Crisis and recovery in the wake of super-salient news: Who moves markets?

Timothy R. Burch* Douglas R. Emery* Michael E. Fuerst*

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JEL classifications: G12, G14

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*Department of Finance, School of Business Administration, University of Miami.

†Correspondence to Doug Emery, University of Miami School of Business, P.O. Box 248094, Coral Gables, FL 33124-6552, demery@miami.edu, 305-284-4430(o), 305-284-4800(f). We thank Pat Fishe, David Heike, David Hirshleifer, Alok Kumar, Steven Sharpe, Tyler Shumway, and seminar participants at the Federal Reserve Board of Governors for helpful comments, and we are grateful to Hua (Allen) Song for valuable research assistance. Any errors are our own.

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Abstract

We compare reactions in the prices and trading patterns of common stocks and closed-end funds, which have substantially different investor clienteles, to the September 11, 2001 terrorist attacks. Even in assets with net institutional buying, retail investor trading moved prices significantly lower. Although greater salience has been shown to reduce underreaction to news, we conclude the extreme salience of this event resulted in overreaction. Subsequent reversals were substantially security-specific and therefore not due simply to improvement in general sentiment. Consistent with microstructure theory, the speed of reversals depended significantly on the relative quality and availability of information about fundamental values.

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1. Introduction

How do stock markets respond to a crisis? A rich literature finds inefficient stock price reactions to common news events.[1] There is relatively little research, however, on market responses to extraordinary news, and in particular, the potentially different roles retail and institutional traders play in causing such responses.[2] This is surprising because unanticipated, extreme news events that affect individual securities (e.g., law suits, revelations of fraud, and bankruptcy filings) or a broad cross-section of assets (e.g., oil spills, powerful weather events, and major industrial accidents) occur frequently. We refer to such extraordinary news events as "super-salient."

Studies such as Dellavigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), and Louis and Sun (2010) find underreaction to news in common stocks. Similarly, Klibanoff, Lamont, and Wizman (1998) find underreaction to news in closed-end funds (CEFs), but also show that such underreaction is less severe when news is more salient. But what is the reaction to super-salient news? The literature on underreaction suggests that super salience could cause underreaction to decline to zero so that, on average, prices fully reflect fundamentals. However, there is also literature that finds financial markets can *overreact* (e.g., Chopra, Lakonishok, and Ritter, 1992; De Bondt and Thaler, 1985, 1987). Hence,

[1] For examples, see Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Klibanoff, Lamont, and Wizman (1998), Anderson, Bollerslev, Diebold, and Vega (2003), Barber and Odean (2008), Barber, Odean, and Zhu (2009), Dellavigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), Louis and Sun (2010), Tetlock (2011), and Giglio and Shue (2012).

[2] For example, although Fair (2002) identifies large movements in the stock market, his study makes no attempt to understand the trading that led to these movements and his sample is constructed solely based on extreme price changes instead of extreme news events. Such price movements could be unrelated to news and instead result from liquidity shocks, herding, technical trading strategies, or positive feedback trading.

it is possible that a stronger psychological reaction to greater salience will cause prices to overreact when news is extraordinarily salient.

In this paper, we examine price movements in common stocks and fixed-income closed-end mutual funds (CEFs) in response to a super-salient news event: the terrorist attacks of September 11, 2001 (hereafter "nine-eleven"). Our main goals are to investigate whether securities prices can overreact to super-salient news, and if so, infer whether it is institutional investors, retail investors, or both that cause the reaction. Although there is now substantial evidence that retail trading indeed affects prices (e.g., Kumar and Lee, 2009; Barber, Odean, and Zue, 2008; Hvidkjaer, 2008; Kumar, 2009), there is little, if any, evidence on how retail and institutional investors trade simultaneously in response to extreme news events, and whether retail trading can move prices opposite to the direction of trading by institutional investors.[3,4]

We begin by showing a precipitous drop and recovery in prices, which appears consistent with overreaction followed by recovery during the weeks following nine-eleven (see Figure 1). Gauging overreaction, however, is difficult without a benchmark, so we use net asset value (NAV) returns as a benchmark for the CEF price returns. Although NAV returns for fixed-income funds were fairly stable following nine-eleven, cumulative price returns di-

[3]Barber, Odean, and Zue (2008) and Hvidkjaer (2008) examine trade level data of stocks and infer retail trader identity from trade size, while Kumar and Lee (2006) and Kumar (2009) examine transaction-level data for a sample of retail investors. None of these studies examines institutional trading, nor do they investigate trading in response to news events. Dennis and Strickland (2002) find that when there are sharp market declines, returns are more negative for stocks with higher levels of institutional ownership. However, they also do not examine trading in response to identified news events, and, moreover, such price declines could be driven by retail selling in stocks that happen to have higher degrees of institutional ownership.

[4]Examples of extreme market movements that are difficult to link to specific news events include the October 1987 crash and the "flash crash" of May 2010.

verged substantially from cumulative NAV returns in a manner that is indeed consistent with prices overreacting and recovering (see Figure 3).[5] Although we do not have an analogous benchmark of fundamental values for common stocks, the striking similarity in price-return patterns between common stocks and fixed-income CEFs suggests that common stock prices could have overreacted as well.

We next explore whether institutional and retail traders responded differently to nine-eleven. To infer whether retail and institutional investors traded differently, we use microstructure trading measures such as trade size and the direction of trade initiation (i.e., buy- versus sell-initiated, as indicated by Lee and Ready's 1991 signing algorithm), and compare trading patterns among securities well-known to have different investor clienteles. For example, retail investors play a more prominent role in the trading of CEFs (Weiss 1989; Lee, Shleifer, and Thaler 1991). In contrast, institutional investors are more dominant in the trading of large-cap common stocks (Sias and Starks 1997). We conclude that retail investors were net sellers while institutional investors were net buyers during the first week following nine-eleven, and yet prices moved lower, even in large-cap stocks.

The main empirical findings in our study are summarized as follows:

- Prices in both common stocks and fixed-income CEFs show a pattern that is consistent with overreaction and recovery following nine-eleven, as manifested by significant price declines during the first post-event trading week and significant price recoveries during the second and third weeks. The similarity in the patterns of price decline and recovery for CEFs and common stocks, together with strong evidence of overreaction in CEF

[5] As we discuss in the paper, our choice of fixed-income funds is motivated by the relatively moderate degree of disruption that fixed-income securities experienced following nine-eleven. Trading in the fixed-income markets resumed only two days after nine-eleven, and bond yields remained fairly stable. NAVs for fixed-income CEFs thus provide a relatively stable fundamentals benchmark against which to gauge CEF price movements.

prices as compared to NAVs, is consistent with news-driven price movements lying on a continuum, from underreaction into overreaction, based on the salience of the news. Our findings also support Tetlock's (2011) use of a return reversal as a measure of overreaction.[6]

- During the first post-nine-eleven trading week, signed trades indicate that buy-initiated dollar volume (relative to sell-initiated dollar volume) declined more significantly for small-cap stocks than for large-cap stocks, consistent with the price return patterns we find for these two groups. Moreover, the majority of dollar volume during this first week was sell-initiated for small-cap stocks, but buy-initiated for large-cap stocks. Given that retail investors play a more prominent role in CEFs and small-cap stocks compared to large-cap stocks, it appears that retail investors were net sellers in the immediate aftermath of nine-eleven, whereas institutions continued to be net buyers. For example, the largest trades (those larger than $50,000) in large-cap stocks had more buy- than sell-initiated trades in every day of trading following nine-eleven.

- Despite net institutional buying during the first post-nine-eleven trading week, prices declined significantly across CEFs and all common stock deciles. Therefore, in the setting we study, correlated trading by retail investors apparently led to significant price movements that were opposite to the direction implied by institutional trading. This finding extends Kumar and Lee (2006) and Barber, Odean, and Zhu (2009) to show that correlated retail trading can move prices not only in normal trading conditions, but also in settings with significant institutional trading in the opposite direction.

- Prices recovered during the second and third post-nine-eleven weeks, and cross-sectional regressions show that the size of a security's recovery was significantly related to the

[6]More specifically, Tetlock (page 1,482) measures overreaction as "the extent to which a firm's initial daily return around a news event negatively predicts its return in the week after the event."

security's initial price decline. Interestingly, these security-specific reversals primarily occurred during the second week for CEFs but during the third week for common stocks. We believe the faster security-specific recoveries in CEFs were due to regularly disclosed NAVs, which provide natural benchmarks for fundamental values. This potential explanation is consistent with classic models such as Grossman and Stiglitz (1980) in which a higher ratio of informed to uninformed investors improves price efficiency. The intuition in these models could be extended to predict that overreaction following a news shock will be reversed faster in assets with more public information about fundamentals.

Although our research setting results from a single event and is thus a case study in some respects, it is important to note that we study the reactions of more than 1600 different securities in several different asset classes. The simultaneity across the securities eliminates the need to align observations into event time that actually occurred at different times, and which therefore could have occurred in substantially different economic environments. In this sense, our study is a natural experiment that shares similarities with others that examine how asset prices react to macroeconomic shocks (e.g., Pearce and Roley, 1985; Anderson, Bollerslev, Diebold, and Vega, 2003).

Super-salient events that have as broad an impact as nine-eleven are relatively infrequent. However, super-salient events that affect an individual security or group of securities, such as revelations of fraud or significant weather events, are fairly common. Our findings offer valuable insights into how markets react to unanticipated, extraordinary news events marked by intense uncertainty and market disruption, and add to a growing body of evidence on the impact of retail trading on asset prices. The pervasiveness of our findings across so many securities points to the intriguing possibility that overreaction to super-salient news is common—even in the face of institutional trading that acts as a corrective force.

2. Background and related literature

Nine-eleven needs no justification as an economically relevant event, but it is useful to review briefly the climate and timing of the markets' extraordinary closures. In the months prior to nine-eleven, the U.S. economy had been showing signs of weakness (the S&P 500 index declined more than 20% during the four months prior to nine-eleven), and many feared the event would push the economy into a steep decline. The U.S. financial markets did not open the morning of nine-eleven, and the equity markets remained closed until Monday, September 17, 2001. On that day the S&P 500 index declined 4.9%, and continued to fall throughout the trading week to close 11.6% below its September 10, 2001 level. The fixed-income markets were also affected—but only moderately. They were closed for only two trading days (September 11 and 12), and Treasury yields actually declined, in part due to Federal Reserve interventions to inject liquidity and stimulate the economy. Although spreads on risky bonds did increase, by Monday, September 17, the 10-year Baa corporate-to-Treasury spread was only about 50 basis points higher than before nine-eleven.

As reviewed in Dimson (1988) and Hirshleifer (2001), a rich literature examines investor under- or overreaction to a corporate event (as opposed to a macroeconomic event as in our study). Many studies examine highly visible but endogenous managerial decisions, and find underreaction (e.g., Kadiyala and Rau 2004; Ikenberry, Lakonishok, and Vermaelen, 1995; Louis and Sun, 2010; Michaely, Thaler, and Womack, 1995). Dellavigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009) argue that investor inattention helps explain underreaction to earnings announcements. Other studies examine long-run returns following extreme price movements, and conclude that financial markets overreact (e.g., Chopra, Lakonishok, and Ritter 1992; De Bondt and Thaler, 1985, 1987).

In addition to empirical work, there are theories that offer explanations for under- and overreaction in security prices. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) propose a theory based on overconfidence and self-attribution bias. Barberis, Shleifer, and Vishny (1998) present a model based on sentiment, and Hong and Stein (1999) provide a model based on cognitive limits.

Our analysis of CEFs, in particular, is related to Klibanoff, Lamont, and Wizman (1998), who find underreaction to new information in closed-end country funds (CEFs whose underlying assets are foreign). They attribute such underreaction to unsophisticated investors who dominate the trading, and note that CEFs, like small-cap stocks, have a small retail investor clientele.[7] Klibanoff, Lamont, and Wizman do not, however, try to discern any differences between retail and institutional investor reactions to information events. Papers that directly focus on individual investor trading include Barber, Odean, and Zhu (2009), Barber and Odean (2008), Hvidkjaer (2008), and Kumar and Lee (2006), all of whom show that correlated retail trading can move prices. Dennis and Strickland (2002) and Lipson and Puckett (2010), in turn, investigate how correlated trading by institutional investors affects prices. None of these studies investigate differences in retail and institutional investor trading in response to a news event.

