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Should Investors Follow the Prophets or the Bears? Evidence on the Use of Public Information by Analysts and Short Sellers

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ABSTRACT: We investigate whether short sellers and analysts differ in their use of information that is predictive of future returns. We find that short interest is significantly associated in the expected direction with all 11 variables examined. In contrast, analysts tend to positively recommend stocks with high growth, high accruals, and low book-to-market ratios, despite these variables having a negative association with future returns. We then investigate the profitability of using short interest in trading. We find abnormal returns (1.11 percent per month) from a zero-investment strategy that (1) shorts firms with highly favorable analyst recommendations (buy signal) but high short interest (sell signal), and (2) buys firms with highly unfavorable analyst recommendations (sell signal) but low short interest (buy signal). Short interest, therefore, appears to capture predictive information that can be used by investors in trading against analysts' recommendations to increase returns.

Keywords: *short interest; analyst recommendations; fundamental analysis; arbitrage*.

Data Availability: *Data are available from the sources identified in the study.*

I. INTRODUCTION

Academic research provides extensive evidence that fundamental analysis can be used to earn abnormal returns (e.g., Frankel and Lee 1998; Piotroski 2000; Swanson et al. 2003). This evidence suggests there is a delay in the price discovery process, which has spawned research into the roles that financial analysts play in this delay (Bradshaw et al. 2001; Jegadeesh

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et al. 2004, hereafter JKKL; Bradshaw 2004; Barniv et al. 2009). Analysts' recommendations are the end-product from an extensive analysis of information, and they affect market prices by stating a specific course of action that an investor should take (Asquith et al. 2005a; Malmendier and Shanthikumar 2007). JKKL 2004 provide evidence, however, that analysts' recommendations are positively associated with some accounting, valuation, and growth characteristics that have a *negative* association with future returns (e.g., low book-to-market, high sales growth, and high accruals). Analysts' incentives to obtain investment banking business and to generate trading commissions are potential explanations for why they tend to over-recommend these stocks (Lin and McNichols 1998; Barber et al. 2007) and, indirectly, why analysts might contribute to a delay in price discovery.

Our study investigates how short sellers use publicly available information. Short sellers are regarded as particularly sophisticated investors under financial economic theory.[1] Similar to analysts, short sellers invest considerable time and resources in analyzing companies, but they face potentially different incentives. Because short sellers place their own capital at risk, they have strong incentives to fully use predictive information. Research on short sellers' use of fundamental information is limited, but Dechow et al. (2001) find that short sellers use fundamentals-to-valuation ratios to identify stocks that are expected to realize negative future returns. We extend Dechow et al. (2001) by investigating how short sellers utilize 11 items of fundamental information identified by JKKL that are predictive of future returns. We also conduct the JKKL analysis of analyst recommendations for our sample to allow a direct comparison of information use by analysts and short sellers. Our investigation provides further evidence on the role of short sellers in capital markets and their ability to interpret publicly available information. While financial analysts are acknowledged for their information intermediary role, we investigate the possibility that short sellers can also serve as an information intermediary and thereby facilitate the price discovery process.

Following the JKKL analysis of analysts' information use, we rank firms into quintile portfolios based on the consensus analyst recommendation. In a corresponding manner, we rank firms into quintile portfolios by the level of short interest to reflect short seller beliefs about future returns. We then employ ordered logistic regression to examine how analysts and short sellers use the company-specific predictive information. We categorize the information into four general types: accounting, valuation, growth, and momentum. We find that short interest is strongly associated with all 11 information items in the direction consistent with their empirical relation to future returns. This result indicates that short sellers are highly informed about how company-specific information is likely to affect future returns. In contrast, we confirm results in JKKL that analysts tend to positively recommend stocks with high growth, high accruals, and low book-to-market ratios, despite these variables having a negative association with future returns. When we examine recommendation revisions, we find similar evidence.

Our finding that short sellers interpret information properly as it relates to future returns supports an information intermediary role for short sellers. Consistent with this role, the SEC (1999, 3) observes that short sellers can "add to stock pricing efficiency because their transactions *inform the market* of their evaluation of future stock price performance" (emphasis added). Pownall and Simko (2005) provide evidence that short sellers can serve as information intermediaries when analyst following for a firm is low. In this situation, there are limited alternative

[1] Diamond and Verrecchia (1987) argue that only informed traders with strong beliefs that stock prices will fall in the near-term will choose to sell stock short. Their reasoning is based on the notion that the high costs of short selling drives out uninformed traders, so that open short positions reflect trades by more informed investors. Boehmer et al. (2008, 491) comment that short sellers "occupy an exalted place in the pantheon of investors as rational, informed market participants who act to keep prices in line."

sources of guidance. Our tests of information use suggest that short sellers can fill a complementary information intermediary role even when coverage by analysts is extensive.[2]

To provide further evidence on short sellers' effectiveness as information intermediaries, we test whether short interest provides value-relevant information about future returns *beyond* that provided by analyst recommendations and the 11 predictive variables. Short positions could provide incremental information because short sellers have sources of information not considered in our models or because they adjust the weights they place on items of information as market conditions change. In a regression model explaining future six-month returns adjusted for characteristic-based portfolio returns (Daniel et al. 1997), we find that the coefficient on short interest is negative (as predicted) and statistically significant after controlling for the information in analyst recommendations and the 11 predictive variables. These results indicate that short interest provides incremental information about future abnormal returns that is orthogonal to the information provided by analysts and the 11 predictive variables. In addition, the significant negative coefficient on the consensus analyst recommendation indicates that more favorable recommendations result in *lower* future returns after controlling for open short interest and the 11 predictive variables. If we consider recommendation revisions, then its coefficient is insignificant and the coefficient on short interest remains negative and significant.

