

## Who are the Sentiment Traders?

### Evidence from the Cross-Section of Stock Returns and Demand

November 18, 2014

LUKE DeVAULT

RICHARD SIAS

and

LAURA STARKS\*

#### ABSTRACT

Recent work suggests that sentiment traders shift from safer to more speculative stocks when sentiment increases. Given that the market clearing condition requires a buyer for every seller, we exploit these cross-sectional patterns and changes in share ownership to test whether investor sentiment metrics capture institutional or individual investors' demand shocks. In contrast to theoretical assumptions and common perceptions, we find no evidence that individual investors' trading is responsible for sentiment-induced demand shocks and mispricing. 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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\* DeVault is from the Department of Finance, Eller College of Management, University of Arizona, Tucson, Arizona, 85721; ldevault@email.arizona.edu. Sias is from Department of Finance, Eller College of Management, University of Arizona, Tucson, Arizona 85721, (520) 621-3462, sias@eller.arizona.edu. Starks is from the Department of Finance, McCombs School of Business, University of Texas at Austin, Austin, Texas 78712, (512) 471-5899, lstars@mail.utexas.edu. We thank seminar participants at Boston College, Cambridge University, Southern Methodist University, the University of Arizona, the University of New South Wales, University of Technology Sydney, the Wharton School, the 2013 European Finance Association Meetings, the 2014 Asian Bureau of Finance and Economic Research Annual Conference, Gennaro Bernile, Doug Foster, Kelvin Law, Charles Lee, and Jeff Wurgler for their helpful comments. We thank Brian Bushee, Ken French, and Jeff Wurgler for providing data. Copyright © 2014 by the authors.

## Who are the Sentiment Traders?

### Evidence from the Cross-Section of Stock Returns and Demand

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

A burgeoning theoretical and empirical literature posits that demand shocks by uninformed sentiment traders impact security prices, which has important implications for both asset pricing and corporate finance. Despite the near universal assumption that, as a group, irrational individual investors are the source of sentiment-based demand shocks captured by sentiment metrics while institutions are smart-money rational investors, we demonstrate that commonly-used measures of investor sentiment capture the demand shocks of institutional, rather than individual, investors.<sup>1</sup> Assuming these metrics capture investor sentiment, then institutional investors, rather than individuals, are the traders who drive sentiment-induced mispricings.

Our empirical analyses build upon the recent insight that investor sentiment has both cross-sectional and time-series implications. Specifically, Baker and Wurgler (henceforth, BW) (2006, 2007) propose that securities with “highly subjective valuations” are more susceptible to the vagaries of sentiment. Consistent with their hypothesis, they show that changes in investor sentiment are positively related to contemporaneous returns for high volatility stocks and negatively related to

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<sup>1</sup> The vast majority of the sentiment literature suggests individual investors are the sentiment traders (see, for example, Shiller (2000), DeLong, Shleifer, Summers, and Waldmann (1990a, 1990b), Lee, Shleifer, and Thaler (1991), Nagel (2005), Barberis and Xiong (2012), and Stambaugh, Yu, and Yuan (2012)). A few early theoretical models, however, suggest institutional investors may engage in noise trading because clients cannot fully distinguish noise trading from informed trading (e.g., Allen and Gorton (1993), Dow and Gorton (1997), and Trueman (1988)). Beyond the introductory quote from (Friedman (1984)), very little work posits that institutional investors would be more susceptible to sentiment than individual investors. Brown and Cliff (2004) find that time-series measures of institutional sentiment and individual investor sentiment are positively correlated and conclude that the strongest relation between sentiment and contemporaneous returns occurs in large stocks using surveys of institutions as measures of sentiment. Hribar and McNinnis (2012) report that analysts’ forecasts for speculative stocks tend to be more optimistic when sentiment levels are high, consistent with the hypothesis that at least one group of sophisticated investors (analysts) are impacted by sentiment.

contemporaneous returns for low volatility stocks.<sup>2</sup> That is, sentiment betas are positive for speculative stocks and negative for safe stocks. The authors also find that, on average, speculative stocks underperform safe stocks following high sentiment levels, but outperform safe stocks following low sentiment levels. They conclude that the combined results are consistent with the hypothesis that sentiment traders' demand shocks impact prices and result in pushing speculative stocks' valuations too high relative to the valuations of safe stocks when sentiment is high (and too low when sentiment is low).

The investor sentiment hypothesis is a demand shock story—it requires *changes* in demand (i.e., in the words of BW (2007, p. 131), “sentiment-based demand shocks”) combined with finite demand and supply elasticities.<sup>3</sup> That is, the sentiment demand shocks imply net buying or selling by sentiment traders, resulting in *changes* in both their ownership levels and security prices. Moreover, because the market clearing condition requires a buyer for every seller, sentiment traders' net demand shocks must be offset by supply from traders who are less subject to the changes in sentiment. For ease of exposition, we denote these latter traders as “liquidity” traders. Of course, at least some of the liquidity traders' supply may be motivated by fundamental trading, e.g., selling overvalued speculative stocks to sentiment traders when sentiment increases.

These two insights from the sentiment literature—sentiment traders' demand shocks must be offset by liquidity traders' supply and speculative stocks have positive sentiment betas while safe stocks have negative sentiment betas—drive our primary approach to identifying the sentiment traders. 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

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<sup>2</sup> BW (2006, 2007) 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.

<sup>3</sup> 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)).

safe stocks. An increase in sentiment, for example, causes sentiment traders to *purchase* risky stocks and *sell* safe stocks, i.e., their buying and selling—their demand shocks—are the drivers of the mispricing in the sentiment literature.

Our key results show that if the BW sentiment metric indeed captures investor sentiment, then institutional investors (in aggregate), rather than individual investors, are the traders driving sentiment induced mispricing.<sup>4</sup> Beyond our results focusing on institutional and individual investors' demand shocks, we further explore the relation between investor sentiment levels and these investors.<sup>5</sup> 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 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 conduct several additional tests designed to examine the relation between investor demand and sentiment more deeply. The results of these tests continue to support the hypothesis that sentiment metrics capture innovations in institutional, rather than individual investors' (direct), demand. First, although we focus on the BW sentiment metric because it is the dominant measure in

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<sup>4</sup> Greenwood and Shleifer (2014) examine six surveys of investors' expectations capturing both individual and sophisticated investors' expected returns and find that all six sentiment surveys are positively correlated with each other and with lag market returns and equity market levels. Further, the survey-based investor expectations are inversely related to model based investor expectations. Noting that someone must offset these investors' extrapolative trades, the authors propose that firms may play an important role in accommodating shifts in investor demand consistent with BW's use of the number of IPOs as one of the sentiment components. Unlike previous research, we focus directly on the question of whose demand shocks are positively correlated with changes in sentiment and who offsets sentiment-based demand shocks within the framework of the BW implications for the cross-section of equity returns.

<sup>5</sup> We focus on institutional and individual investors' demand shocks and changes in sentiment because both institutional investors' ownership levels and sentiment levels are highly persistent, which can lead to problems in inference (see Yule (1926), Granger and Newbold (1974), Ferson, Sarkissian, and Simin (2003), and Novy-Marx (2014)). Our tests based on changes in sentiment (and changes in institutional/individual investor ownership) largely avoid this issue.

recent research on sentiment, we find similar results using consumer confidence measures as alternative proxies for sentiment.<sup>6</sup>

Second, one of the components of the BW sentiment measure—the dividend premium—is computed from the cross-section of securities and therefore has direct implications for 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 and these sentiment-induced demand shocks result in a decline in the dividend premium. A direct implication, therefore, is that sentiment traders' demand shocks for dividend-paying stocks relative to their demand shocks for non-dividend paying stocks should positively covary with the dividend premium. We find evidence consistent with this implication—the dividend premium increases when institutions in aggregate buy dividend-paying stocks from, and sell non-dividend paying stocks to, individual investors.

We next examine potential explanations for why the investor sentiment metrics capture institutional, rather than individual, investor demand shocks.<sup>7</sup> First, we examine two previously proffered rationales for certain types of institutions to trade on sentiment: (i) Hedge funds attempt to profit from riding bubbles in asset prices (e.g., Brunnermeier and Nagel (2004)); and (ii) independent investment advisors and mutual fund managers have reputational concerns that lead them to trade on sentiment (e.g., Dasgupta, Prat, and Verardo (2011b)). To examine these two fundamental hypotheses, we evaluate the relation between the sentiment metrics and institutional demand shocks by institutional type (hedge funds, independent investment advisors, mutual funds,

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<sup>6</sup> For research using the BW metric see, for example, 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). For research using the consumer confidence, see, for instance, Fisher and Statman (2003), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), and Schmeling (2009).

<sup>7</sup> We acknowledge that in this analysis we are operating *under the assumption* that the BW metric does indeed capture investor sentiment. An alternative interpretation is that the sentiment metric does not capture investor sentiment. We discuss this possibility in the final section.

and other institutions) Our analyses do not support the bubble riding by hedge fund explanation but they do support the reputational concerns of independent investment advisors and mutual funds explanation. Specifically, the relation between time-series variation in hedge funds' attraction to speculative stocks and changes in sentiment is not meaningfully different from zero. On the other hand, consistent with the hypothesis that reputational concerns play a role in driving institutional sentiment trading, changes in sentiment are strongly related to time-series variations in mutual funds' and independent advisors' attraction to risky securities.

Second, an alternative explanation for our result that sentiment metrics capture institutional, rather than individual investors' demand shocks is that institutional demand shocks are primarily driven by the underlying investors, either institutional or individual.<sup>8</sup> Thus, we examine whether underlying investor flows can explain the relation between institutions and sentiment.<sup>9</sup> Using the method developed in Griffin, Harris, Shu, and Topaloglu (2011), we partition 13(f) institutional investors' trades into managers' decisions and flow-induced trades. We find the relation between time-series variation in institutional demand shocks for risky stocks and changes in sentiment to be primarily driven by managers' decisions. In contrast, we find no evidence that investor flows to and from 13(f) institutions can explain institutional sentiment trading. Further consistent with the hypothesis that managers' decisions primarily drive institutional sentiment trading, we demonstrate that 13(f) institutions' entry and exit trades (which, by definition, are due to manager decisions), are also strongly related to changes in sentiment.

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<sup>8</sup> Edelen, Marcus, and Tehrani (2010) use Federal Reserve Z.1 data to develop individual and institutional investor sentiment metrics as the ratio of the fraction of each groups' wealth invested in equities relative to the fraction of all wealth invested in equities. The authors find that variation in individual investors' ratio is the primary driver of sentiment induced mispricing at the market level. Beyond the obvious data, sample period, and methodological differences, we differ from this study because we focus directly on the implications of the BW work for the cross-section of equity returns.

<sup>9</sup> A large literature finds that mutual fund investors chase mutual fund returns, but the relation is not symmetric—good performance yields strong inflows, while bad performance yields minimal outflows (e.g., Ippolito (1992), Goetzmann and Peles (1997), Sirri and Tufano (1998)). Similarly, studies find that defined benefit pension plan sponsors also chase returns in their investment advisors (e.g., Del Guercio and Tkac (2002) and Goyal and Wahal (2008)).

It is possible that investor flow-induced trades are more likely to appear in mutual fund trading (where individual investors play a larger role and we can measure flows between funds of the same family). Thus, we further investigate the role of investor flows in explaining institutional sentiment trading by using the Thomson Financial and CRSP mutual fund data. Consistent with the tests using the 13(f) data, we document a strong positive relation between time-series variation in aggregate mutual fund demand shocks for speculative stocks and changes in sentiment. We find that although mutual fund managers' decisions account for the majority of the relation between mutual fund demand shocks and changes in sentiment, flows to mutual funds account for 43% of the relation. In addition, mutual funds' entry and exit trades (again due to managers' decisions) are strongly related to changes in sentiment. Overall, our evidence suggests that managers' decisions, rather than investor flows, play the primary role in driving institutional sentiment trading.

Third, although the relation between changes in sentiment and institutional demand shocks implies that, in aggregate, institutions engage in sentiment trading, most trades are between institutions (rather than between institutions and individual investors) as institutions account for the vast majority of trading.<sup>10</sup> 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. To examine this issue, we partition institutions into those that contribute positively to our measure of aggregate institutional sentiment trading and those that provide liquidity to sentiment traders (i.e., contribute negatively to our measure of aggregate institutional sentiment trading). Consistent with our previous results, we find that 57% of institutions can be classified as sentiment traders, while the remaining 43% would be considered liquidity traders under the

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<sup>10</sup> Estimates suggest that institutional investors have long accounted for 70-96% of trading volume (e.g., Schwartz and Shapiro (1992), Jones and Lipson (2005)).

classification. Thus, although the evidence shows that the majority of institutions (and institutions in aggregate) trade on sentiment, the practice is far from universal.<sup>11</sup>

Fourth, the evidence in BW and Baker, Wurgler, and Yuan (2012) suggests that sentiment traders should suffer lower returns as a result of their sentiment trading (and those investors who are offsetting the sentiment trades should garner higher returns from doing so). To explore this possibility, we partition the institutional investors into quartiles based on their contribution to our measure of aggregate institutional sentiment trading: (i) strong sentiment traders (highest quartile), (ii) strong liquidity traders (lowest quartile), and (iii) neutral or passive institutions (middle two quartiles). We find that those institutions that contribute the most to our aggregate sentiment metric average meaningfully lower returns than those institutions that trade against sentiment. These results suggest that the underlying investors face real costs from their managers' sentiment trading tendencies.

Fifth, theory suggests that sentiment traders trade excessively.<sup>12</sup> Thus, if the relation between institutional demand shocks and sentiment results from institutions trading on sentiment, we expect that those institutions most subject to sentiment will exhibit higher turnover than other institutions. Consistent with the theoretical implications, those institutions that contribute most strongly to our measure of aggregate institutional sentiment trading average higher turnover than other institutions.

In sum, assuming the BW (and consumer confidence/dividend premium) metrics capture investor sentiment, our results support the hypothesis that institutional investors (in aggregate), rather than individual investors, are the sentiment traders who drive sentiment-induced mispricing. Moreover, although intramanager flows (e.g., investors shifting money from a speculative Janus fund

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<sup>11</sup> It is important to recognize that we do not claim all individual investors are liquidity traders or all institutional investors are sentiment traders. Rather, our results suggest that, in aggregate, institutions are sentiment traders and individual investors are liquidity traders.

