0.01)			

Table VIII
Panel Regression: Explaining Aggregate Institutional Demand Shocks

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

	(1)	(2)	(3)
Stock volatility	0.021	0.016	0.007
	(10.82)***	(7.81)***	(3.87)***
Stock volatility*up sent. indicator	0.072	0.071	0.054
	(18.79)***	(18.62)***	(14.54)***
Stock volatility*down sent. indicator	-0.052	-0.050	-0.031
	(-13.78)***	(-13.23)***	(-8.42)***
E(inflow-induced demand)		0.054	0.052
		(26.11)***	(25.59)***
E(outflow-induced demand)		0.121	0.115
		(42.87)***	(41.58)***
No. of inst. buyers$_{t-1}$/No. of inst. traders$_{t-1}$			0.072
			(46.01)***
Return$_{t-1}$			0.131
			(66.89)***
Agg. institutional active weight$_{t=0}$			-0.021
			(-10.98)***
E(Δinstitutional active weight$_t$)			-0.068
			(-19.90)***
Number of observations	478,922	478,922	478,922
Number of clusters	14,798	14,798	14,798
R^2	0.21%	1.52%	4.58%

Table IX
Sentiment Trading by Investor Type

Each quarter, we compute the fraction of positions and portfolio weight for low-volatility stocks (bottom decile based on NYSE breakpoints), mid-volatility stocks (middle eight deciles), and high-volatility stocks (top volatility decile) for the average institution. Panels A and B report the time-series average of these values. The first column reports values for all institutions, the next seven columns report values by institution type, and the last two columns report values for the first four institution types (insurance, pension, banks, unclassified) and the last three institution types (mutual funds, independent advisors, and hedge funds). We also compute the weight of the aggregate institutional portfolio (overall and by type) in the decile of riskiest stocks. Panel C reports the time-series standard deviation of aggregate institutional weight in the decile of riskiest stocks. Panel D reports time-series mean coefficients and associated *t*-statistics (computed from the time-series standard error) associated with cross-sectional regressions of estimated manager flows on lag manager flows and lag manager portfolio returns. Each quarter, we compute the fraction of the aggregate institutional portfolio accounted for by each type of institution. The first row in Panel E the time-series average of the quarterly means over the 123 quarters in our sample. The second row reports the fraction of the correlation between changes in sentiment and time-series variation in institutional investors' attraction to volatile stocks (i.e., the 37.27% figure in Table IV) attributed to each investor type. Bold figures in the second row indicate that the value differs meaningfully from zero at the 5% level (the standard error is based on the time-series of the quarterly contributions for each manager type). The third row reports the ratio of total contribution (second row) to average total ownership by manager type (first row). We also compute each institution's contribution (see Appendix A) to the correlation between changes in orthogonalized sentiment and time-series variation in aggregate institutional demand shocks for volatile stocks. 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). Panel F report the number of institutions and the fraction of institutions that are classified as sentiment traders (bold indicates the fraction differs meaningfully from 0.5 at the 5% level).