Finally, a substantial body of literature investigates a variety of economic aspects of nine-eleven.[8] Epstein and Schneider (2008) argue that "ambiguity-averse" investors react more strongly to bad news than to good news. They view nine-eleven as triggering "a learning process whereby market participants were trying to infer the possibility of a structural change

[7]Supporting this characterization of CEFs' investor clientele, Weiss (1989) finds that institutions own only about seven percent of this asset class, and Lee, Shleifer, and Thaler (1991) find that CEFs have a relatively high proportion of trades smaller than $10,000.

[8]Papers we do not discuss here include Carter and Simpkins (2004), Charles and Darné (2006), Drakos (2004), Ito and Lee (2005), Maillet and Michel (2005), and Nikkinen, Omran, Sahlström, and Äijö (2008).

to the U.S. economy from unfamiliar signals."[9] The notion that a learning process took place is consistent with our finding that the market did not begin to reverse the initial reaction until the second post-nine-eleven trading week. Burch, Emery, and Fuerst (2003) examine the behavior of closed-end mutual fund prices across nine-eleven, and argue that broad small-investor sentiment played an important role in how closed-end fund discounts reacted to the event. Glaser and Weber (2005) examine changes in the expectations of individual investors before nine-eleven (around the weekend of August 4-5, 2001) and after nine-eleven (around the weekend of September 22-23). They find a relatively high expected rate of return and optimism after nine-eleven, and argue their findings do not coincide with those in Graham and Harvey (2003), who report a relatively low expected market return based on data gathered September 12-14, 2001. As we discuss later, we believe our findings reconcile these two survey results.

3. Data

We study both daily and intraday trading data for common stocks and CEFs compiled from the Center for Research in Security Prices (CRSP) and the New York Stock Exchange Trade and Quote (TAQ) databases. Our analysis of the microstructure data covers the period June 1, 2001 to December 31, 2001; we also report pooled cross-sectional time series regressions over the period September 7, 2000 to October 26, 2001. Common stocks are limited to those listed on the New York Stock Exchange (NYSE) that have the necessary coverage in the CRSP and TAQ databases, and we exclude closed-end funds, real-estate investment trusts, companies incorporated outside the US, primes, scores, depository receipts, certificates, shares of beneficial interest, and units. These criteria result in a sample of 1,463 common stocks.

[9] See Kuhnen (2012) for experimental evidence that investors learn from gains differently than they do from losses.

The CEFs we study are those listed on the NYSE, classified as fixed-income funds by *Barron's*, and covered in CRSP and TAQ. The advantage of limiting our focus to fixed-income funds is that we study funds whose fundamental values primarily depend on interest rates and credit spreads. Thus, investors in these funds can not only look to reported NAVs for information about fundamental values, but also to broad interest rate movements and other information derived from the fixed-income markets. An additional restriction we impose is that the CEFs must report NAVs on a daily basis over the June 1, 2001 to October 31, 2001 period (we exclude those reporting only weekly).[10] Requiring daily NAV disclosure further improves the information environment of the CEFs. NAVs are from Thomson Reuters. The various data screens for the CEFs produce a sample of 199 funds, which is slightly larger than the number of stocks in one decile of our stock sample (around 146).

As already noted, fixed-income securities markets were less affected by nine-eleven and reopened after only a two-day suspension (compared to the six-calendar-day closure in the equity markets). Hence, before the NYSE reopened on September 17 (where the CEFs trade), fixed-income CEF investors could easily observe post-nine-eleven market value information from two full days of trading (Thursday, 9/13 and Friday, 9/14) in the fixed-income markets and through NAV disclosures on these days (as we discuss in Appendix A, daily NAVs were updated and disclosed as usual). This should have greatly mitigated any overreaction in fixed-income CEFs when their trading resumed on Monday, 9/17, and thus makes the pattern of overreaction all the more striking.

For each security (common stock and CEF), we construct the following variables:

- *Market capitalization* (*Market cap*) is based on September 10, 2001 closing data.

[10] We also exclude funds that are missing a Friday NAV because some of our analysis examines weekly returns. The patterns around nine-eleven are completely consistent when these funds are included, but the dynamic panel data regression procedure we use requires a balanced panel.

- *Tradesize* is the mean dollar value of all trades during a given day.
- *Share price* is the closing trading price according to CRSP.
- *Effective spread* is the mean of the effective spread for all trades during a given day, where the effective spread for a trade equals the bid-ask spread divided by the midpoint, where the midpoint is the sum of the bid and ask divided by two.
- *Turnover* is the number of shares traded in a given day, divided by the number of outstanding shares.
- *Percentage of buys* is dollar buys divided by the sum of dollar buys and sells during a given day, where buys and sells are identified by the Lee and Ready (1991) trade signing algorithm.
- *Tradesize proportion* is the percentage (based on the number of trades) of all trades during a given day falling into one of five possible size categories (<$5K, $5-10K, $10-20K, $20-50K, and >$50K).

When we calculate one of these security-level metrics for a given multi-day period, we calculate the median across security-days in the time period.

Log price returns are calculated on a close-of-trading-day to close-of-trading-day basis. For example, the return for Monday, 9/17, the first day of trading after nine-eleven, is from the 9/10 close to the 9/17 close. The log price return for a security (stock or CEF) for day t, denoted RP_t, is

$$RP_t = Ln(P_t + D_t) \; - \; Ln(P_{t-1}), \tag{1}$$

where P_t is the closing price on trading day t, D_t is the dividend on trading day t, and Ln is the natural log operator. The log NAV return for a CEF for day t (denoted RN_t) is similarly defined, using NAVs in place of closing prices. Because NAVs are calculated using closing prices of the funds' assets, NAV returns provide a good benchmark for price returns (Klibanoff, Lamont, and Wizman 1998). Therefore, when analyzing CEFs we sometimes include abnormal returns (AR_t), defined as the price return minus the NAV return ($AR_t = RP_t - RN_t$). In Appendix A we address concerns regarding potential measurement errors for the NAVs.

4. Return patterns and investor expectations

We begin our analysis by computing univariate statistics, plotting return patterns, benchmarking returns for CEFs against NAVs, and comparing the overall patterns to investor expectations at the time.

4.1. Return patterns

Table 1 reports cumulative returns over six different time periods for common stocks, CEFs, and also the S&P 500. As is often done to show patterns in common stock data, we report statistics by market-capitalization deciles, which in our case, are measured as of September 10, 2001. Cumulative returns for 6/1-9/10 show the down market in the months prior to nine-eleven. Cumulative returns from the 9/10 close to the 9/21 close showed a large decline during the first post-nine-eleven trading week, followed by a strong rebound in the subsequent trading week (9/21-9/28), for all of the classes of securities except for common stock decile 1. In the third week of trading (9/28-10/05), all security classes continued to recover except for stock deciles 1 and 3. It is interesting to observe that cumulative returns for the broader time period (9/10-10/5) increased almost monotonically across the deciles, with smaller deciles experiencing more pronounced cumulative price declines following nine-eleven. Based on the findings in Sias and Starks (1997) that retail investors play a more significant role in small-cap stocks due to lower institutional trading, these price patterns are consistent with pronounced retail selling of small-cap stocks during the initial trading week following nine-eleven.

Large-cap stocks and the S&P 500 index, by contrast, had considerably smaller price declines than the rest of the common stock deciles. Although our data do not allow us to track investor-specific rebalancing decisions, the price return patterns are consistent with an aggregate flight to quality (or more accurately, a flight away from lower quality, riskier assets). In fact, the evidence we present later implies that institutions as a group were net buyers even during the first post-nine-eleven trading week. As institutions play a more active role in large stocks, it is thus not surprising that the price returns in these stocks displayed smaller initial price declines.

The CEFs we study are not heavily traded by institutional investors (Weiss 1989; and Lee, Shleifer, and Thaler 1991), and yet they experienced smaller price declines (and subsequent recoveries) than large-cap stocks. One potential reason is that a fixed-income CEF is a claim on diversified basket of fixed-income securities, and hence has lower risk than individual stocks. Also, as Bradley, Brav, Goldstein, and Jiang (2010) note, "closed-end funds constantly attract arbitrageurs" who attempt to profit on any mispricing based on spreads between prices and NAVs.

It is also plausible that the less dramatic declines in CEF prices are due to at least some retail investors observing and incorporating NAVs and fixed-income market information into their trading decisions (e.g., not selling upon observing relatively small declines in NAVs and bond market prices in general). The availability of NAVs, as well as other information observed from two full trading days in the fixed-income markets before fixed-income CEFs resumed trading, implies that both retail investors and arbitrageurs should have been better informed about the fair values of fixed-income closed-end funds than those of common stocks.

Classic models such as Grossman and Stiglitz (1980) predict more efficient prices when there is a larger proportion of informed traders relative to uninformed traders. In our setting, such models would point toward less initial overreaction and faster reversals in fixed-income CEFs, due to their superior information environment (i.e., the availability, quality, and timeliness of useful information regarding fundamental values).

Figure 1 illustrates the findings in Table 1 by plotting cumulative price returns during the September 17-October 5 period. Every category shows a sharp drop in the first five days of trading after nine-eleven, followed by a sharp recovery that begins on the sixth day of trading (9/24) and generally continues throughout days seven through fifteen. The only exception is decile 1, which experiences a recovery on the sixth trading day but then shows negative returns throughout the rest of the period.

4.2. Benchmarking return patterns

Tetlock (2011) gauges overreaction from return reversals, and applying this approach would certainly indicate substantial overreaction after nine-eleven. However, overreaction is difficult to establish without an appropriate benchmark. Indeed, Tetlock focuses on the cross-sectional variation in return reversals precisely because "there are many possible explanations for on-average return reversals." For example, a short-term pattern of reaction and subsequent reversal could be due to a short-term change in expected future cash flows, or a short-term change in systematic risk. These potential explanations form the root of the debate over whether post-event abnormal returns are actually anomalous.[11]

An attractive way to address this issue for CEFs is to benchmark price returns against NAV returns. NAVs provide a reasonable measure of fundamental value and hence can be

[11] In particular, some people argue that inadequate asset pricing models and the difficulty of properly controlling for risk may explain return patterns that otherwise seem to indicate mispricing (e.g., Brav, Geczy, and Gompers, 2000; Eckbo, Masulis, and Norli, 2000).

used to control for changes in expected cash flows and systematic risk.[12] In addition, applying this approach to fixed-income CEFs is particularly attractive in the setting we study. As discussed earlier, both the trading and information environments in the underlying assets (fixed-income securities) of these funds were considerably less disrupted by nine-eleven as compared to equity securities.

The approach we use is further supported by Figure 2, which plots March 2001 cumulative price and NAV returns for our sample of fixed-income CEFs and also a sample of 59 equity closed-end mutual funds (whose underlying assets are common stocks), alongside cumulative price returns for the S&P 500 index.[13] This figure illustrates two important points. First, price and NAV returns move together closely within each class of closed-end fund. This illustrates that, although discounts (spreads between prices and NAVs) can change, cumulative NAV returns nonetheless provide a very good benchmark for how cumulative price returns tend to evolve over time.

Second, equity and fixed-income funds have disparate tendencies to move alongside a broader equity market downturn. Specifically, note that price and NAV returns for the equity funds are volatile and strongly correlate with the broader market, whereas returns for fixed-income funds are much more stable and virtually independent of the broader market (this is also the case in other months we checked). In short, we believe that fixed-income funds provide an excellent laboratory in which to examine pricing following nine-eleven. Given that the response to nine-eleven in the fixed-income markets was relatively mild, we would

[12] The existence of NAVs is often cited as a primary reason for studying various phenomenon using closed-end mutual funds (Dimson and Minio-Kozerski, 1999; Gemmill and Thomas, 2002; Klibanoff, Lamont, and Wizman, 1998).

[13] We select March because it is the month during January-August 2001 with the largest single-day price decline in the S&P 500 index, as well as the month with the largest five-day price decline. Hence, it is especially useful for illustrating how closed-end fund returns typically behave during short-term market declines.

expect a similarly mild response in fixed-income CEF prices—unless there is overreaction by the predominantly retail investors in these securities.[14]

Figure 3 plots cumulative price and NAV returns, along with cumulative *abnormal* returns (price returns minus NAV returns) for fixed-income CEFs from September 10 to October 5, 2001. As discussed above and seen in Figure 2, a CEF's NAV provides a clear benchmark against which to measure short-term price reaction, and Figure 3 shows that prior to nine-eleven, cumulative price returns closely tracked NAV returns (note cumulative *abnormal* returns were close to zero). Then, as can be seen dramatically, cumulative price returns fell well below cumulative NAV returns in the first week of trading following nine-eleven, indicating significant overreaction. Cumulative price returns began to recover during the second week and then moved back to roughly track cumulative NAV returns in the third week and beyond. Cumulative abnormal returns indicate the same pattern of overreaction and recovery. In Appendix A we explain why the significant divergence of price from NAV returns cannot be explained by errors in NAVs. In addition, we discuss why the results seem unlikely to be explained simply by a lack of market depth or the information-based closed-end fund discount theory offered in Grullon and Wang (2001).