<sup>12</sup> Overconfidence leads to excessive trading (e.g., Odean (1998), Benos (1998)) and sentiment is a form of overconfidence (Daniel, Hirshleifer, and Subrahmanyam (1998)).



to a safe Janus fund) may play some role in driving institutional sentiment trading, institutional investors' decisions play the primary role.

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 proxies for investor sentiment during a period: the level of closed-end fund discounts, the 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 difference between the average market-to-book ratios for dividend payers versus nonpayers (which is termed the dividend premium).<sup>13</sup> BW define a second proxy, termed orthogonalized sentiment, which is computed as the first principal component of the residuals from regressions of each of the six sentiment proxies on a set of variables related to business cycles: growth in industrial production, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions.

Analogously, the authors measure the change (both raw and orthogonalized) in investor sentiment as the first principal component of changes in the six proxies.<sup>14</sup> Because our demand metrics are based on quarterly holdings, we compute the quarterly change in investor sentiment as

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<sup>13</sup> See BW (2006) for a detailed discussion of the six individual sentiment proxies.

<sup>14</sup> 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). The authors point out that different proxies have different levels of noisiness when moving from levels to changes. A proxy, for instance, may have low error in its levels data (and therefore an important role in the sentiment levels index), but higher error in its changes (and therefore a less important role in the sentiment change index). In addition, BW (2006, 2007) allow both lag and contemporaneous values (depending on which works better) of the six sentiment proxies in forming the principal component for sentiment levels. BW's changes in sentiment metric, however, is based only on contemporaneous values.

the sum of the monthly BW change in sentiment (both raw and orthogonalized) metric over the quarter.<sup>15</sup>

### *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.<sup>16</sup> 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 at the end of the quarter. 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 shares outstanding.<sup>17</sup> We assume that the negative of institutional demand shocks

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<sup>15</sup> We thank Jeff Wurgler for providing these data. In untabulated analysis, we repeat our primary tests based on quarterly (raw and orthogonalized) changes in sentiment computed from the first principal component of the quarterly changes in the six underlying series. Our conclusions remain unchanged.

<sup>16</sup> 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.

<sup>17</sup> 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). Not surprisingly, however, the cross-sectional correlation between the change in the fraction of shares held by institutions and the change in the number of shares held by institutions normalized by end of quarter shares outstanding is very high—averaging 93%. 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).

proxies for individual investors' demand shocks.<sup>18</sup> 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 (that do not show up in the Thomson Reuters/WRDs 13(f) data).<sup>19</sup>

We use two sources for the 13(f) manager classification data. First, we use the "Type" classifications maintained by Brian Bushee to identify mutual funds (Type=3) and independent investment advisors (Type=4).<sup>20</sup> Second, our sample of hedge funds is based on a proprietary Thomson Financial dataset that identifies all hedge fund companies filing 13(f) reports (see Reza, Sias, and Turtle (2014) for details regarding this data). All remaining institutions (e.g., banks, insurance companies, foundations, internally managed pension funds, etc.) are classified as "others."

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

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<sup>18</sup> This assumption has also been made in previous work. See, for example, Gompers and Metrick (2001), Gibson, Safieddine, and Sonti (2004), and Choi and Sias (2012). Sias and Starks (1997) provide some evidence supporting this assumption.

<sup>19</sup> Figures from Agarwal, Jiang, Tang, and Yang's (2013) Table I suggest that confidential filings account for less than 1% of all institutional stock positions.

<sup>20</sup> The type codes from the Thomson Financial 13(f) data available on WRDs are not reliable after 1998. Brian Bushee has taken reliable pre-1998 codes and carried them forward. In addition, he hand-classifies managers that enter the database after 1998. Professor Bushee's institutional classification data are available on his website: <http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html>.

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.<sup>21</sup> The number of securities in our sample averages 3,953 stocks each quarter (ranging from 1,711 to 5,537) between June 1980 and December 2010 ( $n=123$  quarters). Table 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  $t$ .<sup>22</sup>

[Insert Table I about here]

## II. Empirical Results

We begin by confirming the BW (2007) findings (based on monthly data from 1966-2005) that: (i) high volatility stocks exhibit larger sentiment betas than low volatility stocks, and (ii) high volatility stocks tend to underperform (outperform) low volatility stocks following high (low) sentiment levels, hold for our quarterly data from 1980-2010.<sup>23</sup> Specifically, 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

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<sup>21</sup> 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.

<sup>22</sup> 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.

<sup>23</sup> Because the 13(f) data are only available beginning in December 1979, we cannot include the earlier BW sample years in our sample.

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.<sup>24</sup>

As further detailed in Appendix A, we confirm 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 the cross-sectional mean 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

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<sup>24</sup> 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 buying high volatility stocks from liquidity traders and selling low volatility stocks to liquidity traders. 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 shocks (or, equivalently, individual investors' supply shocks) for each volatility portfolio.<sup>25</sup>

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 31.8%) and sell low volatility stocks to individual investors (i.e., the correlation between time-series variation in institutional demand shocks for low volatility stocks and changes in orthogonalized sentiment is -29.1%). 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 buy volatile stocks from, and sell safe stocks to, individual investors when sentiment increases. That is, 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 indicate that the BW metric captures institutional, rather than individual, investors' aggregate demand shocks.

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<sup>25</sup> We recognize that other factors may influence institutional or individual investors' demand shocks. Because our goal is to determine whose demand shocks are captured by these sentiment metrics (e.g., who buys high volatility stocks when sentiment increases regardless of whether other factors influence those decisions), we do not control for other factors.

### 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.<sup>26</sup> Because institutional ownership grows substantially throughout this period (see, for example, Blume and Keim (2014)), 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.<sup>27</sup> We then partition the sample into low (below median) and high beginning of quarter sentiment level periods and compute the time-series mean of the cross-sectional average detrended institutional ownership levels for stocks within each volatility decile during high and low sentiment periods.

Panels A and B in Table III report the mean detrended institutional ownership levels for each volatility portfolio during high and low sentiment and high and low orthogonalized sentiment periods, respectively. Because the average detrended ownership level is zero by definition (i.e., it is a regression residual), the mean value across high and low sentiment periods (for each volatility portfolio) is zero.<sup>28</sup> 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

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<sup>26</sup> As part of Cornell, Landsman, and Stubben's (2012) examination of mispricing and the quality of accounting information, the authors examine *changes* in institutional ownership (i.e., institutional demand shocks) following high sentiment *levels* and find that institutional investors tend to buy speculative stocks and sell safe stocks following high sentiment levels. We differ from their study in research questions, empirical tests, and conclusions.

<sup>27</sup> In Appendix A, we repeat these tests without detrending institutional ownership levels and find similar results.

<sup>28</sup> 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,  $61/123*(\text{low sentiment value}) + 62/123*(\text{high sentiment value}) = 0$ .

with the demand shock analysis (Table II). Both tests support the hypothesis that institutions, rather than individual investors, are the sentiment traders captured by the BW metric.

[Insert Table III about here]

*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 sentiment metrics, these tests focus on time-series variation in cross-sectional averages in the extreme volatility deciles. To broaden our results, we construct an alternative test that uses 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.<sup>29</sup> Panel A in Table IV reports the time-series descriptive statistics—the cross-sectional correlation averages 2.15%. The correlation, however, varies substantially over time—falling as low as -15.19% and rising as high as 17.99%. Thus, although, on average, institutions tend to buy volatile stocks (or, equivalently, individual investors tend to sell volatile stocks), the pattern varies substantially over time. That is, institutions sometimes strongly move toward volatile stocks (e.g., the quarter when the correlation is 17.99%) and, at other times, strongly avoid volatile stocks (e.g., the quarter when the correlation is -15.19%).

[Insert Table IV about here]

Panel B in Table IV reports the time-series correlation between changes in sentiment and variation in institutional demand shocks for risky stocks—as measured by time-series variation in the cross-sectional correlation between institutional demand shocks and return volatility (i.e., the cross-sectional correlations summarized in Panel A). That is, we test whether institutional investors *increase*

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<sup>29</sup> Following BW (2006), volatility is measured over the previous 12 months and winsorized at the 0.5% and 99.5% levels each quarter.



their preference for risky stocks (and decrease their preference for safe stocks) when sentiment *increases*. Consistent with our earlier tests, the results reveal the correlation between time-series variation in institutions' attraction to volatile stocks and changes in sentiment is 37.81% based on raw changes in sentiment and 36.69% based on 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 -36.69%.

#### *D. Consumer Confidence, Speculative Stocks, and Institutional Versus Individual Investor Demand*

Although the BW metric is the dominant sentiment measure in recent research, a number of studies have used consumer confidence as an alternative investor sentiment proxy.<sup>30</sup> Thus, we next examine the relation between institutional demand shocks for risky stocks and changes in consumer confidence. We focus on two measures of consumer confidence—the University of Michigan Survey of Consumer Expectations and the Conference Board Consumer Confidence Index. Both are based on monthly surveys (over our sample period) to households asking for their views on current and future economic conditions.

We begin by examining whether consumer confidence sentiment betas differ for high and low volatility stocks.<sup>31</sup> Specifically, directly analogous to the BW (2007) tests, we regress the equal-weighted portfolio returns for the highest and lowest volatility deciles on the contemporaneous market return and the standardized (i.e., rescaled to unit variance, zero mean) contemporaneous

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<sup>30</sup> See, for example, Fisher and Statman (2003), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), and Schmeling (2009). See Lemmon and Portniaguina for discussion of the similarities and differences between the Baker and Wurgler (2006, 2007) metric and the consumer confidence metrics.

<sup>31</sup> In untabulated analysis, we find that: (i) quarterly changes in both consumer confidence indices are positively related to contemporaneous changes in the raw or orthogonalized BW sentiment metric (all correlations differ meaningfully from zero at the 5% level or better), and (ii) the relation between consumer confidence levels and the difference in *subsequent* returns for high and low volatility stocks is meaningfully negative (statistically significant at the 1% level in both cases), i.e., high volatility stocks tend to underperform low volatility stocks following high consumer confidence levels.

change in consumer confidence. The results, reported in Panel A of Table V, reveal that high volatility stocks tend to outperform low volatility stocks when the Michigan Consumer Confidence increases (statistically significant at the 1% level). Although the point estimate has the expected sign, the difference in sentiment betas for changes in the Conference Board index is not statistically significant.

[Insert Table V about here]

Assuming changes in consumer confidence proxy for changes in sentiment, the results in Panel A suggest, consistent with the BW metric, that sentiment traders increase their demand for speculative stocks when sentiment increases. Thus, we repeat the tests examining the relation between changes in institutions' demand for speculative stocks and changes in sentiment, replacing changes in the BW sentiment metric with changes in the consumer confidence measure. Specifically, we compute the time-series correlation between changes in consumer confidence and time-series variation in institutions' attraction to volatile stocks (as captured by the cross-sectional correlations between institutional demand shocks and return volatility summarized in Panel A of Table IV). Results, reported in Panel B of Table V, show that institutions increase their preference for volatile stocks when consumer confidence increases (statistically significant at the 5% level in both cases). Thus, once again, the results suggest that sentiment metrics capture institutional, rather than individual, investors' demand shocks.

#### *E. Institutional Demand and the Dividend Premium*

BW use six sentiment proxies to form their sentiment indices. One of the six proxies—the dividend premium—is unique from the others in that it is computed directly from the cross-section of securities and therefore has direct implications for the cross-section of securities. Specifically, based on earlier work (BW (2004)), the authors propose that sentiment traders increase their

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

Because this measure is derived from the cross-section of securities, it leads to another direct test of whose demand shocks are captured by changes in this sentiment proxy. Specifically, if an increase in sentiment causes a decline in the dividend premium as a result of sentiment traders' demand shocks (as BW (2004, 2006, 2007) contend), then the difference between sentiment traders' demand shocks for dividend paying stocks and non-dividend paying stocks will be positively correlated with changes in the dividend premium.<sup>32</sup> For instance, an increase in sentiment causes sentiment traders to sell dividend paying stocks to, and buy non-dividend paying stocks from, liquidity traders, resulting in a decline in the dividend premium.

To examine this issue, we divide securities into two groups—those that paid a dividend in the previous 12 months and those that did not. Each quarter, we compute the cross-sectional average institutional demand shock for dividend payers and non-payers, as well as their difference.<sup>33</sup>

We next examine whose demand shocks for dividend paying and non-dividend paying stocks are positively correlated with quarterly changes in BW's raw or orthogonalized dividend premium sentiment variable. Table VI reports the time-series correlations between the changes in the dividend premium and the differences in the average institutional demand shock for dividend payers and non-

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<sup>32</sup> 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 and non-dividend paying stocks are positively correlated with changes in the dividend premium.

<sup>33</sup> 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.

payers. The results reveal a strong positive relation—the correlation is 42% and statistically significant at the 1% level. We find nearly identical results based on changes in the orthogonalized dividend premium. 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, then institutional investors, rather than individual investors, are the sentiment traders.

[Insert Table VI about here]

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

Our analysis demonstrates that sentiment metrics capture institutional, rather than individual, investors' demand shocks. In this section, we test four hypotheses to explain the relation between changes in sentiment and institutional investor trading.

#### *A. Analysis by Investor Type*

Two potential candidate hypotheses to explain institutional sentiment trading are that: (i) institutions attempt to ride bubbles to exploit less sophisticated investors, and (ii) institutions trade on sentiment to preserve reputation. We examine these hypotheses by evaluating the relation between sentiment and institutions by institutional type. First, we propose (as maintained by Brunnermeier and Nagel (2004)) that hedge funds, relative to other institutional types, are the most likely institutional type to attempt to ride bubbles. Thus, if such behavior contributes meaningfully to the relation between institutions and sentiment, we expect to document a strong positive relation between changes in sentiment and changes in hedge funds' attraction to volatile stocks.