Our analyses and the evidence from JKKL indicate that analysts sometimes provide favorable (unfavorable) recommendations for stocks with characteristics that are associated with negative (positive) future equity returns. Since analyst recommendations influence trading decisions and stock prices (Asquith et al. 2005a; Malmendier and Shanthikumar 2007), their recommendations can provide support for stock prices that have temporarily deviated from their fundamental values. We investigate if short interest can be used to identify such stocks. That is, we examine if investors can use short interest together with analyst recommendations to construct a portfolio that is likely to earn abnormal future returns. To our knowledge, ours is the first study to link these two investment signals—both from highly regarded capital market participants—to forecast future long-run returns.

We use a large sample of monthly observations over the period 1994 to 2006 to test alternative trading strategies. We first construct quintile portfolios based on the consensus analyst recommendation and then examine abnormal returns from a trading strategy that invests long (short) in firms comprising the best (worst) recommendation quintile. We find that the hedge return is modestly *negative* at −26 basis points per month for our test period. This result is perhaps surprising given the high esteem placed on financial analysts within the financial community, but it is consistent with our results on information use and the growing literature that questions the investment value of analyst recommendations (Demirakos et al. 2004; Bradshaw 2004; Barniv et al. 2009). We employ the same sorting procedure to form investment portfolios based on levels of short interest, and we obtain a statistically significant hedge return of 56 basis points per month from selling short firms in the highest short interest quintile and buying firms in the lowest quintile. Interestingly, the monthly returns from buying stocks with low short interest (29 basis points) are similar to the returns from selling short stocks with high short interest (27 basis points).

[2] Note that analysts also provide earnings forecasts, price targets, and narrative discussion that can be informative to investors—possibly more informative than their recommendations.

Concurrent research by Boehmer et al. (2010) also finds that significant abnormal returns can be earned by buying stocks with low short interest.[3]

We next examine whether abnormal returns can be improved by using information from both analysts and short sellers. Here, we intersect the analyst recommendation and short interest quintiles to produce 25 portfolios (5 × 5) formed using information from both signals. We find that monthly abnormal returns are insignificant for portfolios containing stocks about which analysts and short sellers strongly concur (e.g., least favorable recommendation and high short interest, or most favorable recommendation and low short interest). In contrast, returns are highly significant for portfolios of stocks in which they strongly conflict, if we trade consistent with the short sellers. Specifically, we find that an investor would obtain an average monthly abnormal return of 111 basis points from a zero-investment strategy that (1) invests long in firms with the worst recommendations (sell signal) but the lowest short interest levels (buy signal), and (2) invests short in firms with the best recommendations (buy signal) but the highest short interest levels (sell signal). The monthly abnormal return from this strategy is statistically significant in each sub-period, ranging from 71 basis points in 2004–2006 to 130 basis points in 1999–2003. Our dual-signal approach, therefore, provides the most investment value during the volatile 1999–2003 sub-period. By comparison, following analyst recommendations would cause investors to experience sizable losses over this sub-period, and the returns to trading on short interest in isolation would be statistically insignificant.

Our study contributes to our understanding of short sellers by (1) documenting their efficient use of a number of predictive variables discussed in the academic literature, (2) showing that open short positions are incrementally useful in predicting future returns after controlling for those predictive variables, and (3) showing that the returns to mimicking the trading of short sellers are much larger when conditioned on conflicting analyst recommendations. Collectively, these findings provide a more complete picture of how short sellers influence equity price formation and should be of interest to academics, investors, and regulators. This topic has assumed considerable importance due to the alleged role of short selling in the dramatic decline in stock prices that began with the 2008 credit crisis (Boehmer et al. 2009). Academics are also likely to be interested in the implications of our empirical results for Miller's (1977) theory that binding short sale constraints cause pessimists to be under-represented in price formation, leading to overvaluation when a strong divergence of opinion exists about a stock. Our evidence shows that short sellers are under-represented in price formation whenever they disagree with analysts, regardless of whether they are the optimists or the pessimists.

Section II describes the selection of our sample. In Section III, we investigate the relation of short interest and analyst recommendations with information that has been shown by prior research to predict future returns. Section IV presents returns from trading strategies that use analyst recommendations, short interest, or both of these signals together. This section also reports the results of several robustness tests. We discuss our results and conclude in Section V.

II. SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

To perform our analysis, we require time-series data on analyst recommendations, open short positions, the 11 predictor variables, and stock returns. We obtain analyst recommendations from

[3] This finding complements earlier studies that find that stocks with high short interest have significant negative abnormal returns (e.g., Asquith and Meulbroek 1995; Asquith et al. 2005b; Desai et al. 2002). Notably, abnormal returns from trading on high short interest are not necessarily indicative of market inefficiency due to limits to arbitrage. In contrast, the finding that stocks with low short interest have significant positive returns is clearly inconsistent with market efficiency since buy-and-hold strategies are not subject to similar constraints (see Boehmer et al. [2010] for further discussion).

the Thompson Financial I/B/E/S Recommendations database. Beginning in late 1993, I/B/E/S provides analyst recommendations for a wide cross-section of firms. I/B/E/S codes recommendations into five ordered categories: strong buy = 1; buy = 2; hold = 3; sell = 4; and strong sell = 5. For analyses using recommendations, we reverse this coding (i.e., strong buy = 5; strong sell = 1) to allow for a more intuitive interpretation of our results. Each month, we calculate the consensus recommendation level (*Rec*) as the mean of all outstanding recommendations issued a maximum of 12 months prior to month-end.[4] We use only the most recent individual analyst recommendation in the calculation. We also require that the individual analyst recommendations be issued on or before the I/B/E/S consensus recommendation date.[5]