Figure 3 provides strong evidence of overreaction and recovery in fixed-income CEFs following nine-eleven. Later, we statistically validate this result through cross-sectional regression analysis, which provides further support for the approach Tetlock (2011) uses in

[14]There are multiple ways that retail investors could have caused price declines to significantly exceed NAV declines. Small investors could have become exceedingly risk averse or more pessimistic about fundamental values than investors trading the assets held by funds, and accepted large price concessions to liquidate their holdings quickly. Another (non-mutually exclusive) channel is that investors in closed-end funds could have perceived a substantial increase in noise trader risk, which in turn would have caused discounts to widen according to DeLong, Shleifer, Summers, and Waldmann (1990) and Lee, Shleifer, and Thaler (1991). We view these possibilities as manifestations of overreaction.

gauging overreaction from return reversals. As discussed later, the regressions also allow us to explore the extent to which recoveries during the second and third trading weeks following nine-eleven are systematic (e.g., an improvement in broad sentiment) versus security-specific reversals.

Having provided evidence that fixed-income CEFs overreacted and recovered following nine-eleven, it is worth revisiting Figure 1 to observe how strikingly similar the price return patterns for NYSE common stocks are to those of fixed-income CEFs. This similarity supports the idea that common stocks also overreacted and recovered, to varying degrees based on their market capitalization.

4.3. Investor expectations

It is interesting to compare the realized price returns shown in Figure 1 with two different sets of expectations gathered after nine-eleven. Graham and Harvey (2003) conduct a survey of Chief Financial Officers (CFOs) and find that on September 12-14, CFOs had lower (compared to pre-nine-eleven) forecasts of the one-year equity premium, implying an expected drop in market prices. In another survey study, Glaser and Weber (2005) find that around the weekend of September 22-23, individual investors expected higher (compared to pre-nine-eleven) returns, which implies an expected increase in market prices. Glaser and Weber compare their findings to those in Graham and Harvey and conclude that these two results "do not coincide."

We believe our findings are consistent with both studies, and attribute the seeming inconsistency to the difference in the timing of the two surveys. The survey from September 12-14 was taken immediately following nine-eleven (during the extraordinary time when the equity markets were closed), and the respondents' expectation of a drop in market prices was realized: Subsequently, the market opened substantially below its pre-nine-eleven close, and continued to fall throughout the entire week ending September 21. In contrast, the survey from around the weekend of September 22-23 was taken after a full trading week of virtually continuous market declines, and those respondents' expectation of an increase in market prices was also realized: Market prices rebounded sharply on the Monday following the survey, and continued to recover in the subsequent two weeks (9/21-10/5). Therefore, subsequent realized returns coincided extremely well with the expectations expressed in both surveys.

5. Trading statistics

We now report trading statistics for the periods before and after nine-eleven, which in most cases are derived from TAQ microstructure data. These patterns shed further light on how investors behaved after nine-eleven, and provide further evidence on the difference in the behavior of retail versus institutional investors. Although we provide a range of statistics, for the sake of brevity, our discussion focuses more heavily on those with greater relevance for our main findings.

5.1. Pre-nine-eleven trading statistics

To establish benchmark trading patterns, we first examine the period from June 1 through September 10, 2001. Panel A of Table 2 reports the medians of the various metrics defined in the data section for eleven different groups of securities. The first ten columns report statistics for the common stocks, partitioned into market capitalization deciles (measured on September 10, 2001), and the last column reports statistics for the fixed-income CEFs. As can be seen, the patterns among the deciles of stocks are quite regular. For example, *tradesize*, *share price*, and *effective spread* change almost monotonically across the decile columns. *Turnover* increases to a maximum for decile 8, and then declines with deciles 9 and 10. Finally, the *percentage of buys* (the percentage of buys among trades whose signs have been identified by the signing algorithm in Lee and Ready 1991) increases monotonically from a low of 44.56% in decile 1 to a high of 56.00% in decile 6, and then remains around 55-56% for the remaining deciles.

Weiss (1989) and Lee, Shleifer, and Thaler (1991) note that closed-end fund investors are predominantly small, retail investors. This could result in their trading characteristics most closely matching those of small stocks, since trading in these stocks is also more heavily influenced by small, retail investors (Sias and Starks 1997). On the other hand, fixed-income CEFs differ from small stocks in that fund shares represent a claim on a diversified basket of fixed-income securities. The trading characteristics of the CEFs could thus differ substantially from those of individual, small stocks, and in fact we find the similarity to small stocks is somewhat mixed.

The fixed-income CEFs are quite similar to small-cap stocks with respect to *turnover* and *share price*. *Turnover* for fixed-income CEFs is 0.077%, which is only slightly larger than that of decile 1 (0.063%), and *share price* for fixed-income CEFs is \$12.81, which is slightly larger than it is for decile 2 (\$11.49).[15] Despite these similarities, fixed-income CEFs have significantly lower values of *effective spread* than small-cap stocks (deciles 1 and 2), and hence trading costs are less than one might expect given the primarily retail-investor base. It seems reasonable that this enhanced liquidity is due to a superior information environment, because of regularly disclosed NAVs and underlying assets that are fixed-income securities. Such a superior information environment should presumably lower the costs and risks of providing liquidity.

[15] It could be that CEFs deliberately maintain a relatively low share price in order to appeal to a small-investor shareholder base. See Fernando, Krishnamurthy, and Spindt (1999) for an analysis of share price management by open-end fund managers.

In Panel B of Table 2, we report the mean distribution of trades in terms of *tradesize* (trade value in dollars). The patterns among the deciles are also quite regular across *tradesize*. For example, the proportion of trades in the smallest dollar category (<$5K) decreases monotonically from the smallest to the largest decile, while the proportion in the two largest dollar value categories ($20K-$50K and >$50K) *increases* monotonically.[16] The percent of trades in the smallest *tradesize* categories for CEFs is similar to that of NYSE stocks in deciles 6-7. However, the *tradesize proportion* of large trades (>$50K) for CEFs is between that of deciles 2 and 3, and hence closer to small-cap stocks. Therefore, although CEFs are not like small-cap stocks in their portions of very small trades, they are fairly similar to small-cap stocks in their *lack* of very *large* trades.

Barber, Odean, and Zhu (2009) find that small trades of $5K or less whose signs have been identified by Lee and Ready's (1991) signing algorithm can be used as a proxy to identify the trades of individual investors. Similarly, Lee and Radhakrishna (2000), and Malmendier and Shanthikumar (2007) use trades of $20K or less to identify small investors and trades of more than $50K to identify institutional investors. With the exception of Malmendier and Shanthikumar (2007), whose data run through July 2001, these studies are based on pre-2001 data. Barber, Odean, and Zhu warn that, starting in 2001, decimalization and increased use of computers to break up institutional trades increases the number of small trades that actually originate from institutions. Nevertheless, the overall *tradesize* distributions are certainly consistent with a significantly smaller institutional presence in the trading of the

[16] Tradesize is markedly skewed for small- and mid-cap stocks, with small trades dominating trading in deciles 1-8, but then being the smallest proportion for decile 10 (the largest-cap stocks). For decile 1, the portions of trades by category decrease monotonically from smallest (< $5K) to largest (>$50K). A similar pattern holds for deciles 2-9, but becomes progressively less pronounced as market cap increases. In decile 10 the pattern is also monotonic—but in the opposite direction, with small trades less common than large trades.

small-cap stocks (consistent with Sias and Starks, 1997) and CEFs (consistent with Weiss, 1989 and Lee, Shleifer, and Thaler, 1991).

Below, we investigate the extent to which institutional investors were net buyers after nine-eleven. Therefore, for completeness we provide a benchmark in Panel C by reporting the median percentage of buys based only on trades larger than $50,000. This panel indicates net institutional buying in all categories except decile 1 and the CEFs during the pre-nine-eleven period.

5.2. Post-nine-eleven trading statistics

In Table 3, we report summary statistics during five time periods, which cover June 1, 2001 through December 31, 2001. In the first row of each panel, we repeat the statistics for the pre-nine-eleven period to aid in making comparisons. In the remaining rows, we report statistics for four post-nine-eleven periods. As in Table 2, the first ten columns report statistics for the common stocks, categorized into *market-cap* deciles, and the last column reports statistics for fixed-income CEFs.

Panel A of Table 3 reports the median *percentage of buys* (based on signed dollar volume) for the five different time periods. We observe that in the second row (the week of 9/17-9/21), *percentage of buys* increases almost monotonically across deciles 1 through 10. In addition, *percentage of buys* was smallest for decile 1 by a wide margin and second smallest for decile 2, also by a wide margin. This suggests that during the first post-nine-eleven trading week, sell-initiated trades were especially dominant in small-cap stocks. To a lesser extent, deciles 3 and 4 also had more sells than buys. For deciles 5 through 10, however, note that the median *percentage of buys* indicates that there were more buy-initiated trades than sell-initiated trades. In fact, in results not tabulated here (but available upon request), there were more buys than sells in deciles 6 through 10 on each individual day during the first trading week. We also note that the *percentage of buys* decreased significantly from pre-nine-eleven levels, but that the decrease was much less severe for large-cap stocks compared to small-cap stocks.

Selling was also pervasive in fixed-income CEFs, as the *percentage of buys* was only 33.37% in the week of 9/17-9/21, slightly lower than for decile 1. We conclude that overall, there was a massive rush by retail investors to sell small-cap stocks and fixed-income CEFs, and that there continued to be more buying than selling in mid- and large-cap stocks just as before the event (although the percentages are slightly lower). Among common stocks, these results are consistent with a relative flight to quality: Large-cap stocks had much lower declines in buy-initiated trades than small-cap stocks, and for large-cap stocks the *percentage of buys* remained above 50%.[17]

Figure 1 shows that price returns rebounded during the second and third post-nine-eleven trading weeks. Thus, it is not surprising to see that *percentage of buys* increased for all common stock categories and fixed-income CEFs during these two weeks (9/24–10/05), and that the swing was strongest in the CEFs and small-cap stocks.[18] On average, net buying continued through the rest of the year as well (10/08–12/31), except for in decile 1 and the CEFs.

Panel B reports the *percentage of buys* based only on signed trades >$50K, which were those likely executed for institutional investors. For every security category, the percent of buys is smaller in the week following nine-eleven (9/17–9/21) than beforehand. Strikingly,

[17] For evidence of a parallel flight to quality in the banking system, see Caballero and Krishnamurthy (2008) and McAndrews and Potter (2002).

[18] Although not calculated in the panel, percentage of buys increased from the first week (9/17-9/21) to the third week (10/01-10/05) by an absolute 11.20%, 10.06%, and 20.02% for decile 1, decile 2, and the CEFs, respectively. These increases were considerably larger than for deciles 3 through 10.

however, there remained net institutional buying in deciles 5 and larger, which provides further evidence consistent with a flight to quality. Furthermore, in untabulated results we find that for the *overall* sample of stocks for this week, the median *percentage of buys* for trades >\$50K was 53.04%.

On the basis of the dramatic reduction in buy-signed trades for both CEFs and small-cap stocks (deciles 1 and 2), together with the small-investor base of these securities, we conclude that retail traders engaged in heavy selling during the first trading week after nine-eleven. The fact that the *percentage of buys* for mid- and large-cap stocks exceeded 50% suggests that if retail investors also sold these stocks heavily, institutional investors must have bought them, on average. Indeed, trades \$50,000 and larger indicate institutional net buying in these deciles. This is key because these buying and selling patterns, together with Figure 1, show that in the wake of super-salient news, correlated retail trading moved prices opposite to the direction implied by institutional trading.

Panel C of Table 3 reports *tradesize* statistics. The fixed-income CEFs and most stock deciles showed modest increases in average *tradesize* in the week following nine-eleven, but decile 10 showed an increase of \$35,414 (a relative increase of 52%) from \$67,951 to \$103,366. This does not seem to have been caused by one-sided trading aimed at liquidating large positions, because Panel B shows that the *percentage of buys* for trades larger than \$50K only fell to 53.33% during this week, from 55.41% beforehand. Hence, any increase in sell-initiated trade size must have been offset by larger buy trades such that the majority of larger trades remained buy-initiated.