Although the idea of profitably riding a bubble appears, at least initially, straightforward (e.g., a smart investor buying NASDAQ at the beginning of 2000 earns a 25% gain over the next 70 days if

she sells at the market peak on March 10, 2000), the market clearing condition still requires that someone must offset these trades. That is, if both sentiment traders and rational speculators (attempting to ride bubbles) buy speculative stocks, some third group of traders must sell speculative stocks.<sup>34</sup> The key takeaway is that not all traders can simultaneously cause the “bubble.” If individual investors’ sentiment-induced demand shocks drive mispricing, then as a group, institutional investors must provide the necessary liquidity even if some smart institutions attempt to ride the bubble. In other words, if individual investors’ aggregate sentiment-induced demand shocks drive mispricing, institutional investors (in aggregate) must sell speculative stocks to, and buy safe stocks from, individual investors (in aggregate) when sentiment increases.<sup>35</sup>

The second hypothesis derives from the reputational trading models, in which managers rationally trade based on perceived reputations (e.g., Scharfstein and Stein (1990), Graham (1999), Dasgupta, Prat, and Verardo (2011a)). Thus, if institutions’ clients’ perceptions are influenced by sentiment, institutions then fear they will lose clients (or fail to gain additional clients) if they fail to trade on sentiment. Specifically, institutional investors ultimately invest on behalf of individuals. Thus, they answer to their firm’s board or those who delegate portfolio management to them such as pension fund boards, foundation boards, individual investors, and the consultants responsible for selecting and retaining their services. If the perceptions of the individuals to whom institutional

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<sup>34</sup> 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.

<sup>35</sup> It is theoretically possible institutional and individual investors are equally likely to be sentiment traders. Thus, individual (or institutional) investors would be equally likely to trade on sentiment as offset sentiment traders’ demand and changes in institutional/individual investor ownership would be independent of changes in sentiment. Another possibility is that all investors are equally subject to sentiment. Under this scenario, an increase in sentiment would increase the value of a speculative stock, but would not result in trading, e.g., if the stock’s initial value was \$1 and an exogenous sentiment shock caused all investors to set a new reservation price of \$2, the price would immediately adjust to \$2 and no trading would occur since no investor would be willing to sell the stock for less than \$2.

investors answer are influenced by sentiment, a rational institutional investor will act accordingly, or face termination and declining revenue. 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.”

Under such a hypothesis, previous work suggests that the institutional investor types most concerned about reputation should be mutual funds and independent investment advisors e.g., Sias (2004) and Dasgupta, Prat, and Verardo (2011b).

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

To test how the relation between institutional demand and sentiment varies by investor type, we repeat the examination of whether time-series variation in institutional demand for volatile stocks is related to changes in sentiment (i.e., the analysis in Table IV) for each investor type. Analogous to our aggregate analysis, for each institutional investor type, we limit the sample to securities that are held by at least five investors of that type. For mutual funds, independent investment advisors, and other institutions, the cross-sectional sample averages 2,582 securities each quarter (ranging from 355 stocks for mutual funds in June 1980 to 4,694 stocks for the other institutional investor types in September 1998). Because there are relatively few hedge companies in our sample at the beginning

of the period, we limit the hedge fund sample to the final 90 quarters.<sup>36</sup> As before (see Panel A of Table IV), each quarter we compute the cross-sectional correlation between institutional demand shocks (by each type of institutional investor, as measured by the change in the number of shares held by that type of institution divided by shares outstanding) and stock return volatility. As shown in Panel A of Table VII, all four manager types exhibit, on average, a positive relation between demand shocks and return volatility. As with aggregate institutional demand (Panel A of Table IV), however, the cross-sectional correlation varies greatly over time for each of the four manager types.

[Insert Table VII about here]

Panel B (analogous to Panel B in Table IV) reports the key test—the correlation between changes in sentiment and time series variation in each manager type’s attraction to speculative stocks (as captured by the cross-sectional correlations summarized in Panel A). The results show no significant relation between changes in sentiment and hedge funds’ demand shocks. The lack of a meaningful relation between changes in sentiment and time series variation in hedge funds’ movement into volatile stocks suggests that institutions attempting to ride bubbles is not the primary factor driving the relation between changes in sentiment and aggregate institutional demand shocks.

In contrast, the results provide strong evidence that mutual funds and independent advisors increase their demand for risky stocks when sentiment increases. Specifically, the correlations for mutual funds and independent advisors range from 32% (independent advisors and changes in orthogonalized sentiment) to 43% (independent advisors and changes in raw sentiment). These results, combined with the lack of significant results for the other institutions, provide support for the hypothesis that institutions’ reputational concerns contribute to institutional sentiment trading,

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<sup>36</sup> Prior to September 1998, each quarter has less than 100 stocks that are held by at least five 13(f) hedge fund companies. The hedge fund sample size in the final 90 quarters averages 1,220 securities each quarter (ranging from 89 in December 1989 to 2,769 in December 2006).

i.e., those investors who are arguably most concerned about reputational effects (mutual funds and independent advisors) exhibit the greatest propensity for sentiment trading.

### *B. Flows, Net Active Buying, and Passive Trades*

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

To test this hypothesis, we follow the method in Griffin, Harris, Shu, and Topaloglu (2011) and estimate three components (details are given in Appendix A) of institutional demand shocks: trades that result from investor flows (*NBFlows*), trades that result from managers' decisions (*Net Active Buying*), and trades that result from reinvested dividends (*Passive*). Specifically, the institutional demand shock for security  $i$  in quarter  $t$  ( $\Delta Inst_{i,t}$ ) can be written:

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

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 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 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 VIII reports the correlation between time-series variation in institutions' demand for risky stocks and changes in orthogonalized sentiment, i.e., the 36.69% 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 intermanager flows 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 96% of the time-series correlation reported in the first column (i.e.,  $0.3514/0.3669$ ).<sup>37</sup>

[Insert Table VIII about here]

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

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<sup>37</sup> In Appendix A, we repeat these tests by 13(f) investor type and find similar results

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. 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).<sup>38</sup> Accordingly, we compute the cross-sectional correlation between aggregate institutional entry/exit demand shocks and securities' return volatility each quarter (these untabulated correlations average 0.98% and range from -12.75% to 14.62%). 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 VIII reveals the correlation is 47.89% (statistically significant at the 1% level). The results provide further evidence that managers' decisions play an important role in driving the relation between time-series variation in institutions' demand shocks for volatile stocks and changes in sentiment.

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 VIII 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)

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<sup>38</sup> 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 decisions.

is 35.09% (statistically significant at the 1% level).<sup>39</sup> Thus, consistent with our results based on 13(f) data, mutual funds buy risky stocks and sell safe stocks when sentiment increases.

The next three columns in Panel C partition the Thomson Financial/CRSP mutual fund correlation into the three components and reveal that, although managers' decisions (net active buying) account for the largest share of the correlation (statistically significant at the 2% level based on bootstrapped  $p$ -values), investor flows to mutual funds account for a substantial component of the correlation (approximately 43%=0.1500/0.3509) and are also statistically significant (based on bootstrapped  $p$ -values) at the 1% level.<sup>40</sup> 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.<sup>41</sup>

As a final test, we examine mutual funds' entry and exit trades which, by definition, reflect mutual fund managers' decisions rather than flow induced adjustments to existing portfolios. Specifically, analogous to the 13(f) entry/exit trade analysis, we compute mutual funds' entry/exit aggregate demand shocks for each security as the change in number of shares held by entering (zero

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<sup>39</sup> 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. Note that Panel C in Table VIII is based on the CRSP/TFN mutual fund data while the mutual fund analysis in Table VII is based on 13(f) data and the Bushee investor type classifications.

<sup>40</sup> As a placebo test, we repeat the mutual fund analysis limiting the sample to mutual funds identified as S&P 500 index funds (via the Lipper Objective and Classification codes in the CRSP mutual fund data). As expected, time-series variation in index funds' attraction to volatile stocks is independent of changes in sentiment. Specifically, the time-series correlation between changes in orthogonalized sentiment and time-series variation in index funds' attraction to volatile stocks is -0.054 and does not differ meaningfully from zero ( $p$ -value=0.56). Further consistent with expectations, none of the index fund components (flows, net active buying, or passive) differ meaningfully from zero.

<sup>41</sup> To further examine the role of intramanager flows, we use the CRSP fund family identification data starting in March 1999 (the first quarter with at least 100 fund families identified that have more than one fund; CRSP begins to populate the family identifier data in December 1997) to compute the three components of mutual fund demand (flows, decisions, passive) for both individual funds and at the family level. We estimate the components at the family level as if we were unable to view the components at the fund level, i.e., analogous to the 13(f) data. The correlation between time-series variation in this sample of mutual funds' demand shocks for volatile stocks (as captured by the cross-sectional correlation between their demand shocks and volatility) is 0.424 (statistically significant at the 1% level). Using the fund-level data, 25% of the correlation (0.106 of 0.424) is attributed to investor flows. Using the family level data (i.e., analogous to the 13(f) data), 13% of the correlation (0.054 of the 0.424) is attributed to flows. Thus, the results support the hypothesis that intrafamily flows contribute to the correlation between changes in sentiment and mutual funds' attraction to volatile stocks. The results, however, also support the explanation that the relation between mutual fund demand shocks and changes in sentiment is *primarily* due to mutual fund managers' decisions.

initial position, non-zero ending position) and exiting (non-zero beginning position, zero ending position) mutual funds scaled by shares outstanding. We then compute the cross-sectional correlation between mutual funds' entry/exit demand shocks and securities' return volatility each quarter (these untabulated correlations average 0.05% and range from -15.17% to 22.36%). We then compute the time-series correlation between changes in orthogonalized sentiment and time-series variation in mutual fund managers' attraction (as captured by their entry/exit trades) to volatile stocks. Panel D in Table VIII reports the correlation is 41.86% (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' decisions appear to be the primary factor driving the relation between institutions' demand shocks and changes in sentiment. Nonetheless, we also 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 sentiment suggests that (in aggregate) individual investors who invest via mutual funds may differ from those who invest directly. 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.”

### *C. Do Most Institutions Trade on Sentiment?*

If sentiment metrics capture investor sentiment and institutions in aggregate are the sentiment traders, then it follows that most institutions trade on sentiment (i.e., it should be, in some sense, systematic to influence prices).<sup>42</sup> Nonetheless, every sentiment-induced trade must be offset by an investor less subject to sentiment, and extant work (e.g., Schwartz and Shapiro (1992), Jones and Lipson (2005)) suggests that institutional investors account for most of the trading in equities. As a result, although institutions, in aggregate, are the sentiment traders identified by common sentiment metrics, it is likely that some institutions trade with sentiment while others provide at least some of the offsetting liquidity. Thus, in this section, we classify all institutions into two groups—sentiment traders and liquidity providers—to examine: (i) the breadth of institutional sentiment trading and (ii) whether some institutions help offset aggregate institutional sentiment trading.

Because covariances are linear in the arguments and aggregate institutional demand shocks are simply the sum of demand shocks across all institutions, we can decompose the correlation between changes in sentiment and the aggregate institutional investors’ attraction to volatile stocks into the contribution by each individual institution (see Appendix A for proof).<sup>43</sup> Thus, we begin by computing each manager’s contribution to the time-series correlation between changes in

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<sup>42</sup> Technically it is possible that most institutions trade against sentiment but institutions in aggregate trade with sentiment (e.g., if only large institutions trade with sentiment). The analysis in this section, however, shows that this is not the case.

<sup>43</sup> A manager’s total contribution will depend on both their cross-sectional contribution (i.e., the extent that their demand shocks across securities relate to return volatility) and their time-series contribution (i.e., the extent that their proclivity to buy high volatility stocks varies with changes in sentiment). Because this is a decomposition of aggregate institutional demand shocks, larger managers will have larger impacts, holding everything else constant. Similarly, a manager’s contribution will depend on how long they survive in the sample, e.g., a manager that exists for a few years will only contribute to the correlation in a few periods. The sign of their contribution, however, should be independent of their size and the time they are in the sample.

orthogonalized sentiment and the cross-sectional correlation between aggregate institutional demand shocks and return volatility reported in Table IV Panel B (i.e., the 36.69% figure). Those managers who contribute positively to the correlation (i.e., those institutions that tend to buy volatile stocks and sell safe stocks when sentiment increases) are denoted sentiment traders. Those managers who contribute negatively to the correlation (i.e., those institutions that tend to sell volatile stocks and buy safe stocks when sentiment increases) are denoted liquidity traders.

Table IX reports for all institutions and then by institutional investor type, the number of institutions in our sample (first column), the fraction of institutions classified as sentiment traders, and the fraction of institutions classified as liquidity traders. The last column reports a binomial  $z$ -score of the null hypothesis that the fraction of institutions classified as sentiment traders does not differ meaningfully from 0.5.

[Insert Table IX about here]

The results in Table IX demonstrate that although the majority (57%) of institutions are classified as sentiment traders (i.e., the last column indicates the fraction that are sentiment traders is meaningfully greater than 50% at the 1% level), 43% of institutions are classified as liquidity traders (i.e., 43% of institutions tend to sell volatile stocks and purchase safe stocks when sentiment increases). Thus, institutional sentiment trading is far from universal. The remaining rows reveal the same pattern for each type of institution. In every case, we can reject the null (at the 1% level) that the fraction of institutions classified as sentiment traders does not differ from 50%.<sup>44</sup> Nonetheless, there exists variation across the manager types. Mutual funds exhibit the greatest propensity for sentiment trading, followed by independent investment advisors. Even in these cases, however,

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<sup>44</sup> The results in Table IX show that 55% of hedge funds are classified as sentiment traders, consistent with hedge funds contributing to sentiment-induced demand shocks. Nonetheless, the results in Tables VII and IX show that mutual funds and independent investment advisors much more strongly engage in sentiment trading. The combined results continue to suggest that hedge funds riding bubbles is not the primary driver of institutional sentiment trading.

there are a large percentage of liquidity traders. For example, approximately one-third of mutual fund companies trade against sentiment (i.e., are classified as liquidity traders).<sup>45</sup>

#### *D. Institutional Sentiment Trading and Returns*

If the BW metrics capture sentiment trading, and institutions trade on sentiment, in the long-run, sentiment trading should harm their returns. To test this hypothesis, we partition institutions into three groups—strong sentiment traders (the top quartile of institutions that contribute the most to our aggregate correlation metric, i.e., the 36.69% correlation reported in Table IV), strong liquidity traders (the bottom quartile of institutions in terms of contribution), and passive institutions (institutions in the middle two quartiles). For each institution, we then estimate abnormal returns as the four factor (excess market return, size, value, and momentum factors) intercept based on a time-series regression of the return from the equity portfolio held by each institution at the beginning of the quarter. Of course, this is an estimate of the actual return earned by the institution because: (i) we cannot observe intraquarter trades (i.e., we implicitly assume all trading occurs at the end of the quarter), and (ii) our sample restrictions prevent the observation of all holdings (e.g., institutions are not required to report small positions, cash holdings, etc.). To increase precision, we estimate the abnormal returns using monthly data (based on holdings that are updated quarterly). We also compute market-adjusted returns for each institutional portfolio.