In the first set of analyses, we conduct separate tests of analysts' and short sellers' use of information that is predictive of future returns. We perform these tests using analyst recommendations and short interest as of the last month in each calendar quarter, consistent with JKKL.[6] We include recommendation revisions in these analyses, given that prior research finds that recommendation revisions might be better indicators of future stock price performance than recommendation levels (Womack 1996; JKKL; Barber et al. 2010). We calculate recommendation revisions as the change in recommendation levels from calendar quarter $t-1$ to quarter t (i.e., consecutive quarters). An increase (decrease) in the consensus recommendation indicates an upgrade (downgrade) in the stock relative to the previous calendar quarter $t-1$.[7]

We obtain short interest data to correspond with our analyst recommendations sample period. The Compustat Monthly Securities Database contains monthly short interest for all firms listed on U.S. exchanges beginning in 2003. For earlier years, we purchased monthly short interest data directly from the NYSE, AMEX, and NASDAQ exchanges, and from an online independent vendor.[8] The stock exchanges report open short positions using the 15th of each calendar month as the settlement date (or the last business day before the 15th). We scale short interest by the number of shares outstanding as reported by CRSP and label the resulting ratio as *SIratio*, which is standard in the literature (e.g., Dechow et al. 2001; Asquith et al. 2005b; Pownall and Simko 2005).[9]

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4 This requirement helps alleviate concerns that our results are being unduly influenced by stale recommendations, and it is similar to the measure used by JKKL. Thompson Financial claims that recommendations not updated for 180 days are excluded from the I/B/E/S consensus recommendation (see Thompson Financial 2009,11); however, we are uncertain as to how long this policy has been in place. Given our long sample period, we follow procedures implemented in prior research.

5 More specifically, I/B/E/S calculates the consensus recommendation on the Thursday before the third Friday of every month (ranging from the 14th to the 20th day of the month). The requirement of excluding recommendations that are issued after this date results in an average delay of 13.7 days between the time when the consensus recommendation is calculated and the beginning of the returns accumulation period. This methodology serves two purposes. First, short interest data are made publicly available mid-month and therefore, both signals—recommendations and short interest—are obtained at approximately the same time during the month. Second, the delay ensures that investors are given ample time to process and impound in price whatever new information is contained in both signals. Thus, we purposely exclude from our tests any drift in stock prices that occurs due to the public disclosure of the signal. In this manner, our methodology differs markedly from the daily rebalancing requirements employed in papers such as Barber et al. (2001) and Barber et al. (2010).

6 Performing these analyses using quarterly data is intuitive given that the majority of the predictor variables (seven of the 11) change on a quarterly basis as financial information is disclosed. We find that all inferences are the same when we perform the analyses using monthly data.

7 Ljungqvist et al. (2009) provide evidence that the I/B/E/S recommendations database contains systematic errors in the pre-2007 files that is likely to overstate the investment value of analysts' recommendations. Our study is among the first to re-examine the investment value of analysts' recommendations using the cleaned 2007 database.

8 Data from the online vendor, shortsqueeze.com, provide less than 1 percent of the total observations. The data cover a period in which we were unable to obtain short interest directly from the NASDAQ. We compared shortsqueeze.com data to that from a six-month period for which we already had short interest data from NASDAQ. The only differences were due to shortsqueeze.com rounding their data to the nearest hundredth place.

9 In the "Robustness Tests" section, we examine the sensitivity of our results to deflating by lagged trading volume.

Similar to JKKL, we select a set of 11 predictor variables for our analysis and winsorize each of the predictor variables at the 2.5 and 97.5 percentiles to control for outliers. We group the predictor variables into one of four classifications based on the nature of the variable (see the Appendix for details on the calculation of each variable). The first group, labeled *Accounting*, consists of earnings surprise (*SUE*), total accruals (*TACCR*), and capital expenditures (*CAPEX*). The *Valuation* group consists of the market-value-of-equity (*MVE*), earnings-to-price ratio (*EP*), book-to-market ratio (*BTM*), and the average daily stock turnover (*TURN*). The *Growth* group consists of realized sales growth (*SG*) and forecasted long-term growth (*LTG*). The fourth group, *Momentum*, consists of earnings forecast revision (*FREV*) and price momentum (*MOM*). These variables have been shown in prior research to be associated with future returns (see the Appendix for specific citations). Thus, we expect that sophisticated capital market participants, such as analysts and short sellers, would use information embedded in these variables when establishing their positions.

Finally, we obtain monthly returns data from CRSP to compute future six-month buy-and-hold abnormal returns (*ARET6*) using characteristic portfolio-matching.[10] Specifically, we define abnormal returns as the raw buy-and-hold return adjusted for the portfolio return from 125 benchmark portfolios formed based on size, book-to-market, and momentum ($5 \times 5 \times 5$), as described in Daniel et al. (1997). We use a holding period of six months for consistency with JKKL, but test the sensitivity of our results to alternative holding periods as a supplemental analysis.