Panel D reports changes in median *turnover*. Not surprisingly, *turnover* increased across all deciles and the CEFs. The largest increase was in decile 10, for which median *turnover* increased from 0.277% to 0.600%, a 116% increase in relative terms (and a 0.32% increase in absolute terms). This is consistent with the substantial increase in *tradesize* for this decile as reported in Panel C.

Panel E of Table 3 reports statistics for *effective spread*. As one might expect in a crisis, *effective spread* was substantially larger for the CEFs and every decile during the week of 9/17-9/21 than during the pre-nine-eleven period. As one might also expect, the largest increases were in the CEFs and deciles 1 and 2. The *percentage of buys* during the first post-nine-eleven trading week (see panel A) indicate that selling pressure was heaviest in these securities, and so it is not surprising that liquidity providers took advantage and were able to increase their compensation for providing such liquidity. In terms of levels, we note that the average spread of 0.82% for the CEFs after nine-eleven places them between deciles 3 and 4, the same as in the pre-nine-eleven statistics.

In summary, the trading patterns show that in the immediate aftermath of nine-eleven there was more dollar selling than buying in common stock deciles 1-4, and more dollar buying than selling in deciles 5-10. The collective evidence is also consistent with retail-investor selling and institutional-investor buying. Given the respective investor bases of small- and large-cap stocks, such disparate trading behavior could explain the differences in return patterns we observe in Figure 1 for small- versus large-cap stocks, in which small-cap stocks had much larger price declines than large-cap stocks. It is also particularly interesting that large-cap stocks suffered significant price declines after nine-eleven despite institutional buying as indicated by more dollar-weighted buys than sells, both overall and in trades >$50K. This finding demonstrates that in the wake of super-salient news, correlated trading by retail investors can temporarily drive prices in the opposite direction of that implied by active institutional trading.

6. Pooled, cross-sectional time series regressions

We now consider cross-sectional regressions of weekly (Friday-to-Friday) returns, to (1) statistically validate the return patterns reported earlier, and (2) learn whether recoveries result solely from a general improvement in sentiment or whether there is also substantial security-specific reversal.

6.1. Regressions of pre-nine-eleven returns

We begin by estimating baseline regressions using 48 weeks of pre-nine-eleven data. These regressions identify weekly autocorrelation patterns that are typical in the various asset classes during the 48-week period prior to nine-eleven. For example, we establish the extent to which a security's return in a given week relates to its return in each of the prior two weeks, thus revealing any patterns of significant price reversal or momentum. All models include unreported security-specific constants (i.e., fixed effects) and allow for autocorrelated and heteroskedastic error terms.[19]

We use a pooled, cross-sectional time-series approach. For all securities, we regress weekly (Friday-to-Friday) price returns on lagged price returns, an event indicator variable, lagged event indicator variables, and interaction terms. For the CEFs, we also estimate

[19] We estimate time-series, cross-sectional models using the Gauss-Newton method of Davidson and McKinnon (1980) to allow for first-order autocorrelation among the residuals of each fund and obtain unbiased estimates of this correlation. In addition, we allow for heteroskedasticity both between funds and between event and non-event weeks. Our approach may differ from that in Klibanoff, et al. (1998) in that we allow for first-order autocorrelation in the residuals. The overreaction and reversal effects in the regressions we document are qualitatively the same if we use alternative techniques, including simple ordinary least squares both with and without fixed effects.

the regression with abnormal returns in place of price returns, where an abnormal return is defined as the price return minus the contemporaneous NAV return.

The model we estimate and report in Table 4 is:

$$R_{i,t} = \alpha_i \ + \ \beta_1 R_{i,t-1} \ + \ \beta_2 R_{i,t-2} \ + \ \varepsilon_{i,t}, \tag{2}$$

where $R_{i,t}$ is the return for security i in week t, and α_i is a security-specific constant (fixed effects).

The first column, which reports regressions of fixed-income CEF price returns, shows a positive coefficient of 0.176 on $R_{i,t-1}$ that is significant both statistically and economically. This indicates a one-week security-specific price momentum of 0.176% for every 1% return in the prior week. The coefficient on $R_{i,t-2}$ is insignificant. The regression in the next column replaces price returns with abnormal (price minus NAV) returns on both the left- and right-hand sides of equation (2), and we observe that the CEFs have modest one-week abnormal return momentum (coefficient for $R_{i,t-1}$ = 0.068, p-value = 0.069), followed by significant two-week reversal (coefficient for $R_{i,t-2}$ = -0.083, p-value $<$ 0.001).

Table 4 also reports baseline regressions for the common stock deciles that show that, on average, stock prices are significantly reversed with a two-week lag during the pre-nine-eleven period as indicated by the significantly negative coefficients on $R_{i,t-2}$ for every decile. The coefficients on $R_{i,t-1}$, however, are mixed—insignificant for some deciles, significant and positive for others, and significant and negative for yet others.

6.2. Regressions of returns before, across, and after nine-eleven

We now turn to regressions that include 48 pre-nine-eleven weekly return observations, the return across the event itself, and five post-nine-eleven weekly observations (a total of 54 weekly observations for each security). Note that the return across nine-eleven spans two calendar weeks, 9/8 to 9/21, because of the market closure. Therefore, we allow for a distinct error term for the return across nine-eleven, which corrects for increased volatility due to the event itself and the greater than usual number of calendar days over this return's measurement period.

One goal of these regressions is to test whether the negative returns across the first post-nine-eleven trading week, and the return reversals that followed during the next two weeks, are statistically significant. Another is to show the extent to which the reversals are systematic versus security-specific. That is, the approach we take distinguishes between general price recoveries, which could be due to a broad-based improvement in investor sentiment, and security-specific reversals that are directly tied to the magnitude of each security's first-week price reaction to nine-eleven.

The model we estimate is:

$$\begin{aligned} R_{i,t} \;=\;& \alpha_i + \lambda_0 E_t + \lambda_1 E_{t-1} + \beta_1(-E_{t-1}R_{i,t-1}) + \lambda_2 E_{t-2} \\ & + \beta_2(-E_{t-2}R_{i,t-2}) + \beta_3(1-E_{t-1})R_{i,t-1} + \beta_4(1-E_{t-2})R_{i,t-2} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $R_{i,t}$ is the return for security i in week t, α_i is a security-specific constant (fixed effects), and E_t is an indicator variable equal to 1 if the weekly return $R_{i,t}$ spans nine-eleven (the return over Friday, 9/7 to Friday, 9/21). Hence, λ_0 measures the systematic reaction to nine-eleven (the first-week reaction), and λ_1 and λ_2 measure systematic recoveries in the second and third weeks, respectively. We also use the E_t indicators to partition how the current return (the left-hand-side variable) depends on lagged returns $R_{i,t-1}$ and $R_{i,t-2}$, based on whether the lagged returns span nine-eleven. Specifically, $R_{i,t-1}$ is partitioned into $E_{t-1}R_{i,t-1}$ and $(1-E_{t-1})R_{i,t-1}$, and $R_{i,t-2}$ is partitioned into $E_{t-2}R_{i,t-2}$ and $(1-E_{t-2})R_{i,t-2}$.

For our purposes, the key variables here are $E_{t-1}R_{i,t-1}$ and $E_{t-2}R_{i,t-2}$. Their coefficients, β_1 and β_2, measure the extent to which security-specific recoveries are directly tied to the initial security-specific price declines. Note that we perform simple transformations and actually use $(-E_{t-1}R_{i,t-1})$ and $(-E_{t-2}R_{i,t-2})$ in the specifications we estimate. By making these terms negative, positive values for β_1 and β_2 indicate recovery, or positive returns. This is because for a given security i, the return $R_{i,t-1}$ is negative when $E_{t-1} = 1$ due to the security's negative return reaction to nine-eleven, and similarly, $R_{i,t-2}$ is negative when $E_{t-2} = 1$. To help clarify the coding scheme, Appendix B illustrates with a numerical example.

6.2.1. CEF regressions

Table 5 presents the results. For the CEF price-return regression (the first column of numbers), the coefficient for E_t is -0.056 which is both economically and statistically significant ($p < 0.001$). This implies that the average first-week price reaction to nine-eleven was -5.6%, after controlling for returns in the prior two weeks. This average return is somewhat smaller than the -7.8% mean return reported in Table 1, but note that the regression controls for the prior two weeks of returns by including the variables $(1-E_{t-1})R_{i,t-1}$ and $(1-E_{t-2})R_{i,t-2}$.

As shown in Table 1, the mean recovery return was 4.56%. The regression shows that the systematic component of this return is statistically significant, but only 0.6% (the coefficient for $E_{t-1} = 0.006$, with p-value = 0.047). In marked contrast, the fund-specific component of this second-week recovery return is quite large: The coefficient on $(-E_{t-1}R_{i,t-1})$ is 0.409, implying that 40.9% of each fund's distinct initial price return decline over the first post-nine-eleven trading week was reversed during the second week. The systematic return in the third week is similar to that in the second week at 0.006, and the third week's fund-specific recovery component is insignificant.

The regression of abnormal (price minus NAV) returns for the CEFs show fairly similar results. One difference, however, is that the security-specific recovery coefficients on *both* $(-E_{t-1}R_{i,t-1})$ and $(-E_{t-2}R_{i,t-2})$ are positive and significant. Specifically, the coefficient and p-value for $(-E_{t-1}R_{i,t-1})$ are 0.557 and less than 0.001, respectively, and those for $(-E_{t-2}R_{i,t-2})$ are 0.077 and 0.036. Hence, this regression provides substantial direct evidence of overreaction: Negative abnormal returns in the first week of trading after nine-eleven were significantly reversed on a *fund-specific basis* during both of the subsequent two weeks.[20]

It is important to note that the security-specific post-nine-eleven event reaction of fixed-income CEFs is in marked contrast to the reaction during non-event time periods. The positive and significant coefficients on $(1-E_{t-1})R_{i,t-1}$ in the two CEF regressions, along with the positive and significant coefficients on $R_{i,t-1}$ in the pre-nine-eleven regressions in Table 4, imply momentum, and hence underreaction to information. This is consistent with the findings in Klibanoff, Lamont, and Wizman (1998), who conclude that closed-end fund prices underreact to news as measured by contemporaneous changes in NAVs. They further conclude that in salient news weeks, such underreaction is significantly smaller. Our results show that abnormal returns were significantly negative in the nine-eleven return week, which given that nine-eleven was a negative news shock, implies *overreaction*. This interpretation is buttressed by the fact that there were significant fund-specific reversals following nine-

[20] In an alternative approach, we construct a systematic sentiment factor which is, for each week, the cross-sectional mean of the difference between the fund price and NAV returns. Including this as a regressor results in a coefficient (p-value) on $(-E_{t-1}R_{i,t-1})$ of 0.472 (<0.001). Separately, we also estimate a regression in which we include the sentiment factor times a fund-specific sentiment beta (estimated using pre-nine-eleven data). In this regression, the coefficient (p-value) on $(-E_{t-1}R_{i,t-1})$ is 0.311 (<0.001). Hence, we conclude the evidence of fund-specific recoveries is robust to these alternative ways of controlling for systematic sentiment.

eleven.[21] Thus, our findings support the idea that when the salience of news is sufficiently great, not only can there be less underreaction, but in fact overreaction.[22]

6.2.2. Common stock regressions

The right-most ten columns in Table 5 show the regression results for the common stock deciles. As expected, the coefficients on E_t, which measure the average price return during the first post-nine-eleven trading week, are significantly negative for every decile group. In the second week, there was significant systematic market-wide recovery in all but decile 1, as coefficients on E_{t-1} are positive and significant. Except for deciles 4 and 9, however, there is no significant evidence of security-specific recovery in the second week, as the coefficients for $(-E_{t-1}R_{i,t-1})$ are insignificant.

The results for the third week are quite different than those for the second week. During this week, there is no evidence of systematic recovery—none of the coefficients on E_{t-2} are significantly positive in any of the deciles.[23] Of note, however, the regressions do show significant security-specific recoveries during the third week following nine-eleven: The coefficients on $(-E_{t-2}R_{i,t-2})$ are uniformly positive and both economically and statistically significant for all deciles. This implies that for common stocks, like fixed-income CEFs, there was a security-specific reversal of the nine-eleven price declines. The difference is that the security-

[21] Evidence in Klibanoff, Lamont, and Wizman shows that prices react to changes in NAVs instead of vice versa, and Figure 3 suggests this was the case after nine-elven. In results we do not tabulate but that are available from the authors, we confirm this econometrically using a vector error-correction model.