The relation between investor returns and sentiment, however, is complicated by several factors. First, trading on sentiment can “work” for an investor with good timing. For instance, between September 1998 and February 2000, the BW change in orthogonalized sentiment metric has a *cumulative* increase of 11.27 (recall monthly changes are standardized with mean zero and unit variance). Over that same period, the NASDAQ index increased 211% versus a 34% increase in the

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<sup>45</sup> The fact that approximately one-third of mutual funds are identified as liquidity traders also supports the hypothesis that institutional sentiment trading primarily results from managers’ decisions rather than underlying investors’ flows.

more conservative DJIA. An investor shifting from DJIA securities to NASDAQ securities would have benefited from those trades throughout this period.

Second, stocks with high exposure to sentiment may have a sentiment risk premium (e.g., DeLong, Shleifer, Summers, and Waldmann (1990a)). Empirically, Chen, Han, and Pan (2014) find that both individual equities and hedge funds that have greater sentiment betas (based on the BW change in sentiment metric) average higher returns consistent with a sentiment-induced risk premium (over their 1997-2010 sample period). It is important to recognize, however, that the return earned by an investor *holding* a portfolio of securities with a high sentiment beta (e.g., volatile stocks) is not the same as the return earned by an investor *trading* on sentiment (e.g., buying volatile stocks when sentiment increases and selling volatile stocks when sentiment decreases). Specifically, the evidence reported by BW and Baker, Wurgler, and Yuan (2012) suggests sentiment trading will tend to erode long term returns, i.e., consistent with Table III, these patterns imply that sentiment traders will tend to have a greater (lower) exposure to volatile stocks when sentiment is high (low) and volatile stocks subsequently underperform (outperform) safer stocks.

To ensure our results are not impacted by a short sample (e.g., a “sentiment institution” that is only in the sample during the rising internet bubble or a “sentiment institution” that is only in the sample during the subsequent crash), we limit the sample to institutions that have at least 60 quarters of data (i.e., approximately half the sample period). Panel A in Table IX reports the cross-sectional mean monthly four-factor alphas and monthly market adjusted return (portfolio return less value weighted market return) for strong sentiment institutions, passive institutions, and strong liquidity institutions (results are in percent per month). The last column reports the difference between strong sentiment institutions and strong liquidity institutions and associated *t*-statistics (computed from a *t*-test for difference in means). The last row reports the number of institutional managers in each group.



[Insert Table X about here]

The results in Panel A demonstrate that strong sentiment institutions garner meaningfully lower abnormal and market-adjusted returns than the strong liquidity institutions. The differences (reported in the last column) are statistically significant (at the 5% level or better). The alpha difference reported in Panel A (-0.037% per month) suggests that, on average, sentiment traders average a 0.44% lower return each year.<sup>46</sup>

One limitation of the 13(f) data is that returns of the underlying securities held by the managers is only a proxy for their actual returns (although it is not clear how this limitation would explain the differences in returns between strong sentiment institutions and strong liquidity institutions).<sup>47</sup> Thus, we next repeat the tests using CRSP mutual funds' reported returns rather than 13(f) institutions' inferred returns. Specifically, as with the 13(f) data, we partition all mutual funds into the three groups—strong sentiment traders, strong liquidity traders, and passive mutual funds. For each fund, we then estimate a time-series regression of monthly fund returns on monthly market, size, value, and momentum factors and use the intercept as our measure of the fund's long-term monthly abnormal return. As before, we also compute each fund's time-series mean monthly market-adjusted return.<sup>48</sup>

Panel B in Table X report the mutual fund results based on the sample of mutual funds (Thomson Financial/CRSP mutual fund data) that have at least 60 quarters of data. Consistent with the 13(f) data results, Panel B provides evidence that mutual funds strongly trading with sentiment average lower abnormal and market-adjusted returns than those mutual funds providing liquidity.

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<sup>46</sup> Interestingly, passive institutions average the lowest market-adjusted return. Once accounting for differences in factor exposures, however, passive managers perform in between strong sentiment institutions and strong liquidity institutions.

<sup>47</sup> At least for mutual funds, Kacperczyk, Sialm, and Zheng (2008) find that the return on the beginning of quarter portfolio is a strong proxy for realized returns. Specifically, the authors report that the correlation between investor returns and the return earned on beginning of quarter holdings averages 97.96%.

<sup>48</sup> A few funds are excluded because they do not report monthly returns. Specifically, we require funds to have at least 60 monthly returns (CRSP mutual fund data) to compute alpha and market adjusted returns (in addition to 60 quarters of Thomson Financial holdings/trading data) to be included in the analysis.

The difference in mean returns is 0.07% per month (approximately 0.87% per year). Differences are statistically significant at the 5% level.<sup>49</sup> In sum, the results in Table X suggest that underlying investors bear a meaningful cost for their managers' sentiment trading.

#### *E. Institutional Sentiment Trading and Turnover*

Baker and Stein (2004) note that high sentiment induces sentiment traders to trade. Moreover, sentiment trading is a form of overconfidence (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998)) and overconfidence leads to excessive trading (e.g., Odean (1998), Benos (1998)). Alternatively, managers may trade excessively in an attempt to signal clients that they are informed (e.g., Trueman, (1988)). As a result, we expect sentiment traders to exhibit higher turnover than non-sentiment traders. Thus, if the BW metric captures sentiment trading and institutions are the sentiment traders, we expect those institutions that contribute the most to sentiment trading will exhibit higher turnover. To examine this possibility, we compute the time-series average of each manager's quarterly cross-sectional turnover percentile.<sup>50</sup> Table XI reports the cross-sectional mean turnover percentile for each manager group for strong sentiment traders (as defined in the previous subsection), passive institutions, and strong liquidity institutions. The last column reports a *t*-statistic of the null hypothesis that the mean turnover percentile for sentiment traders does not differ from that of liquidity traders.

[Insert Table XI about here]

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<sup>49</sup> We also examine the 13(f) and mutual fund data for managers that have at least 30 quarters of data (untabulated to conserve space). We find the same patterns in returns. Although the differences are statistically significant for the 13(f) sample, the differences are not significantly significant for the mutual fund sample.

<sup>50</sup> We calculate turnover as the minimum of the dollar value of a managers' buys and sells normalized by the average of the managers' portfolio size at the beginning and end of the quarter. To account for time-series variation in turnover, we focus on the time-series average of the manager's turnover relative to other managers (i.e., the time-series average of the manager's cross-sectional turnover percentile).

The results reveal that strong sentiment traders average turnover in the 58<sup>th</sup> percentile versus the 56<sup>th</sup> percentile for strong liquidity traders and the 50<sup>th</sup> percentile for passive institutions.<sup>51</sup> We also find (last column) a meaningful difference in the mean turnover percentiles for strong sentiment traders versus strong liquidity traders.<sup>52</sup> Assuming sentiment traders tend to engage in higher turnover, the results are consistent with the hypothesis that institutional investors (or at least a large subset of institutions) trade on sentiment.

## 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 and they simply chase lag returns and their demand shocks do not impact prices.<sup>53</sup> Although this explanation could explain why institutions buy volatile stocks from, and sell safe stocks to, individual investors when sentiment

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<sup>51</sup> Because the values reported in Table XI are computed from the average across institutions and institutions appear in the sample for different numbers of quarters, the mean percentile need not equal 50% (i.e., for our sample, high turnover institutions tend to appear in the sample for shorter periods).

<sup>52</sup> It is likely that the tendency for liquidity traders to exhibit higher turnover than passive traders results, at least in part, from liquidity traders providing liquidity to sentiment traders' sentiment-induced trades. We also find (untabulated) that strong sentiment institutions average meaningfully higher turnover than passive institutions.

<sup>53</sup> The 13(f) data are unique in that they provide the only estimate of aggregate institutional and individual investors' demand shocks. Moreover, given the coarseness of the sentiment data (e.g., the BW metric), it is not clear that one could differentiate sentiment trading from other motives based on finer partitioning (e.g., transaction data) of the demand shocks.

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 would be 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.

Another possible interpretation is that trades resulting from those investors who do not file 13(f) reports (i.e., non-13(f) demand) are not representative of individual investor demand. As noted in our discussion of the data, positions less than 10,000 shares and \$200,000 (both conditions must be met), may be excluded from 13(f) reports, institutions managing less than \$100 million are not required to file 13(f) reports, and some managers are sometimes given an exemption from timely 13(f) filings. Thus, it is possible (although arguably improbable), that non-institutional investors do trade with sentiment, but that small institutions' positions, small institutions, and the few institution-quarter-stocks that receive 13(f) exemptions, trade so strongly against sentiment, that they dominate non-institutional investors' demand shocks. Importantly, however, this would not change the fact that institutions' aggregate demand (at the least the portion we can identify via 13(f) reports) moves with sentiment.

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).<sup>54</sup> 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

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<sup>54</sup> Because we require stocks have at least nine monthly returns prior to the quarter to compute volatility, our sample does not include IPOs.

and insiders appear to trade against sentiment, individual investors account for the vast majority (79%) of the offsetting demand.

It is also possible that sentiment metrics (even when “orthogonalized”) capture economic fundamentals. This explanation, however, is hard to reconcile with the negative sentiment beta for low volatility stocks (see BW (2007) and Appendix A). That is, if an increase in sentiment reflects improving economic fundamentals (and an associated decline in the equity premium), all stock prices should rise (albeit they may rise more for speculative stocks). More important, under this interpretation, our main conclusion remains intact—our evidence shows that investor sentiment metrics capture institutional investors’ demand shocks, not those of individual investors. In short, if cross-sectional return patterns are driven by demand shocks (as the sentiment literature requires), then the sentiment metrics capture institutional investors’ demand shocks.

Last, as noted in the introductory quote, Friedman (1984) argues that perhaps we should expect institutions to be more prone to sentiment. Specifically, Friedman points out four factors (some of which are related to the issues discussed in Section III) that suggest institutions will more likely pay attention to “fads and fashions” than individual investors. First, at least relative to individual investors, institutional investors are a close-knit community with (p. 508) “...constant communication and mutual exposure.” Second, institutional investors’ performance is typically judged relative to other institutions rather than in absolutes, which provides an incentive to follow other institutions. Third, institutions suffer from asymmetry of incentives—the potential rewards for overperformance may not be worth the cost if wrong. Finally, if sentiment does impact prices, smart managers would pay attention to sentiment.

## *B. 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., the non-zero sentiment betas 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.

Inconsistent with conventional wisdom, but consistent with earlier conjectures from Brown and Cliff (2004), 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. In short, we provide strong evidence that investor sentiment metrics capture direct trading by institutional investors, not individual investors. Thus, if sentiment metrics capture sentiment-based demand shocks, institutional investors, rather than individual investors, are the sentiment traders.

Our analysis by institutional investor type provides tests of explanations for why these investors may trade on sentiment. We find some support for the hypothesis that institutional investor sentiment trading arises, at least in part, from their reputational concerns, but we find little evidence that the institutional investor sentiment trading primarily results from hedge funds attempting to ride bubbles. In addition, although we find that the demand of underlying investors (through their

flows into an institution) plays some role in driving the relation between mutual fund trading and sentiment, the institutional managers' decisions play the dominant role in driving the relation between institutional investor demand shocks and changes in investor sentiment. Although institutions, in aggregate, trade on sentiment, institutional investor sentiment trading is not universal—43% of institutions appear to provide liquidity to institutional sentiment traders. Moreover, those institutions who contribute most to our aggregate sentiment metric exhibit higher turnover and suffer lower returns than those institutions that most offset sentiment trading.

## REFERENCES

- Abreu, Dilip, and Markus K. Brunnermeier, 2003, Bubbles and crashes, *Econometrica* 71, 173-204.
- Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2013, Uncovering hedge fund skill from the portfolio holdings they hide, *Journal of Finance* 68, 739-783.
- Allen, Franklin, and Gary Gorton, 1993, Churning bubbles, *The Review of Economic Studies* 60, 813-836.
- Antoniou, Constantinos, John A. Doukas, and Avaniidhas Subrahmanyam, 2013, Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.
- Baker, Malcolm, and Jeremy C. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271- 299.
- Baker, Malcolm, and Jeffrey Wurgler, 2004, A catering theory of dividends, *Journal of Finance* 59, 1125-1165.
- Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.
- Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129-152.
- Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272-287.
- Barberis, Nicholas, and Wei Xiong, 2012, Realization utility, *Journal of Financial Economics* 104, 251-271.
- Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge funds stock trading during the financial crisis of 2007-2009, *Review of Financial Studies* 25, 1-54.
- Benos, Alexandros V., 1998, Aggressiveness and survival of overconfident traders, *Journal of Financial Markets* 1, 353-383.
- Bergman, Nittai K., and Sugata Roychowdhury, 2008, Investor sentiment and corporate disclosure, *Journal of Accounting Research* 46, 1057-1083.
- Blume, Marshall E., and Donald B. Keim, 2014, The changing preferences of institutional investors for common stocks, Working paper, The University of Pennsylvania.
- Brown, Gregory W. and Michael T. Cliff, 2004, Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1-27.
- Brunnermeier, Markus K., and Stefan Nagel, 2004, Hedge funds and the technology bubble, *Journal of Finance* 59, 2013-2040.
- Chen, Yong, Bing Han, and Jing Pan, 2014, Noise trader risk and hedge fund returns, Working paper, Texas A&M University.
- Choi, Nicole, and Richard W. Sias, 2012, Why does financial strength forecast stock returns? Evidence from subsequent demand by institutional investors, *Review of Financial Studies* 25, 1550-1587.