Our final sample, resulting from the intersection of Compustat, CRSP, I/B/E/S, and our short interest database, consists of 80,674 firm-quarter observations over the 52 calendar quarters from 1994 to 2006. For our main analyses, we rank firms into quintile portfolios based on analyst recommendations (both levels and changes) and short interest in each calendar quarter *t*. Thus, we rebalance the portfolios quarterly. For recommendation changes, we ensure that firms without a recommendation revision are included in the middle quintile.

Table 1, Panel A presents descriptive statistics for the variables used in our analyses. The mean (median) value for *Rec* of 3.76 (3.79) indicates that the average analyst recommendation is only moderately less than a "buy" (which would be coded 4). A narrow interquartile range of 0.34 (−0.20 to 0.14) for the consensus recommendation change, *ChgRec*, shows that analyst recommendations are generally sticky. Nevertheless, the minimum and maximum values for *ChgRec* indicate that analysts occasionally downgrade a stock all the way from strong buy to strong sell, and *vice versa*. The mean short interest ratio, *SIratio*, is 3.2 percent, which is considerably larger than the median of 1.8 (due to some large values, as indicated by the maximum of 23.5 percent). The mean six-month abnormal return (*Aret6*) is 1.0 percent, but the median is only −1.9 percent.

With respect to the 11 predictor variables, we find that earnings surprise (*SUE*) has a mean of zero but a slightly positive median of 0.002, consistent with most firms reporting earnings that meet or beat the current analyst forecast. Total accruals (*TACCR*) are negative, on average, due to deducting depreciation. Capital expenditures (*CAPEX*) average approximately 6.3 percent of assets. We find that firm size (*MVE*) is highly skewed, with a mean of $3,578 compared to a median of $775 (in millions). The average earnings-to-price ratio (*EP*) is only 2.0 percent due to some negative values (median 4.3 percent). The book-to-market ratio (*BTM*) has a mean of 0.50 (median 0.42), consistent with prior research. Approximately 0.58 percent of a firm's shares turn over on any given day (*TURN*). Realized sales growth (*SG*) averages 17 percent, and analysts' long-term earnings growth forecasts (*LTG*) average 17.55 percent. Analysts' forecast revisions (*FREV*) have

[10] If a firm delists during the return accumulation period, we compound the delisting return with the buy-and-hold return and assume the liquidating proceeds are reinvested in a portfolio that earns a normal return for the remainder of the period.

TABLE 1
Descriptive Statistics

Panel A: Summary Statistics for Dependent and Explanatory Variables

Variable	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Rec	3.76	0.62	1.00	3.33	3.79	4.17	5.00
ChgRec	−0.03	0.42	−4.00	−0.20	0.00	0.14	4.00
SIratio	3.2%	3.8%	0.0%	0.6%	1.8%	4.2%	23.5%
Aret6	0.010	0.371	−1.000	−0.177	−0.019	0.144	12.525
SUE	0.000	0.029	−0.237	−0.004	0.002	0.006	0.312
TACCR	−0.012	0.035	−0.151	−0.028	−0.011	0.005	0.092
CAPEX	0.063	0.061	0.000	0.022	0.045	0.082	0.341
MVE	3,578	8,421	26	255	775	2,512	65,417
EP	0.020	0.118	−1.553	0.016	0.043	0.065	0.214
BTM	0.500	0.343	0.045	0.262	0.424	0.648	2.647
TURN	0.582	0.273	0.000	0.364	0.614	0.819	1.000
SG	1.17	0.26	0.47	1.02	1.11	1.25	2.35
LTG	17.55	8.02	4.25	12.00	15.44	21.07	55.00
FREV	0.000	0.029	−0.163	−0.005	0.002	0.010	0.219
MOM	0.084	0.421	−0.995	−0.125	0.047	0.228	27.827

Panel B: Analyst Recommendations and Short Interest Values by Calendar Year

Year	n	Mean *Rec*	Mean *SIratio*	Returns for S&P 500
1994	4,319	3.74	1.6%	1.3%
1995	4,586	3.76	1.7%	37.6%
1996	5,046	3.83	1.8%	23.0%
1997	5,554	3.89	2.2%	33.4%
1998	6,021	3.90	2.3%	28.6%
1999	6,514	3.93	1.9%	21.0%
2000	6,099	4.00	2.0%	−9.1%
2001	5,772	3.87	2.9%	−11.9%
2002	6,559	3.73	3.6%	−22.1%
2003	7,403	3.52	4.0%	28.7%

(continued on next page)

Panel B: Analyst Recommendations and Short Interest Values by Calendar Year

Year	**n**	**Mean *Rec***	**Mean *SIratio***	**Returns for S&P 500**
2004	7,686	3.65	4.0%	10.9%
2005	7,663	3.61	4.6%	4.9%
2006	7,452	3.63	5.7%	15.8%
Full Sample	80,674	3.76	3.2%	12.5%

The sample consists of 80,674 firm-quarter observations during the period 1994–2006. See the Appendix for a more detailed description of how each variable is calculated.