[22] Note that Klibanoff, Lamont, and Wizman's finding that CEF prices underreact less to more salient news is an average effect across many distinct news events. It is possible their set of events contains a subset of super-salient news events that result in overreaction instead of just less underreaction.

[23] Note that deciles one and three have significant but negative coefficients for E_{t-2}.

specific reversals for common stocks occur during the third week following nine-eleven instead of the second. We comment further on this result below.

7. Comparing common stocks to CEFs

Benchmarks to calculate abnormal stock price returns are controversial at best, so we do not attempt to create a direct measure of a stock's abnormal return. However, for CEFs, the evidence for abnormal returns leads us to conclude that there was significant overreaction. It is therefore interesting to compare price returns for common stocks with those of fixed-income CEFs.

Figure 1 shows a striking similarity between the pattern of price returns for common stocks and the pattern for fixed-income CEFs. Moreover, both the common stock and CEF regressions statistically validate significant negative returns followed by both systematic and security-specific reversals during the second or third post-nine-eleven trading weeks. In addition, we note that both Figure 1 and the regressions show that initial reactions were more severe for common stocks than for fixed-income CEFs. Finally, our findings of less severe overreaction and faster security-specific reversals in fixed-income CEFs, relative to common stocks, support the intuition in classic models such as Grossman and Stiglitz (1980) in which greater numbers of informed traders make pricing more efficient. Compared to common stocks, CEFs have a superior information environment due to the regular disclosure of NAVs, which should naturally increase the number of informed relative to uninformed traders.

Taken together, we believe these results provide substantial evidence that there was overreaction and recovery in common stocks in the wake of nine-eleven.

8. Conclusion

We exploit the nine-eleven terrorist event to study the roles of retail and institutional traders in the wake of super-salient news. Our analysis benchmarks price returns against NAV returns for fixed-income CEFs, and we find significant retail-investor overreaction during the first post-nine-eleven trading week followed by a security-specific reversal during the second and third weeks. Comparing price returns of these funds to those of NYSE common stocks suggests a similar three-week period of overreaction and security-specific reversal in common stocks. Interestingly, this finding applies even to the largest-cap stocks, despite microstructure data indicating net buying of these stocks by institutional investors in the initial aftermath of the event. This indicates that in the wake of super-salient news, even when institutional investors trade in one direction, correlated trading by retail investors can drive prices in the other direction.

Our study extends the literature in at least four important respects. First, while prior studies examine trading by retail or institutional investors, we examine how both sets of investors trade simultaneously in response to news, and show that correlated trading by retail investors can swamp that of institutional investors and move prices in the opposite direction. This could have implications for how prices respond to super-salient firm-specific news such as major industrial accidents, revelations of fraud, etc. Second, while prior studies find that greater salience leads to less underreaction to news, our results imply that investor reaction to news lies on a continuum wherein greater salience can lead to overreaction when news is sufficiently salient. Third, we find that prices reverse sooner in fixed-income closed-end funds than in common stocks, potentially due to the superior information environment CEFs have as a result of regularly disclosed NAVs. This interpretation is consistent with classical microstructure theory, wherein a greater proportion of informed traders leads to more efficient prices. Finally, our evidence supports Tetlock's (2011) approach of identifying overreaction on the basis of a return reversal.

Our research examines a super-salient negative news shock. Parallel unresolved questions are whether an analogous pattern of overreaction follows super-salient positive news, and whether correlated retail trading can swamp institutional trading in the opposite direction following such positive news. We leave these questions to future research.

Appendix A: Robustness Checks

In this appendix we discuss the robustness of our finding of overreaction in fixed-income CEFs to nine-eleven, and rule out several alternative explanations for the pattern of severe price declines and recoveries.

A.1 Errors in net asset values

We first consider whether the evidence is potentially explained by errors in reported NAVs. Suppose NAVs during the first week after nine-eleven (and on Friday, 9/21, in particular) were overstated because they were not updated after non-eleven due to the disrupted environment. If that were the case, negative abnormal returns could be due to errors in the NAVs. However, we find that only one fund has the same NAV both on the last trading day prior to nine-eleven and at the end of the first trading week (9/21) after nine-eleven. Thus, NAVs were updated during the first trading week following nine-eleven.

Another possibility is that, although reported NAVs were updated, some of the asset prices used in NAV calculations were stale. This could have resulted in valuation errors immediately after nine-eleven. For example, suppose the risk of default increased immediately following nine-eleven. If bond prices for NAV calculations were stale or matrix-priced based on a pre-nine-eleven risk assessment, they would have been too high (relative to true fundamentals), which would have caused overstated fixed-income NAVs.

Figure A1 plots the Baa-rated corporate bond yield spread (above the 10-year treasury yield) and shows that the default premium did increase following nine-eleven. However, the patterns of price and NAV returns are not consistent with NAVs being overstated because of increased default risk. As shown in Figure A1, default premium remain somewhat higher through 10/05. And yet, cumulative price returns recovered to the level of cumulative NAV returns instead of cumulative NAV returns converging to cumulative price returns (see Figure

3). If bond prices were erroneously high and did not reflect the increased default premium at first, then as bond prices became increasingly accurate, cumulative NAV returns should have converged to cumulative price returns instead of vice versa.

As an additional check, we spoke with multiple people responsible for the NAV calculations of a variety of CEFs. They assured us that prior to Friday, 9/21, accurate, updated secondary-market based prices were being used to calculate the NAVs of fixed-income CEFs. The evidence strongly supports the idea that NAVs for Friday 9/21 are appropriately updated and therefore not stale.

A.2 Market depth effects in the closed-end fund shares

The lack of sufficient market depth to accommodate panicked sellers is another potential explanation for severe price declines in CEFs following nine-eleven. Investors could have been willing to pay a premium to liquidate their shares immediately. This is another manifestation of overreaction, where panicked investors liquidated their holdings immediately because they were concerned that liquidation prices in the future would be even lower. Liquidity providers could have taken advantage of this and profited from buying shares at transaction prices that were artificially low compared to NAVs.

To explore the lack of market depth explanation, we calculate each fund's average share *turnover* during the 20 trading days *preceding* nine-eleven. This variable is a proxy for the ability to sell shares without causing significant price movement (i.e., the depth the overall market provides to sellers). We rank order fixed-income CEFs by this variable, and partition them into three equal-sized groups.

The market depth explanation predicts that panicked sellers of funds with lower pre-nine-eleven *turnover* (i.e., lower market depth) will accept lower prices to attract buyers. Therefore, overreaction and reversal patterns should be more (less) pronounced in funds with lower (higher) *turnover*. We add a term to the regression model explaining CEF abnormal returns in Table 5 that interacts the event variable (E_t) with the *turnover*-rank variable. A positive coefficient on this additional variable would indicate that the negative abnormal return is less negative for funds with higher *turnover*. In fact, we find that the coefficient is significantly *negative*, indicating more pronounced overreaction for funds with higher liquidity (as measured by pre-nine-eleven *turnover*). Hence, we conclude the overreaction in fixed-income CEFs is not explained by a lack of market depth.

A.3 Closed-end fund discount explanations

A third potential explanation is that price and NAV returns diverge because a closed-end fund's premium or discount has changed. It is therefore possible that explanations for closed-end fund discounts play a role in the patterns of price and NAV returns. Grullon and Wang (2001) present a model in which closed-end fund discounts (negative premiums) occur when investors in the closed-end funds are less informed than investors in the fund's underlying assets. Their information differential theory is potentially important in our setting because any information differential would have been exacerbated by nine-eleven and the market closure. This implies, however, that the divergence between prices and NAVs (i.e., the widening of discounts) should have been at its most severe at the market's reopening on Monday, 9/17, and then this divergence should have dissipated over the 9/17 – 9/21 trading week as prices and NAVs should have converged (i.e., discounts should have narrowed) throughout the week as CEF investors became more informed about fundamental values by observing market activity, and in particular, disclosed NAVs. Neither of these predictions hold, because the divergence between prices and NAVs steadily grows throughout the 9/17 – 9/21 trading week to its maximum on Friday, 9/21 (see Figure 3).

There are, of course, other proposed explanations for closed-end fund discounts. Among these are unrealized capital gains, managerial performance and agency problems, segmented markets, restricted or illiquid stock holdings, and excessive turnover within the fund's assets (for a review, see Dimson and Minio-Kozerski, 1999). None of these explanations are likely to explain the patterns we observe. To varying degrees, these explanations imply that discounts should have been unaffected around nine-eleven or at their widest on Monday, 9/17, when the market reopened. None of these explanations imply that discounts should have become steeper throughout the first post-nine-eleven trading week of 9/17 – 9/21, only to return to their pre-nine-eleven levels over the second and third trading weeks.reaction.

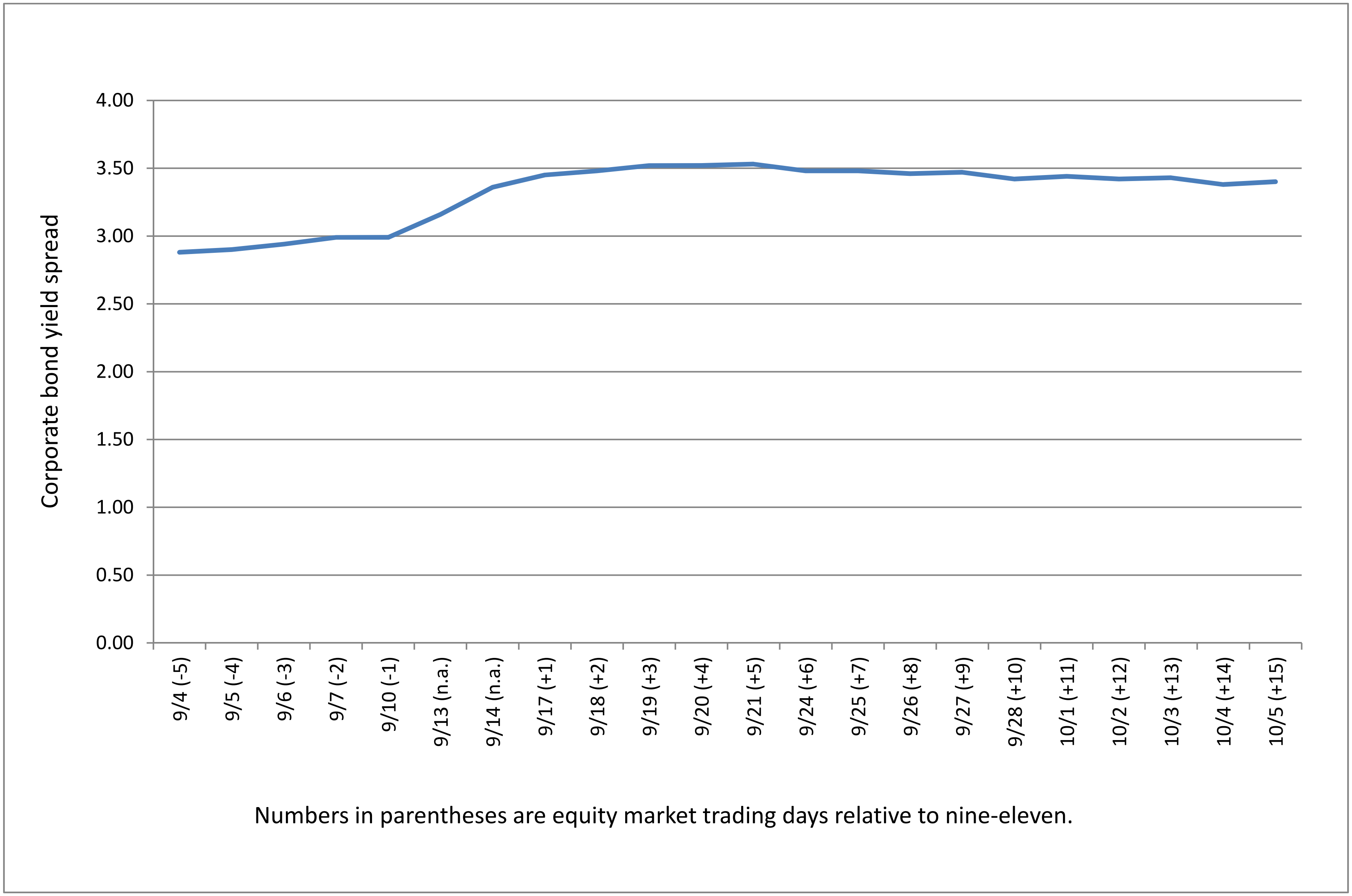

Fig. A1. The spread of the Moody's seasoned Baa corporate bond yield spread over 10-year constant maturity Treasury yields. Both yields are from the Federal Reserve Bank of St. Louis.