- Core, John E., Wayne R. Guay, and S. P. Kothari, 2002, The economic dilution of employee stock options: Diluted EPS for valuation and financial reporting, *The Accounting Review* 77, 627-652.
- Cornell, Bradford, Wayne R. Landsman, and Stephen Stubben, 2012, Does accounting information facilitate efficient markets? Evidence from investor sentiment-related mispricing, Working paper, California Institute of Technology and the University of North Carolina.
- Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839-1886.
- Dasgupta, Amil, Andrea Prat, and Michela Verardo, 2011a, The price impact of institutional herding, *Review of Financial Studies* 24, 892-925.
- Dasgupta, Amil, Andrea Prat, and Michela Verardo, 2011b, Institutional trade persistence and long-term equity returns, *Journal of Finance* 66, 635-653.
- DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990a, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.
- DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.
- Del Guercio, Diane, and Paula A. Tkac, 2002, The determinants of the flow of funds of managed portfolios: Mutual fund vs. pension funds, *Journal of Financial and Quantitative Analysis* 37, 523-557.
- Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: Is there a connection?, *Journal of Finance* 52, 1087-1129.
- Edelen, Roger M., Alan J. Marcus, and Hassan Tehranian, 2010, Relative sentiment and stock returns, *Financial Analysts Journal* 66, 1-13.
- Ferson, Wayne, Sergei Sarkissian, and Timothy Simin, 2003, Spurious regressions in financial economics?, *Journal of Finance* 58, 1393-1414.
- Fisher, Kenneth L., and Meir Statman, 2003, Consumer confidence and stock returns, *Journal of Portfolio Management* 30, 115-127.
- Friedman, Benjamin M., 1984, A comment: Stock prices and social dynamics, *Brookings Papers on Economic Activity* 2, 504-508.
- Gibson, Scott, Assem Safieddine, and Ramana Sonti, 2004, Smart investments by smart money: Evidence from seasoned equity offerings, *Journal of Financial Economics* 72, 581-604.
- Goetzmann, William N., and Nadav Peles, 1997, Cognitive dissonance and mutual fund investors, *Journal of Financial Research* 20, 145-158.
- Gompers, Paul A., and Andrew Metrick, 2001, Institutional investors and equity prices, *Quarterly Journal of Economics* 116, 229-260.
- Goyal, Amit, and Sunil Wahal, 2008, The selection and termination of investment management firms by plan sponsors, *Journal of Finance* 63, 1805-1847.

- Graham, John R., 1999, Herding among investment newsletters: Theory and evidence, *Journal of Finance* 54,169-182.
- Granger, Clive W.J., and Paul Newbold, 1974, Spurious regressions in econometrics, *Journal of Econometrics* 2, 111-120.
- Grantham, Jeremy, 2012, My sister's pension assets and agency problems, GMO quarterly letter.
- Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714-746.
- Griffin, John M., Jeffrey H. Harris, Tao Shu, and Selim Topaloglu, 2011, Who drove and burst the tech bubble?, *Journal of Finance* 66, 1251-1290.
- Hribar, Paul, and John McInnis, 2012, Investor sentiment and analysts' earnings forecast errors, *Management Science* 58, 308-319.
- Investment Company Institute, 2013, 2013 Investment Company Fact Book, [www.icifactbook.org](http://www.icifactbook.org).
- Ippolito, Richard A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45-70.
- Jones, Charles M., and Mark Lipson, 2005, Are retail orders different?, Working paper, Columbia University.
- Kacperczyk Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379-2416.
- Karolyi, G. Andrew, Kuan-Hui Lee, and Mathijs A. van Dijk, 2012, Understanding commonality in liquidity around the world, *Journal of Financial Economics* 105, 82-112.
- Lee, Charles M.C., Andrei Shleifer, and Richard Thaler, 2001, Investor sentiment and the closed-end fund puzzle, *Journal of Finance* 46, 75-109.
- Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer confidence and assets prices: Some empirical evidence, *Review of Financial Studies* 19, 1499-1529.
- Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.
- McLean, R. David, and Mengxin Zhao, 2012, The business cycle, investor sentiment, and costly external finance, *Journal of Finance* 36, 1377-1409.
- Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228-250.
- Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277-309.
- Novy-Marx, Robert, 2014, Predicting anomaly performance with politics, the weather, global warming, sunspots, and the stars, *Journal of Financial Economics* 112, 137-146.
- Odean, Terrance, 1998, Volume, volatility, price, and profit when all traders are above average, *Journal of Finance* 53, 1887-1934.

- Ramadorai, Tarun, 2012, The secondary market for hedge funds and the closed hedge fund premium, *Journal of Finance* 67, 479-512.
- Reca, Blerina Bela, Richard W. Sias, Harry J. Turtle, 2014, Hedge fund crowds and mispricing, Working paper, University of Arizona.
- Rosch, Dominik, Avanidhar Subrahmanyam, and Mathijs A. van Dijk, 2014, An empirical analysis of co-movements in high- and low-frequency metrics for financial market efficiency, Working paper, Rotterdam School of Management and UCLA.
- Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465-479.
- Schmeling, Maik, 2009, Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16, 394-408.
- Schwartz, Robert, and James Shapiro, 1992, The challenge of institutionalization for the equity markets, *Recent Developments in Finance*, 31-45.
- Shiller, Robert J., 2000, Irrational exuberance, Princeton, NJ: Princeton University Press.
- Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.
- Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589-1622.
- Sias, Richard W., 2004, Institutional herding, *Review of Financial Studies* 17, 165-206.
- Sias, Richard W. and Laura T. Starks, 1997, Return Autocorrelations and Institutional Investors, *Journal of Financial Economics* 46, 103-131.
- Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.
- Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2014, The long of it: Odds that investor sentiment spuriously predicts anomaly returns, *Journal of Financial Economics*, forthcoming.
- Trueman, Brett, 1988, A theory of noise trading in securities markets, *Journal of Finance* 43, 83-96.
- Yan, Xuemin, and Zhe Zhang, 2009, Institutional investors and equity returns: Are short-term institutions better informed, *Review of Financial Studies* 22, 893-924.
- Yu, Jianfeng, and Yu Yuan, 2011, Investor sentiment and the mean-variance relation, *Journal of Financial Economics* 100, 367-381.
- Yule, G. Udny, 1926, Why do we sometimes get nonsense-correlations between time-series?--A study in sampling and the nature of time-series, *Journal of the Royal Statistical Society* 89, 1-63.

**Table 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 3,953 securities in the sample each quarter.

	<u>Time-series Descriptive Statistics</u>			
	Mean	Median	10 <sup>th</sup> Percentile	90 <sup>th</sup> Percentile
%Shares held by institutions	35.90%	33.79%	6.52%	68.61%
Raw $\Delta$ (%shares held by institutions)	0.64%	0.31%	-3.02%	4.61%
Institutional demand shock	0.00%	-0.33%	-3.66%	3.97%
Number of institutions trading	66.62	31.98	4.29	168.17
$\sigma$ (Monthly return <sub><math>t=-1</math> to <math>-12</math></sub> )	13.38%	11.45%	5.8%	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
	<u>Panel A: Change in Investor Sentiment</u>										
$\rho(\overline{\Delta Inst_{i,t}}, \Delta Sent_t)$	-0.245	-0.274	-0.335	-0.257	-0.134	-0.135	-0.160	0.149	0.251	0.237	0.273
( <i>p</i> -value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.14)	(0.14)	(0.08)	(0.10)	(0.01)	(0.01)	(0.01)
	<u>Panel B: Change in Orthogonalized Investor Sentiment</u>										
$\rho(\overline{\Delta Inst_{i,t}}, \Delta Sent_t^\perp)$	-0.291	-0.302	-0.377	-0.276	-0.234	-0.151	-0.102	0.086	0.202	0.318	0.343
( <i>p</i> -value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.10)	(0.27)	(0.35)	(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)
<u>Panel A: Detrended Fraction of Shares held by Institutional Investors (%) for High and Low Sentiment Level Periods</u>											
High sentiment	-0.84	-0.20	-0.36	0.05	-0.11	0.10	0.25	0.53	0.53	1.03	1.88
Low sentiment	0.86	0.20	0.37	-0.05	0.11	-0.10	-0.25	-0.53	-0.54	-1.05	-1.91
High-low sent.	-1.70	-0.40	-0.73	0.11	-0.22	0.21	0.50	1.06	1.08	2.08	3.78 (4.79)***
<u>Panel B: Detrended Fraction of Shares held by Institutional Investors (%) for High and Low Orthogonalized Sentiment Level Periods</u>											
High sentiment $\perp$	-0.50	-0.09	-0.17	0.25	-0.01	0.47	0.65	0.85	0.86	1.39	1.89
Low sentiment $\perp$	0.51	0.09	0.17	-0.26	0.01	-0.48	-0.66	-0.86	-0.88	-1.41	-1.92
High-low sent. $\perp$	-1.01	-0.18	-0.33	0.51	-0.01	0.94	1.31	1.71	1.74	2.80	3.81 (4.83)***

**Table 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
$\rho_t(\Delta Inst_{i,t}, \sigma_{i,t})$	2.15% (4.46)***	5.35%	-15.19%	17.99%
Panel B: Time-series Correlation between Changes in Sentiment and Institutional Demand Shocks for Volatile Stocks ( $n=123$ quarters)				
	$\Delta$ Sentiment ( $p$ -value)	$\Delta$ Orthogonalized Sentiment ( $p$ -value)		
$\rho(\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta Sent_t)$	37.81% (0.01)	36.69% (0.01)		

**Table V**  
**Time-series Variation in Institutional Demand for Volatile Stocks**  
**and Changes in Consumer Confidence**

Panel A reports consumer confidence sentiment betas computed from time-series regressions ( $n=123$  quarters) of the equal-weighted portfolio returns for stocks in the top volatility decile, stocks in the bottom volatility decile, and their difference, on contemporaneous market returns and contemporaneous (standardized) changes in consumer confidence. The third row reports their difference and associated  $t$ -statistics. 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 of Table IV) and changes in consumer confidence (and associated  $p$ -values).  $\Delta\text{Michigan}_t$  is the quarter  $t$  change in the University of Michigan Survey of Consumer Expectations and  $\Delta\text{Conference}_t$  is the quarter  $t$  change in the Conference Board Consumer Confidence Index. Statistical significance at the 1% level is indicated by \*\*\*.

Panel A: Consumer Confidence "Sentiment" Betas ( $t$ -statistics)		
	$\Delta\text{Michigan}_t$ ( $t$ -statistic)	$\Delta\text{Conference}_t$ ( $t$ -statistic)
High $\sigma$ portfolio return $_t$	0.040	0.017
Low $\sigma$ portfolio return $_t$	0.003	-0.002
High $\sigma$ – Low $\sigma$	0.038 (3.06)***	0.018 (1.44)
Panel B: Time-series Correlation between Changes in Consumer Confidence and Institutional Demand Shocks for Volatile Stocks ( $n=123$ quarters)		
	$\Delta\text{Michigan}_t$ ( $p$ -value)	$\Delta\text{Conference}_t$ ( $p$ -value)
$\rho(\rho_t(\Delta\text{Inst}_{i,t}, \sigma_{i,t}), \Delta X_t)$	0.181 (0.05)	0.257 (0.01)



**Table VI**  
**Time-series Variation in Institutional Demand for Dividend Paying Stocks**  
**and Changes in the Dividend Premium**

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

Time-series Correlation between the Difference in Institutional Demand Shocks for Dividend Payers and Non-payers and Changes in the Dividend Premium		
	$\Delta$ Dividend Premium ( <i>p</i> -value)	$\Delta$ Orthogonalized Dividend Premium ( <i>p</i> -value)
$\rho(\overline{\Delta Inst Div Payer}_i - \overline{\Delta Inst Non Div Payer}_i, \Delta Div Prem_i)$	41.73% (0.01)	41.40% (0.01)

**Table VII**  
**Time-series Variation in Institutional Demand for Volatile Stocks**  
**and Changes in Sentiment by Investor Type**

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between security return volatility and demand shocks by hedge funds, mutual funds, independent investment advisors, and other institutional investors. Volatility is based on returns over the previous 12 months. Panel A reports the time-series mean, standard deviation, minimum, and maximum cross-sectional correlation and associated  $t$ -statistics (in parentheses) computed from the time-series of cross-sectional correlations. Panel B reports the correlation between time-series variation in each type of institutional investors' attraction to volatile stocks (i.e., the cross-sectional correlation between volatility and the changes in the fraction of shares held by each type of institution summarized in Panel A) and changes in raw or orthogonalized investor sentiment. Statistical significance at the 1% level is indicated by \*\*\*.

Panel A: Descriptive Statistics for Cross-sectional Correlation between Institutional Demand Shocks (by Type) and Volatility				
$\rho_t(\Delta Inst_{i,t}, \sigma_{i,t})$	Mean ( $t$ -statistic)	Standard Deviation	Minimum	Maximum
$\Delta$ Hedge funds ( $n=90$ quarters)	4.68% (4.31)***	10.29%	-20.43%	42.37%
$\Delta$ Mutual funds ( $n=123$ quarters)	3.00% (4.24)***	7.85%	-20.87%	27.94%
$\Delta$ Independent advisors ( $n=123$ quarters)	2.65% (5.32)***	5.51%	-12.02%	18.63%
$\Delta$ Other institutions ( $n=123$ quarters)	1.58% (3.79)***	4.62%	-11.58%	15.21%

Panel B: Time-series Correlation between Changes in Sentiment and Institutional Demand Shocks (by Type) for Volatile Stocks		
$\rho[\rho_t(\Delta Inst_{i,t}, \sigma_{i,t}), \Delta Sent_t]$	$\Delta$ Sentiment ( $p$ -value)	$\Delta$ Orthogonalized Sentiment ( $p$ -value)
$\Delta$ Hedge funds ( $n=90$ quarters)	11.54% (0.28)	9.48% (0.38)
$\Delta$ Mutual funds ( $n=123$ quarters)	39.92% (0.01)	35.14% (0.01)
$\Delta$ Independent advisors ( $n=123$ quarters)	43.44% (0.01)	31.54% (0.01)
$\Delta$ Other institutions ( $n=123$ quarters)	13.98% (0.13)	14.62% (0.11)

**Table VIII**  
**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 (see 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.