Table IX
Sentiment Trading by Investor Type

	All	Insurance (a)	Pension (b)	Banks (c)	Unclas. (d)	Mutual Funds (e)	Indep. Advisors (f)	Hedge Funds (g)	(a+b+c+d)	(e+f+g)
	Panel A: : Institutional Investors' Fraction of Positions in Low, Mid, and High Volatility Portfolios									
Low volatility	0.123	0.142	0.130	0.164	0.129	0.101	0.118	0.083	0.144	0.111
Mid volatility	0.783	0.776	0.797	0.785	0.778	0.786	0.788	0.743	0.783	0.783
High volatility	0.094	0.081	0.073	0.051	0.093	0.113	0.094	0.173	0.073	0.106
	Panel B: Institutional Investors' Weights in Low, Mid, and High Volatility Portfolios									
Low volatility	0.145	0.175	0.175	0.213	0.159	0.131	0.131	0.091	0.183	0.124
Mid volatility	0.792	0.784	0.791	0.770	0.781	0.802	0.801	0.775	0.779	0.800
High volatility	0.063	0.041	0.034	0.017	0.059	0.067	0.067	0.135	0.038	0.076
	Panel C: Institutions Willingness to Adjust Exposure to Risky Stocks									
σ(High vol. wt.)	0.025	0.017	0.018	0.016	0.019	0.030	0.030	0.069	0.017	0.031
	Panel D: Coefficients from Regression of Flows on Lag Flows and Lag Returns									
Lag flows	0.037	0.007	0.021	-0.045	0.018	0.082	0.072	-0.071	-0.002	0.049
	(5.62)***	(0.29)	(1.06)	(-3.83)***	(1.45)	(3.31)***	(9.09)***	(-2.59)**	(-0.19)	(6.12)***
Lag returns	0.026	-0.002	0.003	-0.005	0.007	0.059	0.046	-0.009	0.004	0.039
	(5.83)***	(-0.12)	(0.21)	(-0.63)	(0.60)	(3.29)***	(7.19)***	(-0.45)	(0.59)	(6.77)***
	Panel E: Contribution to Sentiment Trading by Investor Type									
%Agg. Inst. Port.	1.000	0.057	0.072	0.233	0.141	0.128	0.353	0.016	0.503	0.497
%Total Cont.	**1.000**	0.027	-0.005	0.042	0.048	**0.294**	**0.458**	**0.136**	0.012	**0.888**
Cont./Ownership	1.000	0.472	-0.068	0.179	0.341	2.290	1.297	8.689	0.222	1.787
	Panel F: Fraction Sentiment Trading by Investor Type									
No. Managers	5,683	133	129	578	732	150	3,030	931	1,572	4,111
%Sent. Traders	**0.581**	0.549	**0.597**	**0.607**	**0.567**	**0.667**	**0.582**	**0.561**	**0.583**	**0.580**

Table X
Explaining Sentiment Trading across Institutions

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

		Interacted with up sentiment indicator	Interacted with down sentiment indicator
Manager high σ tilt	-0.116	0.016	-0.008
	(-17.19)***	(1.70)*	(-0.75)
Transient dummy	0.057	0.042	-0.111
	(6.51)***	(2.53)**	(-5.90)***
Non-trans. dummy	-0.027	-0.014	0.051
	(-6.10)***	(-2.07)**	(7.27)***
Lag flows	0.011	0.005	0.009
	(2.15)**	(0.57)	(0.82)
Manager size	0.006	0.002	-0.001
	(1.72)*	(0.32)	(-0.01)
Number of obs.	144,651		
Number of clusters	4,702		
R^2	1.39%		

Table XI
The Roles of Tilts and Trading in Understanding Returns and Flows

We estimate a panel regression of an institution's portfolio return in quarter *t* on the extent that a manager tilts their portfolio toward volatile stocks at the beginning of the quarter, the extent the manager shifts their own portfolio toward risky stocks in the quarter (measured as the sum across the institution's holdings of the product of stock volatility and changes in the manger's portfolio weight due to trading over quarter *t*), the extent the manager shifted their own portfolio toward riskier stocks in quarter *t*-1, the manager's quarter *t*-1 portfolio return, and the manager's *t*-1 flow. All variables are measured relative to managers of the same type by computing the difference between the value for the manager and the median value for other same type managers the same quarter. The first three variables are also interacted with indicators for extreme up sentiment quarters and extreme down sentiment quarters. All variables are standardized each quarter (de-meaning each quarter is equivalent of adding fixed time effects). The last three columns repeat the analysis when the dependent variable is the manager's quarter *t* flows. Standard errors are clustered at the manger level. Statistical significance at the 1%, 5%, and 10% level are indicated by ***, **. and *, respectively.

	Regression 1 Dependent variable: Portfolio Return			Regression 2 Dependent variable: Flows		
		Interacted with up sentiment period	Interacted with down sentiment period		Interacted with up sentiment period	Interacted with down sentiment period
Manager high σ tilt	0.054	0.280	-0.459	0.007	0.025	-0.013
	(8.99)***	(30.58)***	(-38.61)***	(1.69)*	(3.25)***	(-1.51)
Trading toward	-0.001	0.018	0.039	-0.006	0.020	0.022
riskier	(-0.17)	(2.07)**	(4.26)***	(-0.96)	(1.76)*	(1.81)*
Lag trading toward	-0.006	0.015	0.003	-0.006	0.010	0.006
riskier	(-1.39)	(1.80)*	(0.32)	(-1.08)	(0.99)	(0.57)
Lag return	0.016			0.032		
	(4.04)***			(9.13)***		
Lag flow	-0.003			0.040		
	(-1.01)			(7.07)***		
Number of obs.	144,651			144,651		
Number of clusters	4,702			4,702		
R^2	5.70%			0.33%		