Variable Definitions:

Rec = consensus analyst recommendation in the last month of the calendar quarter, where 5 = strong buy, 4 = buy, 3 = hold, 2 = sell, and 1 = strong sell. We calculate *Rec* as the mean of all outstanding recommendations issued a maximum of 12 months prior to month-end. In calculating means, we use only the most recent individual analyst recommendation issued on or before the I/B/E/S consensus recommendation date;
ChgRec = change in the consensus analyst recommendation from the previous quarter;
SIratio = number of shares sold short as reported for the last month of the calendar quarter divided by the number of shares outstanding as of the same date;
Aret6 = six-month abnormal return (adjusted for firm size, book-to-market ratio, and past returns) beginning the first day of quarter $t+1$;
SUE = seasonally adjusted earnings change scaled by price for fiscal quarter q;
TACCR = total accruals scaled by average assets measured at the end of fiscal quarter q;
CAPEX = rolling sum of the preceding four quarters of capital expenditures ending at fiscal quarter q divided by total assets;
MVE = market value of equity at the end of fiscal quarter q;
EP = ratio of the rolling sum of earnings over the preceding four quarters to price at the end of fiscal quarter q;
BTM = ratio of book value of equity to market value of equity as of the end of fiscal quarter q;
TURN = average daily volume per share over the preceding six months;
SG = rolling sum of sales growth over the preceding four fiscal quarters;
LTG = consensus long-term earnings growth forecast at the end of calendar quarter t;
FREV = rolling sum of the preceding six-month earnings forecast revisions scaled by price; and
MOM = price momentum, measured as the six-month raw return ending one month prior to the end of the fiscal quarter q.

a mean of zero but a slightly positive median of 0.002. Price momentum (*MOM*) averages 8.4 percent for the preceding six months (median 4.7 percent).

Table 1, Panel B reports mean analyst recommendations, short interest, and market returns (using the S&P 500 portfolio) for each year from 1994 to 2006. From 1994 to 2000, we observe a monotonic increase in the average analyst recommendation, which peaks at 4 in 2000. The average recommendation then declines in years 2001 through 2003, and remains at a lower level through the end of our test period. This shift corresponds with criticism of analysts that led to the Global Research Analysts Settlement, NASD 2711, and NYSE Rule 472. One line of criticism focused on analysts' conflicts of interest, including their incentive to maintain a positive relation with corporate managers in order to generate investment banking business and to obtain earnings guidance.

Table 1, Panel B also reports another noteworthy change over our test period. The mean level of short interest is around 2 percent from 1994 to 2000. The level then increases appreciably over the next six years, reaching 5.7 percent in the final year of our sample period. This shift, which corresponds with a dramatic increase in the number of hedge funds, increases the importance of research that furthers an understanding of the role of short selling in the price formation process. Note that shifts over time have a minimal effect on our results because we rank firms into quintiles based on their relative values at a given point in time.

III. PREDICTIVE INFORMATION USED BY ANALYSTS AND SHORT SELLERS

In this section, we first examine whether analyst recommendations and short interest incorporate fundamental and other information in the manner shown by prior research to be predictive of future returns. We then investigate whether analyst recommendations and short interest provide information that is incremental to that information.

Univariate Evidence

Table 2 presents mean values for each of the 11 predictive variables by quintile for recommendation levels, recommendation changes, and short interest levels. The quintiles correspond to portfolios that we later use in trading analyses. In Panel A, as we move down each column from the worst to the best recommendations, we find a monotonic (or near monotonic) increase for eight of the 11 variables. The increase for *SUE*, *EP*, *FREV*, and *MOM* is consistent with analyst recommendations properly incorporating the relation of these measures with future returns. In contrast, the increase for *TACCR*, *CAPEX*, *SG*, and *LTG* indicate that analysts misuse this information, which could cause more favorable recommendations to portend lower investment returns. The overall pattern of information use indicates that analysts tend to issue more favorable recommendations for glamour stocks, even though prior studies show that these stocks earn lower subsequent returns (Lakonishok et al. 1994; La Porta 1996; Sloan 1996; Beneish et al. 2001). Examining changes in recommendations, Panel B shows a clear pattern for only three variables; but in each case, the change is consistent with the relation of the information with future returns established in prior research. Specifically, as we move down the columns from downgrades to upgrades, we observe a monotonic increase for earnings forecast revisions (*FREV*) and stock price momentum (*MOM*), and a monotonic decrease for long-term growth (*LTG*). While prior research has generally found that recommendation revisions are better predictors of future returns than are recommendation levels, this analysis indicates that recommendation revisions fail to incorporate eight of the 11 items of predictive information. These results for recommendation levels and changes are similar to the results documented in JKKL.

Panel C of Table 2 provides the corresponding analysis for short interest quintiles. The book-to-market variable (*BTM*) decreases monotonically as the level of short interest increases, so short sellers tend to take greater positions in firms with a higher market value relative to their book

TABLE 2

Mean Values by Quintile for 11 Variables Associated with Future Returns

Panel A: Recommendation Levels

	QRec	n	*Rec*	*SUE*	*TACCR*	*CAPEX*	*MVE*	*EP*	*BTM*	*TURN*	*SG*	*LTG*	*FREV*	*MOM*
Worst	0.00	16,216	2.92	−0.005	−0.015	0.057	1,923	−0.010	0.659	0.523	1.082	15.16	−0.008	−0.014
	0.25	15,857	3.45	−0.002	−0.013	0.063	4,185	0.020	0.512	0.595	1.134	16.30	−0.002	0.041
	0.50	17,119	3.80	0.001	−0.012	0.065	4,716	0.029	0.468	0.586	1.164	17.42	0.001	0.088
	0.75	15,704	4.07	0.003	−0.010	0.065	4,763	0.031	0.417	0.621	1.212	18.75	0.004	0.139
Best	1.00	15,778	4.59	0.003	−0.009	0.065	2,256	0.031	0.443	0.584	1.237	20.20	0.006	0.171