	$\rho[\rho_t(\Delta X_{i,t}, \sigma_{i,t}), \Delta Sent_t^\perp]$ ( $p$ -value)	Contribution to $\rho[\rho_t(\Delta X_{i,t}, \sigma_{i,t}), \Delta Sent_t^\perp]$ 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	36.69% (0.01)	0.74% (0.78)	35.14% (0.01)	0.81% (0.61)
Panel B: All 13(f) Institutions – Demand due to Entry and Exit Trades Only				
13(f) entry/exit trades	47.89% (0.01)			
Panel C: CRSP/TFN Mutual Fund Data				
$\Delta$ CRSP/TFN Mutual funds	35.09% (0.01)	15.00% (0.01)	19.35% (0.02)	0.73% (0.85)
Panel D: CRSP/TFN Mutual Fund Data – Demand due to Entry and Exit Trades Only				
$\Delta$ CRSP/TFN MF entry/exit trades	41.86% (0.01)			

**Table IX**  
**Institutional Sentiment Trading and Liquidity Trading**

We 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 reported in Panel B of Table IV (i.e., the 36.69% figure). Each institution is then classified as a sentiment trader (contribution to the correlation is greater than zero) or a liquidity trader (contribution to the correlation is less than zero). The first three columns report the number of institutions, the fraction that are classified as sentiment traders, and the fraction that are classified as liquidity traders, respectively. The last column reports a  $\chi$ -statistic associated with the null hypothesis that the fraction classified as sentiment traders does not differ meaningfully from 50%. Statistical significance at the 1% level is indicated by \*\*\*.

	Number of Institutions	%Sentiment Traders	%Liquidity Traders	$\chi$ -statistic (Ho: %Sent=0.5)
All 13(f) institutions	5,368	57.30%	42.70%	20.69***
Hedge funds	966	55.18%	44.82%	3.19***
Mutual funds	139	67.63%	32.37%	4.07***
Independent advisors	2,883	58.07%	41.94%	8.64***
Other institutions	1,380	56.16%	43.84%	4.55***

**Table X**  
**Institutional Sentiment Trading and Manager Returns**

We compute each institution's contribution (see Appendix A) to the correlation between time-series variation in institutional investors' attraction to volatile stocks and changes in orthogonalized sentiment reported in Panel B of Table IV (i.e., the 36.69% figure). We then partition institutions into three groups—the top quartile (denoted “strong sentiment institutions”), the middle two quartiles (denoted “passive institutions”), and the bottom quartile (denoted “strong liquidity institutions”). For each institution, we then estimate a time-series regression of monthly portfolio returns (inferred from beginning of quarter holdings) on monthly market, size, value, and momentum factors and use the intercept as our measure of the institution's monthly abnormal return. We also compute each institution's time-series mean monthly market adjusted return. We require institutions to have at least 60 quarters of data to be included in this analysis. The last column reports the mean return difference between strong sentiment institutions and strong liquidity institutions (the associated  $t$ -statistic is computed from a difference in means test). Sample sizes (number of institutions) appear in the bottom row. Panel B reports analogous tests for mutual funds. Mutual fund returns and holdings/trades are based on Thomson Financial/CRSP mutual fund data. Statistical significance at the 1%, and 5% level are indicated by \*\*\* and \*\*, respectively.

Return	Strong Sentiment Institutions	Passive Institutions	Strong Liquidity Institutions	Strong Sent. – Strong Liq. ( $t$ -statistic)
Panel A: 13(f) Institutions				
4-factor alpha	0.024	0.061	0.061	-0.037 (-3.03)***
Ret.-VW Mkt.	0.070	0.035	0.104	-0.034 (-2.52)**
$N$	421	157	340	
Panel B: CRSP/TFN Mutual Funds				
4-factor alpha	-0.085	-0.052	-0.014	-0.072 (-2.16)**
Ret.-VW Mkt.	-0.095	-0.040	-0.009	-0.086 (-2.30)**
$N$	101	8	65	

**Table XI**  
**Institutional Sentiment Trading and Turnover**

We compute each institution’s contribution (see Appendix A) to the correlation between time-series variation in institutional investors’ attraction to volatile stocks and changes in orthogonalized sentiment reported in Panel B of Table IV (i.e., the 36.69% figure). We then partition institutions into three groups—the top quartile (denoted “strong sentiment institutions”), the middle two quartiles (denoted “passive institutions”), and the bottom quartile (denoted “strong liquidity institutions”). We then compute the time-series average of each institution’s cross-sectional quarterly turnover percentile. This table reports the cross-sectional average turnover percentile for institutions within each group. The last column reports the difference in turnover for strong sentiment institutions and strong liquidity institutions and the associated *t*-statistic associated with the null hypothesis that these two groups exhibit equal turnover. Statistical significance at the 1% level is indicated by \*\*\*.

Strong Sentiment Institutions	Passive Institutions	Strong Liquidity Institutions	Strong Sent. – Strong Liq. ( <i>t</i> -statistic)
58.32%	50.12%	55.71%	2.61% (3.03)***

## Appendix A. Robustness Tests, Proofs, and Estimation Details

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## A1. Quarterly sentiment betas (1980-2010)

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

Figure A.1 reveals that the sentiment betas increase monotonically across the volatility-sorted portfolios. Controlling for market returns, a one standard deviation increase in quarterly orthogonalized sentiment is associated with a 4.1% higher quarterly return for stocks in the most volatile decile and a -1.7% quarterly return for stocks in the least volatile decile. The coefficients for the high and low volatility portfolios differ significantly at the 1% level (untabulated). Nearly identical to the analysis BW (2007, Figure 4B), the results are consistent with the BW hypothesis that an increase in sentiment causes sentiment traders to sell safe stocks and buy risky stocks and these sentiment induced demand shocks impact prices.<sup>1</sup>

[Insert Figure A.1 about here]

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



## A2. Sentiment levels and subsequent returns (1980-2010)

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

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

[Insert Figure A.2 about here]

Further following BW (2006), we regress subsequent quarterly returns for the highest volatility portfolio, the lowest volatility portfolio, and their difference, on beginning of the quarter sentiment levels. We estimate the regressions using the beginning of quarter sentiment levels (raw or

orthogonalized) as the only independent variable and also including the contemporaneous quarter's excess market return as well as size, value, and momentum factors.<sup>2</sup> Once again, the results are fully consistent with those reported by BW (see BW (2006) Table V). Specifically, the estimated coefficients, reported in Table A.I, reveal that the return difference between high volatility stocks and low volatility stocks is inversely related to beginning of quarter sentiment levels (statistically significant at the 1% level in all four cases) even when controlling for standard asset pricing variables. In sum, although based on a different sample period and periodicity, Table A.I and Figures A.1 and A.2 are fully consistent with BW and Baker, Wurgler, and Yuan (2012).

[Insert Table A.I about here]

### **A3. Alternative measures of a stock's sensitivity to sentiment**

Following BW (2007), we use return volatility as the measure of a stock's susceptibility to sentiment. In their earlier paper (BW (2006)), the authors examine a number of alternative characteristics to measure a stock's susceptibility to sentiment induced demand shocks. In this section we focus on four additional metrics that BW (2006, Table V) find generate the same monotonic pattern in returns following high and low sentiment levels: firm size, firm age, companies with positive earnings versus companies with negative earnings, and dividend paying versus non-dividend paying stocks.<sup>3</sup>

Following BW (2006), we partition stocks into three groups by market capitalization (using NYSE breakpoints each quarter): firms in the top three deciles are denoted large, firms in the middle four deciles are classified as medium, and firms in the bottom three deciles are denoted small. We

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<sup>2</sup> Market, size, value, and momentum factors are from Ken French's website.

<sup>3</sup> In addition to the five metrics we examine (return volatility, size, age, profitability, and dividends), BW (2006) also examine two measures of tangibility (fixed assets to assets and research and development to assets) and three measures of "growth opportunities and distress" (book to market, external finance to assets, and sales growth decile). The authors, however, fail to find a meaningful monotonic relation between the tangibility and growth/distress metrics and sentiment levels. As a result, we focus on the first five metrics where BW do find monotonic relations.

analogously define three portfolios based on firm age (number of months since first appearing on CRSP). We define dividend paying firms as companies that paid a dividend in the 12 months preceding the start of the quarter and define profitable firms as firms that had positive cumulative income (Compustat IBQ) in the 12 months preceding the start of the quarter.

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

[Insert Table A.II]

We next examine the relation between changes in sentiment and institutional/individual investor demand shocks for each of the portfolios discussed above. Specifically (analogous to Table II), we compute the cross-sectional mean institutional demand shock (i.e., the change in the number of shares held by institutions for stock  $i$  divided by shares outstanding less the mean ratio across all stocks in quarter  $t$ ) for securities within each size, age, profitability, and dividend portfolio. We then calculate the time-series correlation between changes in sentiment and the contemporaneous quarterly cross-sectional average institutional demand shocks (or, equivalently, individual investors' supply shocks) for each portfolio.

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

#### **A4. Raw institutional ownership levels and sentiment levels**

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

Panels A and B in Table A.III report the results based on sentiment levels and orthogonalized sentiment levels, respectively. The last column reports the difference in mean institutional ownership

levels for high and low volatility stocks. Regardless of sentiment levels, institutional ownership of low volatility stocks is, on average, higher than their ownership of high volatility stocks (although institutional ownership levels are highest for stocks in the middle volatility deciles), i.e., differences reported in the last column of the first two rows in Panels A and B are negative. Nonetheless, inconsistent with the hypothesis that individual investors are the sentiment traders, institutional investors' preference for risky stocks *relative* to their preference for safe stocks is larger when sentiment is high, i.e., the differences reported in the third row of the last column in Panels A and B are positive and statistically significant (at the 1% level).<sup>4</sup>

[Insert Table A.III about here]

#### **A5. Flows, net active buying, and passive trades by 13(f) investor type**

In this section, analogous to Panel A of Table VIII, we partition the correlations between time-series variation in each investor types' attraction to volatile stocks and changes in orthogonal sentiment (i.e., the correlations reported in the last column of Panel B in Table VII) into the portion due to investor flows (net buying flows), manager decisions (net active buying), and reinvested dividends (passive). Table A.IV reports the results. The *p*-values reported in the last three columns are based on bootstrapped estimates with 10,000 iterations (see Appendix A10 for details). For mutual funds and independent investment advisors (i.e., the two investor types with a meaningful correlations in the first column), the relation between time-series variation in their demand shocks for risky stocks and changes in sentiment is driven by managers' decisions (statistically significant at the 1% level in both cases) and not intermanager flows.

[Insert Table A.IV about here]

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<sup>4</sup> Institutional ownership levels across all portfolios are higher when sentiment is lower (i.e., the differences in the third row of Panels A and B are negative for all volatility deciles). This occurs because there are more high sentiment periods in the earlier half of our sample and institutional ownership levels increase over time (see, for example, Blume and Keim (2014)). Thus, the detrended ownership level results are more appropriate.

## **A6. Offsetting institutional demand: Companies, insiders, and individuals**

As noted in Section I of the paper, because we want to capture institutional demand shocks, we measure the change in institutional ownership as the change in the number of shares held by institutions scaled by the end of quarter shares outstanding. Thus, for example, an employee exercising an option for 200 shares (and therefore increasing the number of outstanding shares) in a quarter where institutions, in aggregate, net purchased 100 shares, does not appear as a negative institutional demand shocks (i.e., although, in aggregate, institutions purchased 100 shares, the fraction of shares held by institutions declined due to the increase in the number of shares outstanding as a result of the employee exercising the option).

In our main tests we attribute all offsetting supply (i.e., -1 times the change in the number of shares held by institutions divided by end of quarter shares outstanding) as individual investor supply. However, in some cases the offsetting supply may arise from insiders or the company themselves rather than individual investors (where we are defining individual investors as different than insiders, even though insiders are usually individuals). In this section, we partition the institutional demand shock into three components—supply from the company, supply for insiders, and supply from individual investors. Specifically, the change in the (split-adjusted) number of shares held by institutions can be partitioned into the change in the number of shares outstanding (company supplied), net insider demand (insider supplied), and the remainder (individual investor supplied). The institutional demand shock (change in number of shares held by institutions divided by end of quarter shares outstanding) is simply the sum of the changes in the number of shares for each of the suppliers (company, insiders, and individuals) divided by end of quarter shares outstanding. For example, assume: (1) company ABC had 95 shares outstanding at the beginning of the quarter and 100 shares at the end of the quarter, (2) institutions held 60 shares at the beginning of the quarter and 70 shares at the end, and (3) insiders sold 1 share over the quarter. In this case,

the institutional demand shock ( $10\% = (70-60)/100$ ) is offset by the company supply shock ( $5\% = (100 - 95)/100$ ), an insider supply shock ( $1\% = 1/100$ ), and the remainder ( $4\%$  individual supply =  $10\%$  institutional demand –  $5\%$  company supply –  $1\%$  insider supply) is attributed to individual investors.

Occasionally, companies have very large changes in the number of shares outstanding due to private transactions.<sup>5</sup> To ensure our results are not driven by these outliers, we limit the sample in this section to securities whose split-adjusted change in shares outstanding is less than 10% in absolute value. This filter eliminates approximately 4.7% of firm-quarter observations.<sup>6</sup>

The data on insider demand comes from two sources. We use Securities and Exchange Commission's Ownership Reporting System (ORS) for the sample period from the quarter ending June 1980 through the quarter ending December 1995.<sup>7</sup> For the remainder of our sample (quarter ending March 1996 through quarter ending December 2010) we use SEC Form 4 filings provided by the Thomson Reuters insider filings database. We exclude blockholder trades from the insider demand metric.<sup>8</sup> Insider demand is defined as the net number of shares of security  $i$  purchased by insiders scaled by the number of shares outstanding. Following previous work (e.g., Peress (2010)), we winsorize the inside demand shocks (at the 0.5% and 99.5% each quarter).

Last, we estimate the net shares purchased by individual investors as the net shares purchased by institutions less the net shares sold by the company less the net shares sold by insiders. We then scale each term by the end of quarter shares outstanding to compute the *net* fraction of end of quarter shares purchased by institutions, sold by the company, sold by insiders, and sold by

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<sup>5</sup> Pacific Capital Bancorp (PCBC, permno=83551), for example, has 46,895,000 shares outstanding at the end of June 2010, 2,908,038,000 shares outstanding at the end of September 2010 and no change in the CRSP cumulative adjustment factor.