Appendix B: Numerical Illustration of Coding for Table 5 Regressions

To illustrate the codings and coefficient sign interpretations, consider the simple example in Appendix Table B1 in which a security has a negative 10% return over the nine-eleven trading week (which is week 49 in the regression data). Note that the left-hand side variable is R_t, and that R_{t-1} and R_{t-2} are not included on the right-hand side on their own—they are only shown to clarify how the interaction-term variables are coded. For the week-49 observation, the non-zero regressor variables are coded as $E_t = 1$, $(1-E_{t-1})R_{i,t-1} = 3\%$, and $(1-E_{t-2})R_{i,t-2} = 1\%$. Because E_t is coded zero for all other weeks, the estimated coefficient for E_t in the cross-sectional regression will measure the average nine-eleven return that is not explained by the prior two lagged returns.

For the first recovery return week (which is week 50, the second week of trading after nine-eleven), the security experiences a positive return of $R_t = 7\%$. Our goal is to determine how much of the 7% recovery return is systematic across all securities in the regression, and how much is tied to a security-specific reversal of the security's prior-week return of -10%. The non-zero regressors for this observation (t = 50) are $E_{t-1} = 1$, $(-E_{t-1}R_{i,t-1}) = 10\%$, and $(1-E_{t-1})R_{i,t-1} = 3\%$. Note that E_{t-1} is coded zero in all other weeks. The coefficient estimated for E_{t-1} in the cross-sectional regression will thus measure the recovery return that is common across all securities in the regression, and the coefficient on $(-E_{t-1}R_{i,t-1})$ will measure the extent to which the recovery returns are directly proportional to the security-specific initial return reactions to nine-eleven. Note also that recoveries (positive returns) are indicated by positive coefficients on these two variables. For example, given that $E_{t-1} = 1$ for $t = 50$, a coefficient of 0.05 on E_{t-1} would imply that 5% out of the 7% return in the $t = 50$ recovery week, or 71.4% (5/7), is due to a systematic recovery shared by all securities in the regression. And given that $(-E_{t-1}R_{i,t-1}) = 10\%$ for the $t = 50$ recovery week, a coefficient of 0.15 on $(-E_{t-1}R_{i,t-1})$ would imply that another 1.5% (which is 0.15 x 10%) out of the 7% recovery return, or 21.4% (1.5/7), is directly tied to the security's specific 10% loss during the nine-eleven trading week of $t = 49$.

The interpretations are similar for E_{t-2} and $(-E_{t-2}R_{i,t-2})$. The codings for week $t = 51$ (the second week of recovery) imply that the coefficient on E_{t-2} will measure the second week of recovery common across all securities, and that on $(-E_{t-2}R_{i,t-2})$ will measure the portion of the second week's recovery return that is directly linked to a security's initial nine-eleven return reaction.

Appendix Table B1

Illustrative coding for one security, in which R_t = return (either price return or abnormal return) for week *t*. $E_t = 1$ if the return for week *t* includes nine-eleven.

	Trading week	Friday-to-Friday return week period	Dep Var. R_t	(These are not included as stand-alone regressors) R_{t-1}	R_{t-2}	Regressor variables included in Table 4, Panel B regressions E_t	E_{t-1}	E_{t-2}	$(-E_{t-1}R_{t-1})$	$(-E_{t-2}R_{t-2})$	$(1-E_{t-1})R_{t-1}$	$(1-E_{t-2})R_{t-2}$
	46	8/17 - 8/24	-3%	-1%	-2%	0	0	0	0%	0%	-1%	-2%
	47	8/24 - 8/31	1%	-3%	-1%	0	0	0	0%	0%	-3%	-1%
	48	8/31 - 9/7	3%	1%	-3%	0	0	0	0%	0%	1%	-3%
9/11 week	49	9/7 - 9/21	**-10%**	3%	1%	1	0	0	0%	0%	3%	1%
	50	9/21 - 9/28	7%	**-10%**	3%	0	1	0	**10%**	0%	0%	3%
	51	9/28 - 10/5	8%	7%	**-10%**	0	0	1	0%	**10%**	7%	0%
	52	10/5 - 10/12	2%	8%	7%	0	0	0	0%	0%	8%	7%
	53	10/12 - 10/19	1%	2%	8%	0	0	0	0%	0%	2%	8%
	54	10/19 - 10/26	0%	1%	2%	0	0	0	0%	0%	1%	2%

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Table 1

Means of cumulative log price returns during six different time periods before, across, and after nine-eleven, for ten market-capitalization-based deciles of 1,463 NYSE-listed stocks, 199 fixed-income closed end funds, and the S&P 500 Stock Index. Decile partitions for common stocks (D1-D10) are based on market capitalizations as of September 10, 2001.

	Common stock deciles partitioned by market capitalization											
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	CEFs	S&P 500
Pre: 6/1-9/10	-21.89%	-9.82%	-8.29%	-5.35%	-11.61%	-6.70%	-5.34%	-12.37%	-8.04%	-11.20%	4.38%	-13.93%
9/10-9/21	-16.69%	-19.14%	-21.02%	-17.89%	-16.71%	-13.95%	-14.54%	-15.79%	-12.49%	-12.49%	-7.80%	-12.33%
9/21-9/28	-2.11%	1.26%	6.62%	6.46%	5.79%	5.87%	6.55%	6.14%	6.13%	6.81%	4.56%	7.49%
9/28-10/5	-1.53%	1.72%	-0.51%	2.46%	2.99%	2.68%	2.42%	2.97%	2.24%	2.05%	1.50%	2.88%
9/10-10/5	-20.33%	-16.17%	-14.91%	-8.97%	-7.93%	-5.41%	-5.57%	-6.68%	-4.12%	-3.63%	-1.74%	-1.96%
10/5-12/31	2.89%	11.26%	15.57%	14.17%	13.60%	15.18%	12.63%	12.16%	6.43%	3.88%	6.91%	7.16%

Table 2

Summary statistics during the pre-nine-eleven period, June 1 through September 10, 2001, for ten market-capitalization-based deciles of 1,463 NYSE-listed stocks and 199 fixed-income closed end funds. Decile partitions for common stocks (D1-D10) are based on market capitalizations (*Market Cap*) as of September 10, 2001. The reported statistics are medians of security-day observations, except *Tradesize* distributions (panel B) which are means. *Tradesize* is the mean dollar value of all trades during a given day. *Share price* is the closing price. *Effective spread* is the mean of the effective spread for all trades during a given day, where the effective spread for a trade equals the bid-ask spread divided by the midpoint (i.e., the sum of the bid and ask divided by 2). *Turnover* is the number of shares traded in a given day, divided by the number of outstanding shares. *Percentage of buys* is dollar buys divided by the sum of dollar buys and sells during a given day, where buys and sells are identified by the Lee and Ready (1991) trade signing algorithm. Distribution of trades by *Tradesize* shows the percentage (by number of trades) of all trades during a given day falling into a particular size category.

	Common stock deciles partitioned by market capitalization										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	CEFs
Panel A: Median characteristics											
Market Cap ($m)	52	170	331	539	860	1,290	2,077	3,470	6,996	23,985	194
Tradesize ($)	3,218	6,576	9,360	12,236	16,772	19,667	25,844	30,987	39,243	67,951	11,835
Share price ($)	3.37	11.49	15.85	19.90	25.11	27.08	31.39	30.40	39.90	44.81	12.81
Effective Spread	2.27%	0.84%	0.57%	0.41%	0.30%	0.26%	0.20%	0.17%	0.14%	0.10%	0.46%
Turnover	0.063%	0.127%	0.175%	0.208%	0.294%	0.310%	0.345%	0.376%	0.327%	0.277%	0.077%
Percentage of buys	44.56%	51.44%	53.30%	54.66%	55.46%	56.00%	55.87%	56.09%	55.30%	55.03%	49.45%
Panel B: Distribution of trades by *Tradesize*											
Trades < $5K	77.11%	65.98%	57.77%	49.85%	42.13%	37.05%	30.39%	26.64%	20.63%	12.07%	34.75%
Trades $5-$10K	12.44%	15.87%	18.04%	19.75%	19.69%	20.69%	19.39%	19.75%	20.56%	16.95%	23.31%
Trades $10-$20K	6.51%	9.77%	12.69%	14.90%	17.73%	18.73%	19.96%	19.56%	20.15%	18.42%	23.46%
Trades $20-$50K	3.08%	5.80%	7.84%	10.55%	13.52%	15.12%	18.43%	19.80%	22.04%	25.26%	15.31%
Trades > $50K	0.85%	2.57%	3.66%	4.94%	6.93%	8.41%	11.83%	14.25%	16.62%	27.30%	3.17%
Trades < $20K	96.06%	91.62%	88.49%	84.50%	79.55%	76.47%	69.73%	65.95%	61.34%	47.44%	81.52%
Panel C: *Percentage of buys* ($ buys / ($ buys + $sells)) among Lee and Ready signed trades larger than $50,000											
Percentage of buys (>$50K)	46.37%	54.03%	56.29%	57.28%	57.17%	57.59%	56.57%	57.12%	56.10%	55.41%	41.34%

Table 3

Summary statistics during five different time periods between June 1 and December 31, 2001 for ten market-capitalization-based deciles of 1,463 NYSE-listed stocks and 199 fixed-income closed end funds. Decile partitions for common stocks (D1-D10) are based on market capitalizations as of September 10, 2001 (*Market Cap*). The reported statistics are medians of security-day observations in the time period. *Percentage of buys* is dollar buys divided by the sum of dollar buys and sells during a given day, where buys and sells are identified by the Lee and Ready (1991) trade signing algorithm. *Tradesize* is the mean dollar value of all trades during a given day. *Turnover* is the number of shares traded in a given day, divided by the number of outstanding shares. *Effective spread* is the mean of the effective spread for all trades during a given day, where the effective spread for a trade equals the bid-ask spread divided by the midpoint (i.e., the sum of the bid and ask divided by 2).

	Common stock deciles partitioned by market capitalization										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	CEFs
Panel A: *Percentage of buys* ($ buys / ($ buys + $sells)) among Lee and Ready signed trades											
Pre: 6/1-9/10	44.56%	51.44%	53.30%	54.66%	55.46%	56.00%	55.87%	56.09%	55.30%	55.03%	49.45%
9/17-9/21	33.65%	41.99%	47.24%	48.22%	50.98%	52.11%	53.37%	53.66%	53.31%	53.37%	33.37%
Change (from pre-nine-eleven)	-10.9%	-9.5%	-6.1%	-6.4%	-4.5%	-3.9%	-2.5%	-2.4%	-2.0%	-1.7%	-16.1%
9/24-9/28	47.55%	51.71%	56.06%	56.68%	56.29%	56.81%	56.25%	56.84%	55.61%	56.36%	53.35%
Change (from pre-nine-eleven)	3.0%	0.3%	2.8%	2.0%	0.8%	0.8%	0.4%	0.8%	0.3%	1.3%	3.9%
10/1-10/05	44.85%	52.05%	53.64%	56.62%	56.77%	57.15%	56.53%	57.58%	57.08%	57.56%	53.39%
Change (from pre-nine-eleven)	0.3%	0.6%	0.3%	2.0%	1.3%	1.2%	0.7%	1.5%	1.8%	2.5%	3.9%
10/8-12/31	48.02%	51.51%	53.85%	55.85%	56.13%	56.48%	56.70%	56.70%	56.18%	55.86%	45.31%
Change (from pre-nine-eleven)	3.5%	0.1%	0.6%	1.2%	0.7%	0.5%	0.8%	0.6%	0.9%	0.8%	-4.1%
Panel B: *Percentage of buys* ($ buys / ($ buys + $sells)) among Lee and Ready signed trades larger than $50,000											
Pre: 6/1-9/10	46.37%	54.03%	56.29%	57.28%	57.17%	57.59%	56.57%	57.12%	56.10%	55.41%	41.34%
9/17-9/21	41.58%	43.96%	49.34%	46.38%	52.04%	54.78%	53.78%	54.38%	53.34%	53.33%	9.89%
Change (from pre-nine-eleven)	-4.8%	-10.1%	-6.9%	-10.9%	-5.1%	-2.8%	-2.8%	-2.7%	-2.8%	-2.1%	-31.5%
9/24-9/28	60.67%	62.07%	59.62%	57.48%	56.30%	56.17%	56.07%	56.86%	56.48%	56.64%	59.84%
Change (from pre-nine-eleven)	14.3%	8.0%	3.3%	0.2%	-0.9%	-1.4%	-0.5%	-0.3%	0.4%	1.2%	18.5%
10/1-10/05	68.49%	56.66%	53.58%	59.08%	57.36%	58.25%	56.25%	58.71%	58.10%	58.13%	48.19%
Change (from pre-nine-eleven)	22.1%	2.6%	-2.7%	1.8%	0.2%	0.7%	-0.3%	1.6%	2.0%	2.7%	6.9%
10/8-12/31	53.00%	56.61%	57.23%	57.54%	57.22%	57.39%	57.41%	57.99%	56.77%	56.46%	31.16%
Change (from pre-nine-eleven)	6.6%	2.6%	0.9%	0.3%	0.1%	-0.2%	0.8%	0.9%	0.7%	1.0%	-10.2%