Panel B: Recommendation Changes

	QChgRec	n	*ChgRec*	*SUE*	*TACCR*	*CAPEX*	*MVE*	*EP*	*BTM*	*TURN*	*SG*	*LTG*	*FREV*	*MOM*
Down	0.00	16,113	−0.18	0.000	−0.011	0.064	2,711	0.025	0.503	0.597	1.184	17.80	−0.004	0.026
	0.25	13,869	−0.05	0.000	−0.013	0.068	5,633	0.021	0.445	0.653	1.188	17.75	0.000	0.062
No	0.50	22,799	0.00	−0.001	−0.012	0.059	1,903	0.014	0.574	0.497	1.142	17.54	0.000	0.072
	0.75	11,690	0.04	0.001	−0.012	0.066	6,328	0.025	0.421	0.651	1.182	17.46	0.003	0.130
Up	1.00	16,070	0.15	0.001	−0.012	0.063	3,059	0.021	0.499	0.574	1.148	17.20	0.003	0.147

Panel C: Short Interest Levels

	QSIratio	n	*SIratio*	*SUE*	*TACCR*	*CAPEX*	*MVE*	*EP*	*BTM*	*TURN*	*SG*	*LTG*	*FREV*	*MOM*
Low	0.00	16,118	0.3%	0.000	−0.012	0.059	3,643	0.022	0.622	0.346	1.120	16.10	0.001	0.065
	0.25	16,144	1.1%	0.001	−0.012	0.059	5,287	0.028	0.501	0.492	1.129	15.77	0.001	0.083
	0.50	16,145	2.0%	0.000	−0.012	0.061	4,156	0.025	0.474	0.588	1.142	16.63	0.001	0.096
	0.75	16,144	3.5%	0.000	−0.012	0.065	2,972	0.018	0.459	0.686	1.177	18.28	0.000	0.094
High	1.00	16,123	8.9%	−0.001	−0.011	0.072	1,832	0.009	0.446	0.796	1.259	20.97	−0.002	0.083

The sample consists of 80,674 firm-quarter observations during the period 1994–2006. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated.

value. Three variables increase monotonically as the level of short interest increases: capital expenditures (*CAPEX*), stock turnover (*TURN*), and sales growth (*SG*). In each case, the pattern of information use is consistent with their relation to future returns documented in prior research. Comparing the high and low short interest quintiles for the other variables shows that short positions are generally consistent with how the variables map into future returns, but the relation is not monotonic.

Multivariate Evidence

We next use ordered logistical regression analysis to provide a multivariate test of the relation between analyst and short seller investment signals and the 11 predictor variables. In all regression analyses, we assess statistical significance using test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month (Petersen 2009; Gow et al. 2010). Table 3, Panel A reports results using analyst recommendations and recommendation revision quintiles as the dependent variable, with quintiles coded from 1 to 5.[11]

For recommendation levels, we find that analysts correctly incorporate the implications for future returns of only one of the *Accounting* variables: unexpected earnings (*SUE*). Analysts favorably recommend firms with high total accruals (*TACCR*), and do not consider capital expenditures (*CAPEX*), despite evidence that increases in those accounting measures are associated with lower future returns (Sloan 1996). Examining the *Valuation* measures, analysts correctly favor smaller firms (*LNMVE*) and those with a higher earnings-to-price ratio (*EP*). However, they also favor firms with a low book-to-market ratio (*BTM*) and high growth (*SG*, *LTG*), despite evidence that stock prices of such firms underperform the market. Examining the *Momentum* variables, analysts correctly favor firms with high earnings momentum (*FREV*) and stock price momentum (*MOM*).

The results for revisions in analysts' recommendations are reported on the right side of Table 3, Panel A. Examining the *Accounting* variables, we find that all three variables (*SUE*, *TACCR*, and *CAPEX*) are statistically significant, but with the unexpected sign. For the *Valuation* and *Growth* variables, the evidence is mixed: *EP* and *TURN* are statistically significant in the expected direction, but *BTM* is statistically significant in the unexpected direction. The coefficient on *LTG* is also significant in the unexpected direction. For the *Momentum* variables, we find that both *MOM* and *FREV* are statistically significant in the expected direction. Finally, we find that recommendation changes are negatively associated with past recommendation levels. This result makes intuitive sense because the highest (lowest) recommendations can only be revised down (up).

Considering the types of information used by analysts in both their recommendations and recommendation revisions, analysts' correctly favor stocks with positive price momentum (*MOM*), positive earnings momentum (*FREV*), and high earnings-to-price (*EP*). They incorrectly favor stocks with high forecasted growth (*LTG*), high accruals (*TACCR*), and low book-to-market value (*BTM*). Thus, financial analysts view higher past and future growth and higher accruals as positive features in recommending stocks, despite research that shows the opposite relation (Lakonishok et al. 1994; La Porta 1996; Sloan 1996). In addition, analysts also tend to issue more favorable recommendations for firms with low book-to-market ratios, even though prior research shows a positive association with subsequent returns (Fama and French 1992). This evidence indicates that

[11] Note that quintiles are of approximate equal size (after adjusting for ties and including all recommendation revisions of zero in the middle quintile). Due to the low frequency of strong sell and sell recommendations issued by analysts, the most unfavorable recommendation quintile contains some "hold" recommendations.