<sup>6</sup> We also repeat this tests limiting the filter to securities with changes in the number of split-adjusted shares outstanding between -20% and +20%. Our results (unablated) remain nearly unchanged.

<sup>7</sup> We thank David Whidbee for providing these data.

<sup>8</sup> We exclude blockholder trades (relationship codes of "B", "BC", or "BT") to eliminate the possibility of double-counting as these trades may also be captured in the 13(f) inferred demand shock. Nonetheless, we find (unablated) essentially identical results when including blockholder trades in our insider demand metric.

individuals. The last three terms sum to the first term, i.e.,  $institutional\ demand\ shock_{i,t} = company\ supply\ shock_{i,t} + insider\ supply\ shock_{i,t} + individual\ investors\ supply\ shock_{i,t}$ .<sup>9</sup>

We examine the supply components of net institutional demand shock by first computing the cross-sectional correlation between institutional demand shocks and security return volatility for our restricted sample (i.e., directly analogous to Panel A of Table IV, but limited to securities with less than 10% increase or decrease in split-adjusted shares outstanding). These cross-sectional correlations range from -16.36% to 15.56% (untabulated). We then compute the time-series correlation between institutional investors' attraction to volatile stocks and orthogonal changes in sentiment. The first column of Table A.V reports the correlation is 35.72% (statistically significant at the 1% level) and nearly identical to the correlation of 36.69% reported in the last column of Panel B in Table IV. Thus, once again, the results reveal that an increase in sentiment is associated with institutional investors buying volatile stock and selling safe stocks.

[Insert Table A.V about here]

Directly analogous to the methodology we used to decompose institutional demand into flow based shocks, net active buying, and passive trades in Panel A of Table VIII (see proof in Appendix A9), we can partition the time-series correlation between institutional investors' attraction to volatile stocks and changes in sentiment into the portion attributed to the company's net supply, insiders' net supply, and individual investors' net supply. Results are reported in the last three columns in Table A.V. Because this is a linear decomposition of the correlation reported in the first column, the sum of the last three columns is identical to the 35.72% correlation reported in the first column. The  $p$ -values for the last three columns are based on a bootstrap procedure with 10,000 iterations (see Appendix A10 for details).

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<sup>9</sup> Note because they are net figures, any of these terms can be positive or negative.



The results reported in Table A.V suggest that individual investors primarily offset the institutional demand shocks. Specifically, individual investors' net supply accounts for 79% of the correlation (i.e., 0.2820/0.3572) between time-series variation in institutional investors' attraction to volatile stocks and changes in sentiment. We also find a positive contribution by both companies and insiders, although only the latter differs meaningfully from zero. The meaningful relation for insiders is consistent with BW's (2006) hypothesis that insiders likely trade against sentiment.<sup>10</sup> In sum, the results in Table A.V suggest that individual investors are the group that primarily offsets aggregate institutional sentiment trading.<sup>11</sup>

#### A7. Decomposing 13(f) demand into flows, decisions, and passive trades

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

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

where  $P_{i,t}$  is the price of security  $i$  at the end of quarter  $t$ ,  $H_{i,k,t}$  is the numbers of shares of security  $i$  held by investor  $k$  at the end of quarter  $t$ ,  $R_{i,t}$  is security  $i$ 's quarter  $t$  return, and there are  $N_t$  securities

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<sup>10</sup> BW (2006) propose that insider trading as a potential (counter) sentiment metric. They authors, however, do not use insider demand in their final sentiment metric due to limited availability over their sample period.

<sup>11</sup> Our results do not imply that no individual investors trade on sentiment. Rather, given a buyer for every seller and aggregate institutional sentiment trading, individuals, *in aggregate*, appear to offset sentiment-induced demand shocks (or the BW metric does not capture investor sentiment).

in the market in quarter  $t$ . Following Griffin, Harris, Shu, and Topaloglu, we winsorize the flow ratio at the 5<sup>th</sup> and 95<sup>th</sup> percentile for the 13(f) data.<sup>12</sup>

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

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

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

$$NBFlows_{i,k,t} = \frac{\left( \frac{P_{i,t-1}H_{i,k,t-1}(1 + R_{i,t})}{\sum_{i=1}^N P_{i,t-1}H_{i,k,t-1}(1 + R_{i,t})} \right) \left( \sum_{i=1}^{N_i} (P_{i,t}H_{i,k,t} - P_{i,t-1}H_{i,k,t-1}(1 + R_{i,t})) \right)}{P_{i,t}S_{i,t}}. \quad (A.3)$$

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

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

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

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

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<sup>12</sup>As Griffin, Harris, Shu, and Topaloglu (2011) point out, outliers can occur in the 13(f) data if an institution moves from non-equity holdings to equity holdings.

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

The numerator of Equation (A.5) is the difference between the dollar value of end of quarter  $t$  holdings of security  $i$  by manager  $k$  and the expected value of manager  $k$ 's holdings of security  $i$  if the manager made no deviations in his portfolio weights and invested all flows at end of quarter portfolio weights. Dividing by price ( $P_{i,t}$ ) yields the net number of shares purchased by the manager due to active decisions and further dividing by shares outstanding ( $S_{i,t}$ ) yields the change in the fraction of outstanding shares due to manager  $k$ 's active trades of security  $i$  in quarter  $t$ .

Following Griffin, Harris, Shu, and Topaloglu (2011), we define manager  $k$ 's passive changes in holdings of security  $i$  in quarter  $t$  as:

$$Passive_{i,k,t} = \frac{(P_{i,t-1}H_{i,k,t-1}) \times (1+R_{i,t}) - P_{i,t}H_{i,k,t-1}}{P_{i,t}S_{i,t}}. \quad (A.6)$$

Note that if the security pays no dividend, passive trading is equal to zero (i.e.,  $P_{i,t} = P_{i,t-1}(1+R_{i,t})$ ). If security  $i$  pays a dividend, Equation (A.6) assumes institution  $k$  reinvests the dividend in security  $i$ .

Summing Equations (A.2), (A.4), and (A.6) simply yields the change in the number of split-adjusted security  $i$ 's shares held by investor  $k$  over quarter  $t$  divided by security  $i$ 's shares outstanding:

$$\Delta Inst_{i,k,t} = NBFloWS_{i,k,t} + Net \ Active \ Buying_{i,k,t} + Passive_{i,k,t}. \quad (A.7)$$

Summing Equation (A.7) across institutions yields the institutional demand shock and its three components (flows, decisions, and passive) for security  $i$  in quarter  $t$ :

$$\Delta Inst_{i,t} = \sum_{k=1}^K \Delta Inst_{i,k,t} = \sum_{k=1}^K NBFloWS_{i,k,t} + \sum_{k=1}^K Net \ Active \ Buying_{i,k,t} + \sum_{k=1}^K Passive_{i,k,t}. \quad (A.8)$$

Equation (A.8) is effectively identical to Griffin, Harris, Shu, and Topaloglu's (2011) Equation (2).<sup>13</sup>

#### **A8. Decomposing mutual fund demand into flows, decisions, and passive trades**

Our mutual fund demand decomposition also follows Griffin, Harris, Shu and Topaloglu (2011). We merge Thompson N-30D mutual fund holdings data and CRSP mutual fund data using WRDs Mutual Fund Links. We delete observations where the difference in shares held from the previous and current report differs from the reported change in shares. We limit the sample to stocks with CRSP share codes 10 and 11 that are listed on NYSE, Amex, or Nasdaq. If a report date does not fall on the last trading day of the month we assume it is equal to the last trading day of the current (previous) month if the report date occurs after (before) the 15th of the month.

For the CRSP mutual fund data we require funds to have non-missing returns and total net assets data for all share classes. We also require funds to report in consecutive quarters. We calculate quarterly fund returns by computing each share class' quarterly returns and then value weighting the returns using beginning of quarter total net assets.<sup>14</sup> We restrict the sample to domestic equity funds by deleting all funds with Lipper asset codes not equal to 'EQ,' equity codes not equal to 'E,' and funds with common stock investments that make up less than 50% of their portfolio. We also limit the sample to funds with Lipper class codes equal to one of the following: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLVE, SCCE, SCGW, SCVE, or whose Lipper objective

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<sup>13</sup> Our notation differs slightly from Griffin, Harris, Shu, and Topaloglu (2011). Specifically, the first two terms on the right hand side of their Equation (2) is identical to the negative of our numerator in Equation (A.6) because Griffin, Harris, Shu, and Topaloglu write net active buying as a function of passive and flows (whereas we write institutional demand shock as the sum of the three components). If one moves the right hand side of their Equation (2) to the left-hand side, the equation becomes the dollar value of institutional demand due to net active buying, reinvested dividends (passive), and flows. If estimated at the stock level, dividing by market capitalization yields the net fraction of shares purchased by institutions in security  $i$  over quarter  $t$  (i.e., our Equation (A.8)). In short, we follow their exact method.

<sup>14</sup> Because most mutual funds only report quarterly total net assets prior to 1992, we differ slightly from Griffin, Harris, Shu, and Topaloglu (2011) in that we value-weight quarterly returns using quarterly total net assets while the authors use monthly total net assets. Our method results in a substantially larger sample size, especially early in our sample period when few funds report monthly return data.

code equals one of the following: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, SCG. Finally, we exclude funds whose name contains the word ‘Global,’ ‘International,’ ‘Europe,’ or ‘Emerging.’

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

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

where  $TNA_{k,t}$  is the total net assets (the sum of the total net assets for all share classes) as reported by CRSP for mutual fund  $k$  at the end of quarter  $t$  and  $R_{k,t}$  is the return for mutual fund  $k$  in quarter  $t$  where returns are value weighted across all share classes.<sup>15</sup> Given the mutual fund flow ratio, we use Equations (A.2)-(A.6) to decompose mutual fund demand shocks into flow induced trades, net active buying, and passive trades.

#### A9. Decomposing the correlation into flows, decisions, and passive trades

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

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

where  $XS$  denotes cross-sectional,  $\Delta Inst_{i,t}$  is the aggregate institutional demand shock (i.e. the change in the fraction of shares held by institutions) for stock  $i$  in quarter  $t$ ,  $\overline{\Delta Inst}_t$  is the cross-sectional

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<sup>15</sup> For a few outliers, the flow ratios are unreasonably large or small. As a result, we winsorize the mutual fund flow ratio at the 1<sup>st</sup> and 99<sup>th</sup> percentiles.

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

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

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

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

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

$$\rho_{XS,t}(\Delta Inst_{i,t}, \sigma(ret_{i,t})) = \sum_{k=1}^K Cont_{k,t}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma(ret_{i,t}))). \quad (\text{A.13})$$

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

$$\begin{aligned}
Cont_{k,t}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma(ret_{i,t}))) &= \frac{1}{N_t} \sum_{i=1}^{N_t} \left[ \left( \frac{NBflows_{i,k,t} - \left( \frac{NBflows_t}{K_{i,t}} \right)}{\sigma(\Delta Inst_t)} \right) \left( \frac{\sigma(ret_{i,t}) - \overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))} \right) \right] + \\
&\frac{1}{N_t} \sum_{i=1}^{N_t} \left[ \left( \frac{NAB_{i,k,t} - \left( \frac{NAB_t}{K_{i,t}} \right)}{\sigma(\Delta Inst_t)} \right) \left( \frac{\sigma(ret_{i,t}) - \overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))} \right) \right] + \\
&\frac{1}{N_t} \sum_{i=1}^{N_t} \left[ \left( \frac{Passive_{i,k,t} - \left( \frac{Passive_t}{K_{i,t}} \right)}{\sigma(\Delta Inst_t)} \right) \left( \frac{\sigma(ret_{i,t}) - \overline{\sigma(ret_t)}}{\sigma_{XS}(\sigma(ret_t))} \right) \right]. \tag{A.14}
\end{aligned}$$

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

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

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

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

where  $TS$  denotes time series and  $T$  is the total number of quarters. Substituting Equation (A.13)

into Equation (A.16) yields:

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

Rearranging yields:

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

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

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



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

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

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

$$\begin{aligned} Cont_k(\rho_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})), \Delta Sent)) = \\ \frac{1}{T} \sum_{t=1}^T \left( \frac{\left[ \overline{NBFlows Cont_{k,t}} - \frac{\overline{NBFlows Cont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})))} \right) \left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right) + \\ \frac{1}{T} \sum_{t=1}^T \left( \frac{\left[ \overline{NABCont_{k,t}} - \frac{\overline{NABCont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})))} \right) \left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right) + \\ \frac{1}{T} \sum_{t=1}^T \left( \frac{\left[ \overline{Passive Cont_{k,t}} - \frac{\overline{Passive Cont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})))} \right) \left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right). \end{aligned} \quad (A.21)$$

Thus, each manager’s contribution to the time series correlation between changes in sentiment and the cross-sectional correlation between institutional investors’ demand shocks and stock volatility is

simply the sum of the components due to investor flows, managers' decisions, and reinvested dividends:

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

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

$$\begin{aligned} \rho_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})), \Delta Sent) = & \\ & \frac{1}{T} \sum_{t=1}^T \left[ \sum_{k=1}^K \left( \frac{\left[ \frac{NBFlowsCont_{k,t} - \overline{NBFlowsCont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})))} \right) \right] \left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right) + \\ & \frac{1}{T} \sum_{t=1}^T \left[ \sum_{k=1}^K \left( \frac{\left[ \frac{NABCont_{k,t} - \overline{NABCont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})))} \right) \right] \left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right) + \\ & \frac{1}{T} \sum_{t=1}^T \left[ \sum_{k=1}^K \left( \frac{\left[ \frac{PassiveCont_{k,t} - \overline{PassiveCont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma_{XS}(ret_{i,t})))} \right) \right] \left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right). \end{aligned} \quad (A.23)$$

#### A10. Bootstrapped $p$ -values

We use a bootstrap procedure to generate  $p$ -values for contributions due to flows, net active buying, and passive trades reported in Table VIII. Specifically, we randomly assign (without

replacement) standardized sentiment, i.e.,  $\left( \frac{\Delta Sent_t - \overline{\Delta Sent}}{\sigma_{TS}(\Delta Sent)} \right)$  to each term in square braces in

Equation (A.23). For example, we assign standardized sentiment from random quarter  $x$ , to flows in quarter  $t$ :

$$\left[ \sum_{k=1}^K \left( \frac{\left[ \frac{NBFlows\ Cont_{k,t} - \overline{NBFlows\ Cont}}{K_t} \right]}{\sigma_{TS}(\rho_{XS,t}(\Delta Inst_{i,t}, \sigma(ret_{i,t})))} \right) \right]. \quad (A.24)$$

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

## References

- Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.
- Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129–152.
- Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012, Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272–287.
- Blume, Marshall E., and Donald B. Keim, 2014, The changing preferences of institutional investors for common stocks, Working paper, The University of Pennsylvania.
- Griffin, John M., Jeffrey H. Harris, Tao Shu, and Selim Topaloglu, 2011, Who drove and burst the tech bubble? *Journal of Finance* 66, 1251-1290.
- Peress, Joel, 2010, Product market competition, insider trading, and stock market efficiency, *Journal of Finance* 65, 1-43.