Table 3 (continued)

	Common stock deciles partitioned by market capitalization										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	CEFs
Panel C: *Tradesize* (dollars)											
Pre: 6/1-9/10	3,218	6,576	9,360	12,236	16,772	19,667	25,844	30,987	39,243	67,951	11,835
9/17-9/21	3,115	6,990	10,294	14,164	18,505	22,287	29,613	35,639	45,795	103,366	13,407
Change (from pre-nine-eleven)	-103	414	933	1,928	1,734	2,620	3,769	4,652	6,552	35,414	1,572
9/24-9/28	2,824	6,374	9,560	11,641	15,536	19,290	24,314	29,970	38,581	75,036	11,779
Change (from pre-nine-eleven)	-395	-202	200	-595	-1,236	-377	-1,530	-1,017	-662	7,085	-56
10/1-10/05	2,518	5,720	8,167	10,181	14,292	16,660	22,806	26,935	35,964	64,083	11,587
Change (from pre-nine-eleven)	-700	-856	-1,194	-2,055	-2,480	-3,007	-3,038	-4,051	-3,278	-3,868	-248
10/8-12/31	2,729	5,217	7,736	9,960	12,923	15,844	21,478	25,326	33,362	59,301	11,456
Change (from pre-nine-eleven)	-489	-1,359	-1,624	-2,276	-3,849	-3,823	-4,366	-5,661	-5,880	-8,651	-379
Panel D: *Turnover* (shares traded / shares outstanding)											
Pre: 6/1-9/10	0.063%	0.127%	0.175%	0.208%	0.294%	0.310%	0.345%	0.376%	0.327%	0.277%	0.077%
9/17-9/21	0.096%	0.185%	0.260%	0.322%	0.445%	0.477%	0.579%	0.693%	0.599%	0.600%	0.142%
Change (from pre-nine-eleven)	0.03%	0.06%	0.08%	0.11%	0.15%	0.17%	0.23%	0.32%	0.27%	0.32%	0.07%
9/24-9/28	0.085%	0.196%	0.238%	0.281%	0.411%	0.465%	0.508%	0.568%	0.497%	0.453%	0.100%
Change (from pre-nine-eleven)	0.02%	0.07%	0.06%	0.07%	0.12%	0.16%	0.16%	0.19%	0.17%	0.18%	0.02%
10/1-10/05	0.068%	0.144%	0.172%	0.239%	0.353%	0.377%	0.437%	0.525%	0.426%	0.386%	0.089%
Change (from pre-nine-eleven)	0.00%	0.02%	0.00%	0.03%	0.06%	0.07%	0.09%	0.15%	0.10%	0.11%	0.01%
10/8-12/31	0.082%	0.118%	0.177%	0.213%	0.282%	0.317%	0.352%	0.394%	0.352%	0.309%	0.086%
Change (from pre-nine-eleven)	0.02%	-0.01%	0.00%	0.01%	-0.01%	0.01%	0.01%	0.02%	0.02%	0.03%	0.01%

Table 3 (continued)

	Common stock deciles partitioned by market capitalization										
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	CEFs
Panel E: *Effective spread*											
Pre: 6/1-9/10	2.27%	0.84%	0.57%	0.41%	0.30%	0.26%	0.20%	0.17%	0.14%	0.10%	0.46%
9/17-9/21	3.47%	1.33%	0.88%	0.61%	0.43%	0.37%	0.29%	0.25%	0.19%	0.15%	0.82%
Change (from pre-nine-eleven)	1.2%	0.5%	0.3%	0.2%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.4%
9/24-9/28	3.51%	1.27%	0.80%	0.59%	0.41%	0.32%	0.26%	0.22%	0.17%	0.13%	0.70%
Change (from pre-nine-eleven)	1.2%	0.4%	0.2%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.2%
10/1-10/05	3.46%	1.15%	0.72%	0.52%	0.38%	0.31%	0.24%	0.20%	0.16%	0.12%	0.63%
Change (from pre-nine-eleven)	1.2%	0.3%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%
10/8-12/31	2.62%	0.97%	0.60%	0.42%	0.30%	0.25%	0.20%	0.17%	0.13%	0.10%	0.54%
Change (from pre-nine-eleven)	0.4%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%

Table 4

Pooled, cross-sectional time-series regressions for ten market-capitalization-based deciles of 1,463 NYSE-listed stocks and 199 fixed-income closed end funds that explain weekly Friday-to-Friday returns for the 48 return-weeks immediately preceding nine-eleven. Decile partitions for common stocks (D1-D10) are based on market capitalizations as of September 10, 2001. The regression specification is $R_{i,t} = \alpha_i + \beta_1 R_{i,t-1} + \beta_2 R_{i,t-2} + e_{i,t}$, where $R_{i,t}$ is the cumulative log return for security i in week t, and α_i is a security-specific constant (i.e., fixed effects, the coefficients on which are not reported in the table for brevity). Cumulative log price returns are used except for the closed-end fund regression with the dependent variable labeled abnormal, in which case the return is the cumulative log price return minus the cumulative log NAV return. Heteroscedasticity is modeled between funds and also within funds for event and non-event weeks; in addition, first-order autocorrelation is permitted in the error terms of each fund, as well as a distinct error term across nine-eleven. The Chi-square p-value measures the joint significance of only the coefficients reported (it excludes the unreported fixed effects indicator variables), and *p*-values are shown in parentheses beneath coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

			Common stock deciles partitioned by market capitalization									
Sample	CEFs	CEFs	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Dependent var. return type:	price	abnormal	price	price	price	price	price	price	price	price	price	price
R_{t-1} (lagged return)	0.176***	0.068*	-0.034	0.184***	0.108**	-0.117**	-0.032	-0.051	-0.110**	0.011	-0.049	-0.028
	(<0.001)	(0.069)	(0.474)	(<0.001)	(0.024)	(0.023)	(0.551)	(0.298)	(0.045)	(0.833)	(0.264)	(0.545)
R_{t-2} (twice-lagged return)	-0.016	-0.083***	-0.038***	-0.089***	-0.067***	-0.074***	-0.061***	-0.051***	-0.068***	-0.069***	-0.108***	-0.132***
	(0.348)	(<0.001)	(0.004)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Wald Statistic	33.53***	44.84***	9.26***	25.91***	15.75***	26.51***	23.40***	16.46***	23.36***	28.72***	76.36***	116.97***
Chi-square p-value	(<0.001)	(<0.001)	(0.010)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Table 5

Pooled, cross-sectional time-series regressions for ten market-capitalization-based deciles of 1,463 NYSE-listed stocks and 199 fixed-income closed end funds that explain weekly Friday-to-Friday returns over the 48 weeks immediately preceding nine-eleven, the return across nine-eleven, and five weekly returns after the nine-eleven return week (54 total return week observations). Decile partitions for common stocks (D1-D10) are based on market capitalizations as of September 10, 2001. The regression specification is $R_{i,t} = \alpha_i + \lambda_0 E_t + \lambda_1 E_{t-1} + \beta_1 (-E_{t-1}R_{i,t-1}) + \lambda_2 E_{t-2} + \beta_2 (-E_{t-2}R_{i,t-2}) + \beta_3 (1-E_{t-1})R_{i,t-1} + \beta_4(1-E_{t-2})R_{i,t-2} + e_{i,t}$, where $R_{i,t}$ is the cumulative log return for security i in week t, α_i is a security-specific constant (i.e., fixed effects, the coefficients on which are not reported in the table for brevity), and E_t is and indicator variable set to one if the return $R_{i,t}$ spans nine-eleven (the return over 9/7 – 9/21). The negative signs on $-E_{t-1}R_{i,t-1}$ and $-E_{t-2}R_{i,t-2}$ are so that positive coefficients indicate recoveries in the second and third return weeks following nine-eleven. Cumulative log price returns are used except for the closed-end fund regression with the dependent variable labeled abnormal, in which case the return is the cumulative log price return minus the cumulative log NAV return. Heteroscedasticity is modeled between funds and also within funds for event and non-event weeks; in addition, first-order autocorrelation is permitted in the error terms of each fund, as well as a distinct error term across nine-eleven. The Chi-square p-value measures the joint significance of only the coefficients reported (it excludes the unreported fixed effects indicator variables), and p-values are shown in parentheses beneath coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

				Common stock deciles partitioned by market capitalization									
Sample		CEFs	CEFs	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Dependent. var. return type:		price	abnormal	price	price	price	price	price	price	price	price	price	price
First-week reaction to nine-eleven (negative coefficient indicates negative return reaction)													
E_t	(Systematic reaction)	-0.056***	-0.042***	-0.117***	-0.141***	-0.150***	-0.143***	-0.144***	-0.132***	-0.136***	-0.135***	-0.118***	-0.111***
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Second-week systematic and security-specific reactions to nine-eleven (positive coefficients indicate recovery)													
E_{t-1}	(Systematic reaction)	0.006**	0.005**	0.001	0.034***	0.066***	0.029***	0.042***	0.062***	0.054***	0.057***	0.043***	0.070***
		(0.047)	(0.033)	(0.928)	(0.002)	(<0.001)	(0.008)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$-E_{t-1}R_{t-1}$	(Security-specific reaction	0.409***	0.557***	0.015	-0.092	-0.008	0.159**	0.089	-0.067	0.041	-0.023	0.130*	0.002
		(<0.001)	(<0.001)	(0.839)	(0.135)	(0.891)	(0.021)	(0.229)	(0.349)	(0.578)	(0.710)	(0.066)	(0.977)
Third-week systematic and security-specific reactions to nine-eleven (positive coefficients indicate recovery)													
E_{t-2}	(Systematic reaction)	0.006***	-0.001	-0.031***	-0.010	-0.018**	0.001	-0.004	-0.006	-0.004	-0.009	0.001	-0.007
		(0.001)	(0.755)	(0.001)	(0.253)	(0.038)	(0.852)	(0.644)	(0.470)	(0.596)	(0.227)	(0.858)	(0.308)
$-E_{t-2}R_{t-2}$	(Security-specific reaction	-0.014	0.077**	0.143**	0.087*	0.073*	0.109**	0.133***	0.185***	0.138***	0.184***	0.115**	0.126***
		(0.644)	(0.036)	(0.017)	(0.063)	(0.053)	(0.014)	(0.009)	(<0.001)	(0.003)	(<0.001)	(0.023)	(0.010)
Correlations with non-nine-eleven lagged returns (positive coefficients indicate momentum, negative coefficients indicate reversals)													
$(1-E_{t-1})R_{t-1}$	(Once-lagged return)	0.192***	0.083**	-0.019	0.195***	0.064	-0.024	0.026	0.018	-0.029	0.120***	-0.008	0.088**
		(<0.001)	(0.023)	(0.696)	(<0.001)	(0.169)	(0.620)	(0.618)	(0.696)	(0.581)	(0.008)	(0.858)	(0.031)
$(1-E_{t-2})R_{t-2}$	(Twice-lagged return)	-0.047***	-0.095***	-0.031**	-0.094***	-0.060***	-0.055***	-0.055***	-0.048***	-0.050***	-0.079***	-0.103***	-0.132***
		(0.006)	(<0.001)	(0.016)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Wald Statistic		2329.50***	1728.60***	207.77***	459.91***	513.09***	688.67***	629.46***	584.76***	623.30***	685.60***	677.09***	703.50***
Chi-square p-value		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