TABLE 3

Use of Predictive Information by Analysts and Short Sellers

Panel A: Explaining Recommendation Levels and Changes (Using Ordered Logistic Regression)

		Recommendation Levels		Recommendation Changes	
Variable	**Predict**	**Coefficient**	**Chi-Square**	**Coefficient**	**Chi-Square**
Accounting					
SUE	Pos	1.837	15.70***	−0.743	13.81***
TACCR	Neg	0.994	21.16***	0.424	4.52**
CAPEX	Neg	0.006	0.00	0.437	8.42***
Valuation					
LnMVE	Neg	−0.034	8.78***	0.008	1.34
EP	Pos	2.278	73.73***	0.564	20.31***
BTM	Pos	−0.714	119.05***	−0.170	31.79***
TURN	Neg	−0.032	0.17	−0.319	58.70***
Growth					
SG	Neg	0.781	213.28***	−0.015	0.15
LTG	Neg	0.041	202.87***	0.015	61.73***
Momentum					
FREV	Pos	8.254	115.68***	5.170	76.91***
MOM	Pos	0.473	33.60***	0.499	71.64***
LAG_QRec	Neg			−0.926	1052.85***
Pseudo R^2		0.138		0.098	

(continued on next page)

Panel B: Explaining Short Interest (Using Ordered Logistic Regression)

Variable	Predict	Short Interest Coefficient	Short Interest Chi-Square
Accounting			
SUE	Neg	−1.777	21.93***
TACCR	Pos	1.527	21.63***
CAPEX	Pos	1.974	32.66***
Valuation			
LnMVE	Pos	0.080	2.83*
EP	Neg	−0.698	18.04***
BTM	Neg	−0.245	14.46***
TURN	Pos	4.198	484.78***
Growth			
SG	Pos	0.410	45.46***
LTG	Pos	0.014	23.66***
Momentum			
FREV	Neg	−2.138	15.27***
MOM	Neg	−0.096	5.25**
Pseudo R^2		0.332	

*, **, *** Indicate statistical significance at the α = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test.

n = 80,674 firm-quarters.

This table reports estimation results when analysts' recommendation and short interest quintile assignments are regressed (using ordered Logit) on 11 variables shown to be predictive of future returns. We do not report the intercepts for parsimony. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. The "Predict" column reports the predicted relation between the explanatory variable and future returns as indicated in prior research. We report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

sell-side analysts tend to favorably recommend "glamour stocks." JKKL reached the same conclusion based on an analysis of an earlier time period.

Table 3, Panel B reports results from a model using short interest quintiles as the dependent variable. We find that all 11 variables are statistically significant with coefficient signs in the expected direction.[12] Additionally, we note that the explanatory power of this model (Panel B, pseudo $R^2 = 33.2$ percent) is more than double that for the model using recommendation levels (Panel A, pseudo R^2 of 13.8 percent) and more than triple that for the model using recommendation revisions (Panel A, pseudo R^2 of 9.8 percent).[13] Thus, consistent with our univariate analysis, we find that short interest is explained better by the predictive information in *Accounting*, *Valuation*, and *Growth* variables than is analyst recommendation levels or changes. Our evidence is consistent with other studies that examine the association between short interest and indicators of future returns (Dechow et al. 2001; Cao et al. 2007; Seybert and Wang 2009). Our study extends this research by employing several predictive variables simultaneously in the same regression model, and by comparing results for short sellers to those for analysts.

Incremental Information About Future Returns

In this section, we investigate whether recommendations, recommendation changes, and short interest contain incremental information about future returns, beyond the information in the 11 predictive variables. Using the methodology in JKKL, we convert the continuous predictor variables into binary signals based on a median split. For all variables where the expected relation with future returns is positive (negative), the binary variable is coded 1 when its value is greater (less) than its median for a given quarter, and 0 otherwise. Thus, we expect a positive coefficient on all predictor variables.

Table 4 presents the results from our analysis. The model on the left includes both recommendation level quintiles (*QRec*) and short interest quintiles (*QSIratio*). Each of these quintiles is scaled to range from 0 to 1 to facilitate interpretation of coefficients. The coefficient on *QRec* indicates that analysts' recommendations are incrementally informative about future abnormal returns, but the coefficient is negative. This result suggests that buy-and-hold investors would do better to trade against the consensus analyst recommendation. In contrast, the coefficient on *QSIratio* is significantly negative, indicating that short interest provides incremental information for predicting future returns even after controlling for the information contained in the 11 predictor variables. The negative sign indicates that, as would be expected, a higher (lower) level of short interest is associated with lower (higher) future abnormal returns. The coefficient magnitude for *QSIratio* of -0.029 can be interpreted as the six-month return earned on an investment portfolio that is formed optimally to exploit the information in short interest that is orthogonal to the information in analysts' recommendations and the predictive variables. Thus, while short sellers use the information contained in the investment signals (as indicated by the significant associations reported in Table 3), the results in Table 4 show that short sellers also develop information to predict future returns that goes beyond what is contained in those variables. Examining the predictor variables, we find significant coefficients in the expected direction for *TACCR*, *SG*, and *FREV*.[14]

[12] Note that the explanatory variables have the opposite predicted sign in the short interest model (compared to the recommendation models).

[13] Since the dependent variables differ across models, it is not possible to test for differences in explanatory power. However, given that we have standardized the dependent variables by ranking them into quintiles, their variation is similar. Specifically, the standard deviations of the quintile ranking of analyst levels, analyst changes, and short interest are 1.41, 1.38, and 1.41, respectively. Thus, we believe a comparison of pseudo R^2s is informative.