**Table A.I**

**Regression of subsequent quarterly high and low volatility portfolio returns on sentiment levels**

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

Dependent variable	Sentiment <sub><math>t-1</math></sub>	Sentiment <sub><math>t-1</math></sub> (controlling for market, size, value, and momentum factors)	Sentiment $\perp$ <sub><math>t-1</math></sub>	Sentiment $\perp$ <sub><math>t-1</math></sub> (controlling for market, size, value, and momentum factors)
High $\sigma$ portfolio return <sub><math>t</math></sub>	-0.028	-0.016	-0.022	-0.015
Low $\sigma$ portfolio return <sub><math>t</math></sub>	0.020	0.009	0.021	0.090
High $\sigma$ return <sub><math>t</math></sub> – Low $\sigma$ return <sub><math>t</math></sub>	-0.049 (-3.19)***	-0.025 (-2.86)***	-0.043 (-2.84)***	-0.024 (-2.75)***

**Table A.II**  
**Institutional sentiment trading based on alternative**  
**classifications of risky and safe stocks**

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

	Sentiment beta		Correlation between institutional demand shock and changes in sentiment	
	$\Delta Sent_t$ ( $t$ -statistic)	$\Delta Sent_t^\perp$ ( $t$ -statistic)	$\rho(\overline{\Delta Inst_t}, \Delta Sent_t)$ ( $p$ -value)	$\rho(\overline{\Delta Inst_t}, \Delta Sent_t^\perp)$ ( $p$ -value)
Panel A: Capitalization				
Small	2.19%	1.58%	9.63%	10.92%
Medium	0.49%	-0.07%	1.10%	2.35%
Large	-0.32%	-0.19%	-12.33%	-22.22%
Small-Large	2.50% (3.38)***	1.76% (2.38)**	12.12% (0.19)	20.08% (0.03)
Panel B: Age				
Young	2.61%	1.91%	31.94%	26.34%
Medium	0.45%	0.31%	-25.09%	-11.14%
Old	-1.67%	-1.44%	-28.21%	-34.35%
Young-Old	4.28% (8.50)***	3.35% (6.16)***	31.19% (0.01)	34.09% (0.01)
Panel C: Profitable and unprofitable firms				
Earnings<0	4.40%	3.85%	18.75%	27.28%
Earnings>0	-0.08%	-0.44%	-15.75%	-20.95%
<0 - >0	4.48% (5.44)***	4.30% (5.30)***	18.51% (0.05)	26.33% (0.01)
Panel D: Dividend payers and non-dividend payers				
Dividends=0	3.70%	2.65%	33.90%	21.56%
Dividends>0	-1.32%	-1.62%	-31.60%	-30.66%
=0 - >0	5.02% (8.02)***	-4.27% (6.55)***	-37.32% (0.01)	-29.87% (0.01)

**Table A.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 institutional ownership level (i.e., fraction of shares held by institutions) for securities within each volatility decile (sentiment levels and ownership levels are measured at the same point in time). Panels A and B reports raw ownership levels for high and low sentiment and orthogonal sentiment periods, respectively. The final column reports the difference in institutional ownership levels for the high volatility portfolio and the low volatility portfolio. The third row reports the difference and associated *t*-statistics (based on a *t*-test for difference in means).

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

**Table A.IV**

**Flow induced demand, net active buying, and passive demand for volatile stocks and changes in sentiment by investor type**

Each quarter (between June 1980 and December 2010) we compute the cross-sectional correlation between security return volatility and demand shocks by each 13(f) institution type. Volatility is based on returns over the previous 12 months. The first column in Panel A reports the time-series correlation (and associated  $p$ -values) between institutional demand shocks for volatile stocks and orthogonalized changes in investor sentiment (i.e., the values reported in Panel B of Table VII). 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 A10 for details). The hedge fund sample is limited to the final 90 quarters.

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

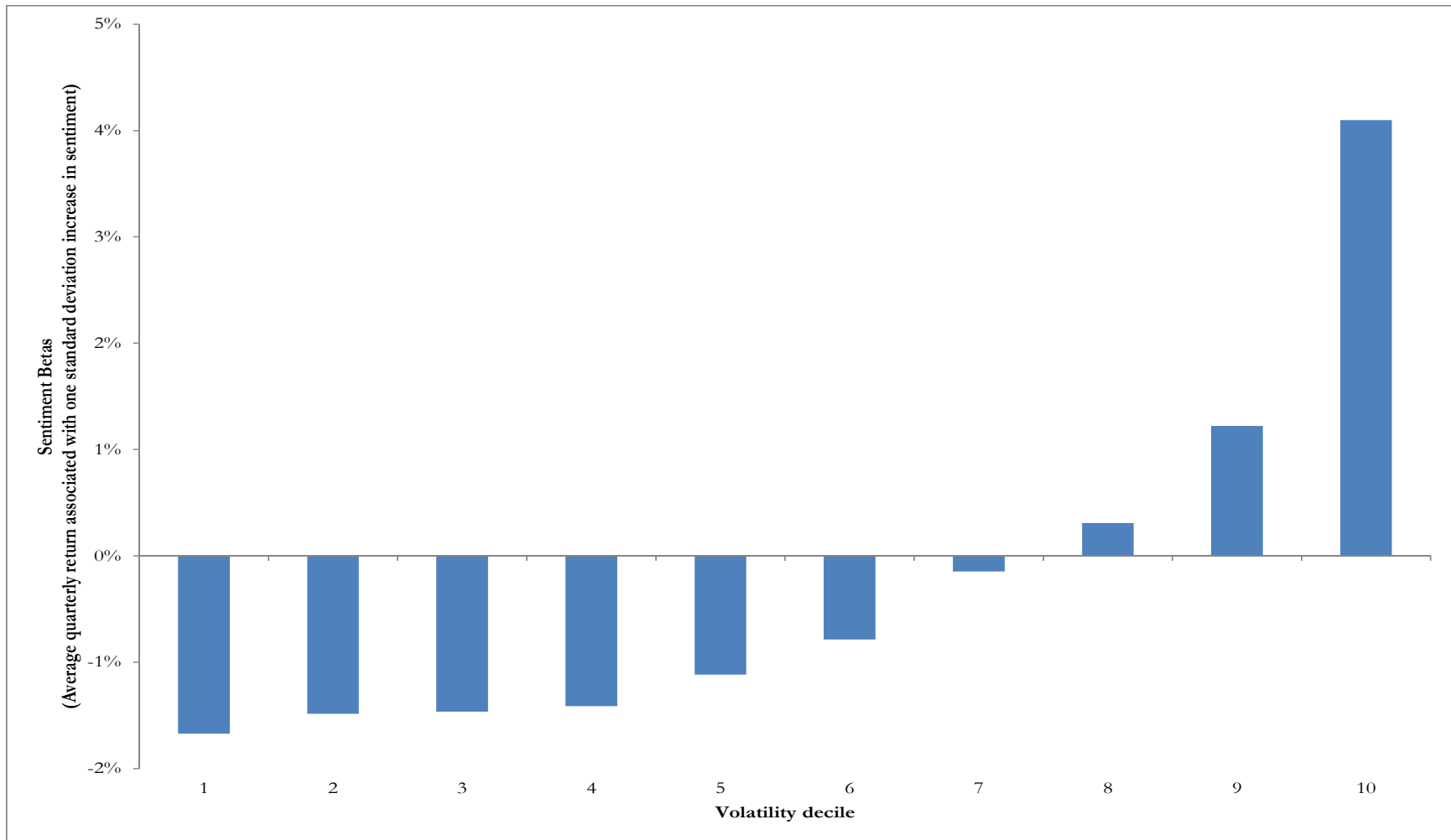


**Table A.V**

**Changes in sentiment and supply shocks by companies, insiders, and individual investors**

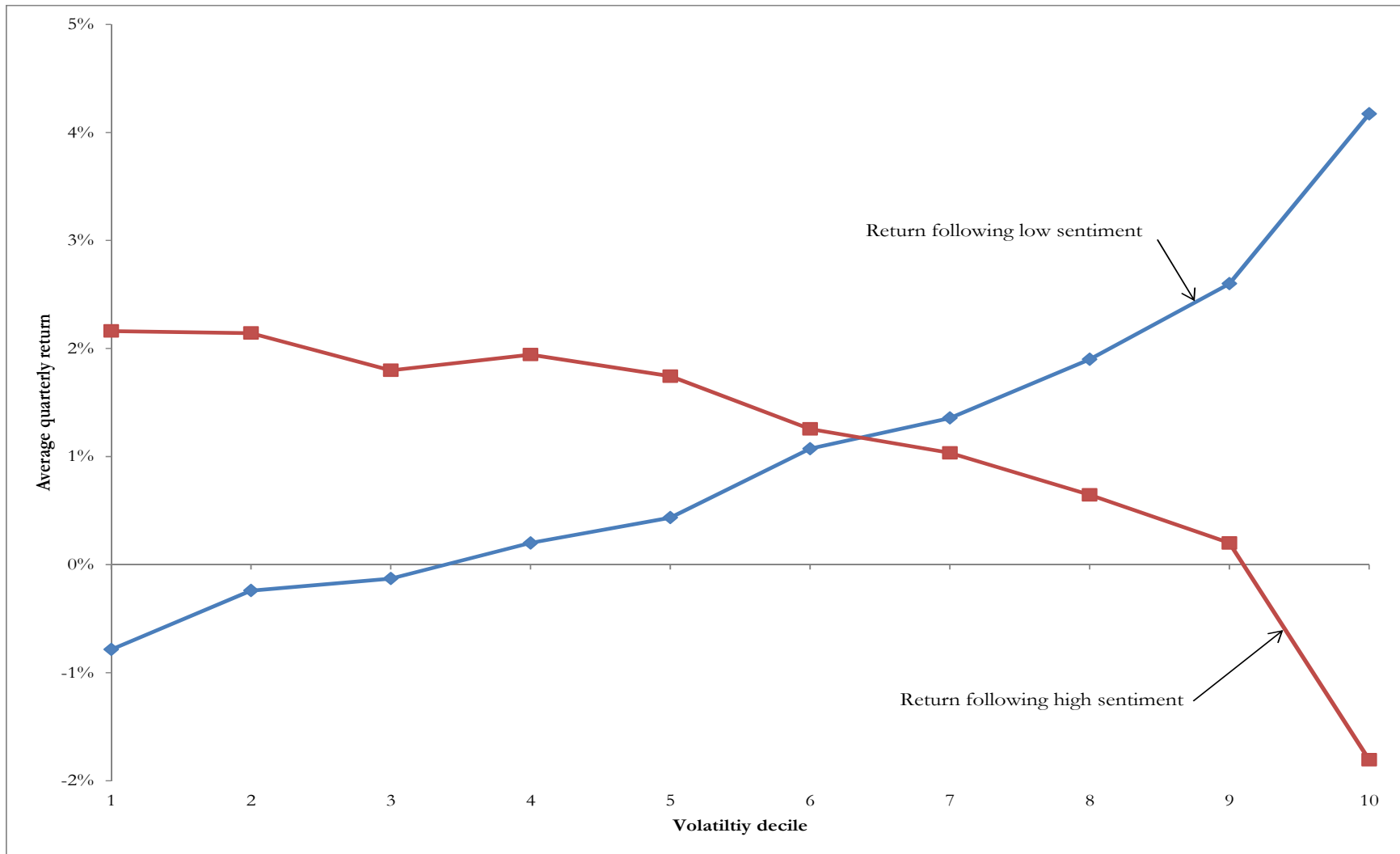
Each quarter (between June 1980 and December 2010,  $n=123$  quarters) we compute the cross-sectional correlation between security return volatility and demand shocks by all 13(f) institutions. We limit the sample to securities that have an absolute percent change in (split adjusted) shares outstanding of less than 10%. Volatility is based on returns over the previous 12 months. The first column reports the time-series correlation (and associated  $p$ -values) between aggregate institutional demand shocks for volatile stocks and orthogonalized changes in investor sentiment. We then decompose the net institutional demand shock correlation into the portion attributed to net supply from companies, net supply from insiders, and net supply from individual investors. 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.

	$\rho[\rho_t(\Delta X_{i,t}, \sigma_{i,t}), \Delta Sent_t^\perp]$	Contribution to $\rho[\rho_t(\Delta X_{i,t}, \sigma_{i,t}), \Delta Sent_t^\perp]$ due to:		
	Net institutional demand ( $p$ -value)	Net company supply ( $p$ -value)	Net insider supply ( $p$ -value)	Net individual investor supply ( $p$ -value)
All 13(f) institutions	35.72% (0.01)	4.04% (0.82)	3.11% (0.01)	28.20% (0.01)



**Figure A.1. Sentiment betas for volatility sorted portfolios**

We regress the time series of quarterly portfolio returns for volatility sorted portfolios on the value-weighted market return and the quarterly orthogonalized change-in-sentiment index. The quarterly orthogonalized change-in-sentiment is re-scaled to mean zero and unit variance. The bars represent the relation between a one standard deviation increase in quarterly changes in orthogonalized sentiment and contemporaneous quarterly returns.



**Figure A.2. Sentiment levels and future returns**

The figure plots the average market-adjusted quarterly return for stocks within each volatility decile following both high (red line) and low (blue line) sentiment periods. High (low) sentiment is defined as a period with above (below) median sentiment.