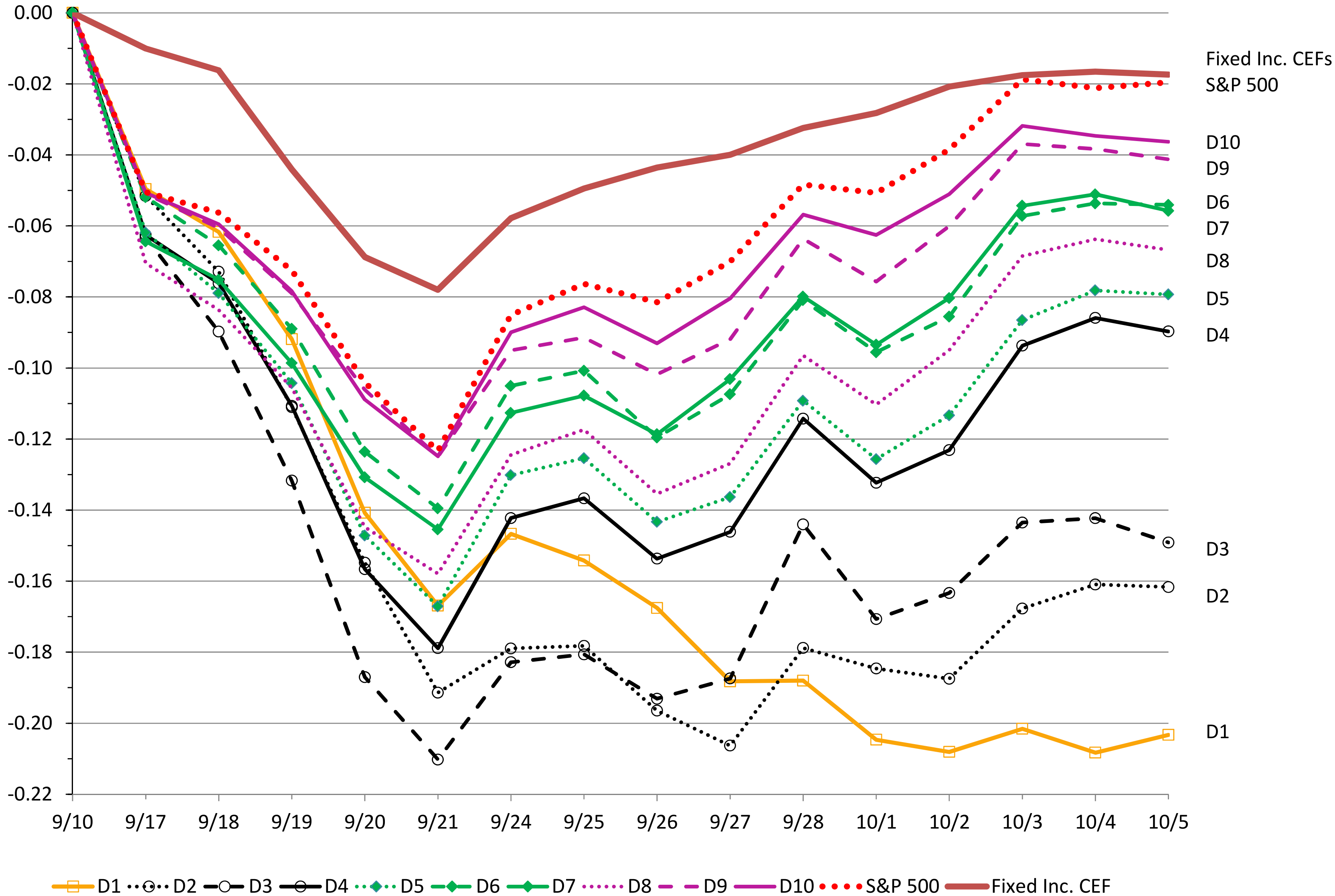

Fig. 1. Cumulative log price returns for ten market-capitalization-based deciles of 1,463 NYSE-listed stocks, the S&P 500 Stock Index, and 199 fixed-income closed-end funds over the September 10 through October 5, 2001 period. Decile partitions for common stocks (D1-D10) are based on market capitalizations as of September 10, 2001.

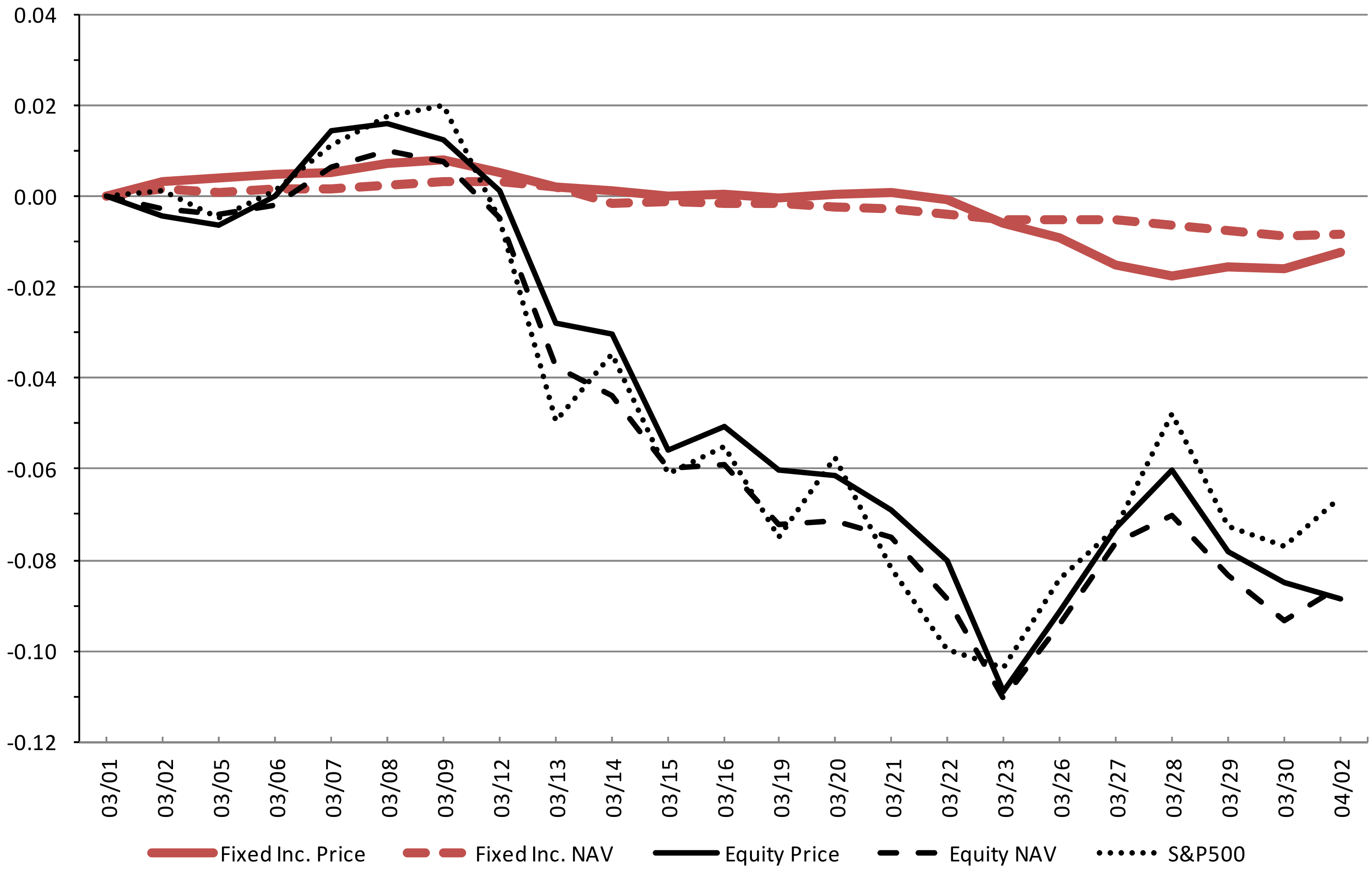

Fig. 2. Cumulative log price returns and cumulative log NAV return for 199 fixed-income funds and 59 equity closed-end funds, and cumulative price returns for the S&P 500 Stock Index, during March 2001.

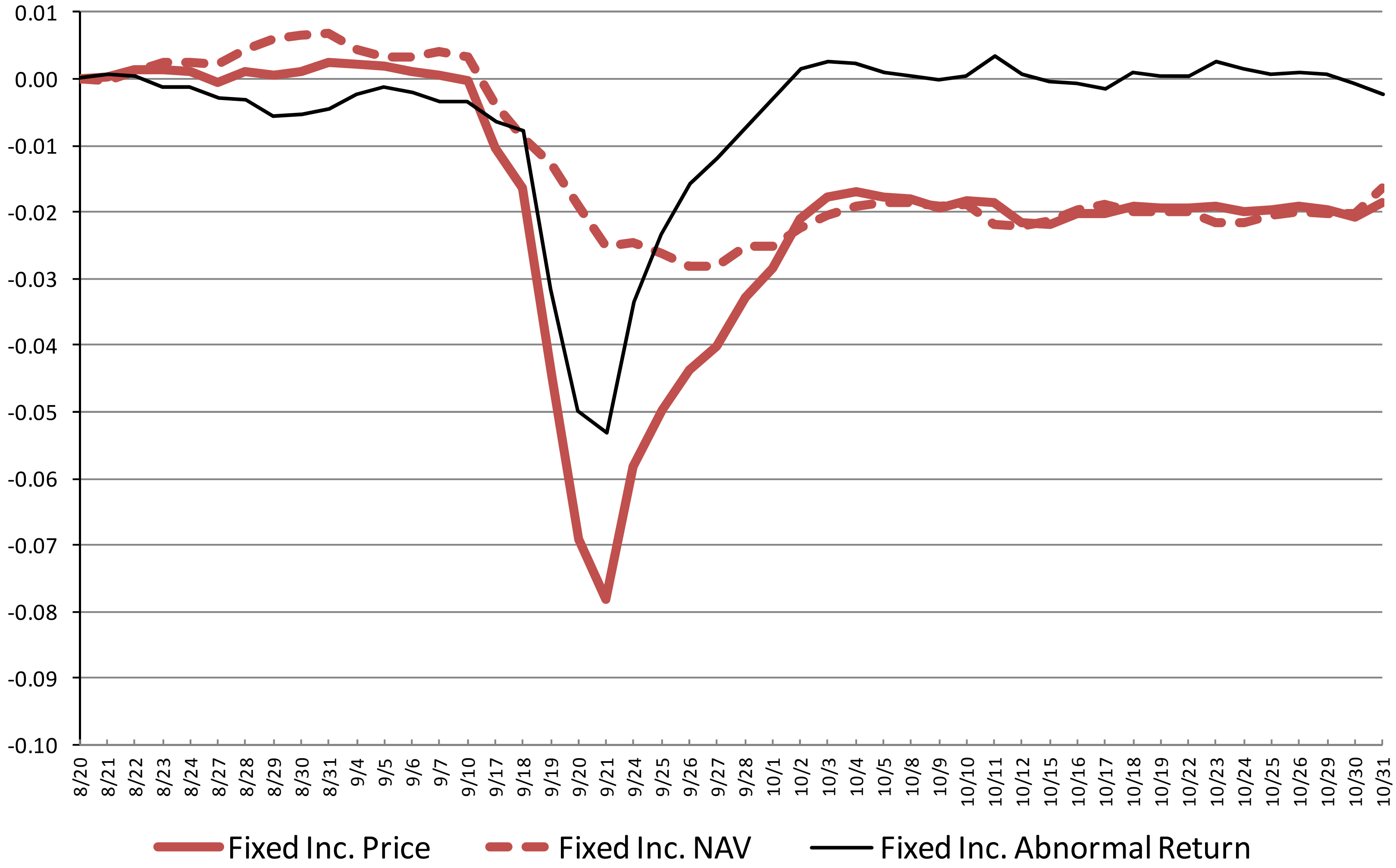

Fig. 3. Cumulative log price returns, cumulative log NAV returns, and cumulative abnormal returns (log price returns minus log NAV returns) for 199 fixed-income funds during August 20, 2001 and October 31, 2001.