[14] The coefficient for *TURN* is marginally significant with the wrong sign. This appears to be driven by its high correlation with short interest (greater than 50 percent). When *QSIratio* is excluded from the model, the coefficient for *TURN* is not

TABLE 4

Incremental Information about Future Returns Provided by Recommendations, Recommendation Revisions, and Short Interest

Variable	Recommendations and Short Interest		Recommendation Changes and Short Interest	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**
Intercept	0.009	0.70	−0.003	−0.31
QRec	−0.019	−2.55**		
QChgRec			0.003	0.59
QSIratio	−0.029	−3.91***	−0.027	−3.77***
DSUE	0.004	0.79	0.003	0.63
DTACCR	0.025	7.10***	0.025	7.23***
DCAPEX	0.004	0.75	0.004	0.72
DLnMVE	0.003	0.72	0.003	0.68
DEP	−0.003	−0.45	−0.004	−0.54
DBTM	0.005	0.93	0.007	1.19
DTURN	−0.012	−1.85*	−0.012	−1.80*
DSG	0.015	2.43**	0.016	2.66***
DLTG	−0.009	−1.08	−0.007	−0.85
DFREV	0.011	2.05**	0.009	1.75*
DMOM	0.009	1.13	0.007	0.94
Adj-R^2	0.003		0.003	

*, **, *** Indicate statistical significance at the α = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test.

n = 80,674 firm-quarters.

This table reports estimation results when future six-month abnormal returns (calculated as in Daniel et al. [1997]) are regressed on analysts' recommendations and short interest data along with 11 variables that prior research shows to be predictive of future returns. *QRec* is the quintile assignment based on recommendation levels. *QChgRec* is the quintile assignment based on recommendation revisions. *QSIratio* is the quintile assignment based on short interest. *QRec, QChgRec,* and *QSIratio* are scaled to range between 0 and 1 (0.00, 0.25, 0.50, 0.75, 1.00) to facilitate the interpretation of the coefficients. Using the methodology in Jegadeesh et al. (2004), we convert the continuous predictor variables into binary signals based on a median split. For all variables where the expected relation with future returns is positive (negative), the binary variable is coded 1 when its value is greater (less) than its median for a given quarter, and 0 otherwise. See Table 1 for descriptions of each variable, and the Appendix for detailed explanations of how each variable is calculated. We report test statistics based on standard errors that are adjusted for two-way clustering of residuals by firm and calendar month.

The model on the right side of Table 4 provides a similar analysis for recommendation revision quintiles (*QChgRec*) and short interest (*QSIratio*) quintiles. The coefficient on *QChgRec* is positive as expected, but is not significantly different from zero, suggesting that recommendation revisions do not provide information about future returns that is incremental to short interest and to the other publicly available investment signals. The coefficient on *QSIratio* is again significantly negative. The coefficients and significance levels for the predictor variables are similar to those reported in the recommendation level regressions.[15]

statistically significant (t-stat = −0.52). In contrast, *QSIratio* remains highly significant when *TURN* is excluded from the model.

15 We also estimated a regression equation that includes *QRec*, *QChgRec*, and *QSIratio* together with the other 11 predictive variables. Results from this regression are qualitatively equivalent to what is reported in Table 4, except that

We draw the following general conclusions from the results presented in Table 3 and Table 4. First, analysts' recommendations do a poor job of incorporating information about future returns provided by the predictor variables, and buy-and-hold investors would actually do better by trading against analyst recommendations. Second, analyst recommendation revisions also do a poor job of using predictive information, and they do not contribute information beyond what is contained in the predictor variables and short interest. Third, short sellers correctly incorporate publicly available information that is predictive of future returns and, furthermore, short sellers are able to generate information that is orthogonal to the set of predictive variables we use in our analysis. In the next section, we explore the success of trading strategies that are designed to exploit the above results.

IV. INVESTMENT PERFORMANCE BASED ON ANALYST RECOMMENDATIONS AND SHORT INTEREST

The results reported in Section III suggest that investors might improve their returns by using short interest as a supplementary investment signal. Indeed, many of the associations between analyst recommendations and variables that are predictive of future returns suggest that analysts might actually impede the price discovery process. Pownall and Simko (2005) provide evidence that short positions can help to fill an information intermediary gap for companies with low analyst following. Our results suggest that short interest can be used as an information signal for investors, regardless of the analyst following. The benefit of short interest is likely to be greatest when this signal contradicts the signal from analysts' recommendations. Specifically, the results in Table 4 suggest that investors would profit from a buy-and-hold strategy that (1) trades against analyst recommendation levels and (2) trades with short interest. This conjecture is based on the signs of the statistically significant coefficients for analyst recommendations and short interest in Table 4.[16]

The trading strategies we consider are implementable and follow the portfolio construction methodology outlined in Jegadeesh and Titman (1993).[17] Under this methodology, the strategies hold a series of sub-portfolios that formed in the current month and in each of the previous five months (six-month holding period).[18] Thus, we simulate a portfolio where a 1/6 fraction of the stocks are reassigned to portfolios each month. We rebalance the portfolios monthly to maintain equal weights on each security and calculate the mean abnormal return for each portfolio. This results in a time-series of monthly portfolio returns that is free of overlapping return accumulation periods. As discussed in further detail below, we also calculate hedge portfolio returns that go long and short in particular portfolios.

Since the consensus analyst recommendation and the short interest ratio change each month, each portfolio is based on information from analysts and/or short sellers from the current month and from each of the past five months. In our initial tests, we examine the signals from analysts or short sellers separately. We then combine recommendations and short interest to develop a trading strategy that exploits the information contained in both signals. When combining the signals, we intersect the analyst recommendation and short interest quintiles to produce 25 portfolios (5×5).

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the coefficient on *QChgRec* becomes marginally significantly positive.

16 In this section, we do not report trading strategies that use recommendation revisions because results from these tests are generally consistent with our earlier analyses that show they contain no incremental information about future returns beyond short interest.

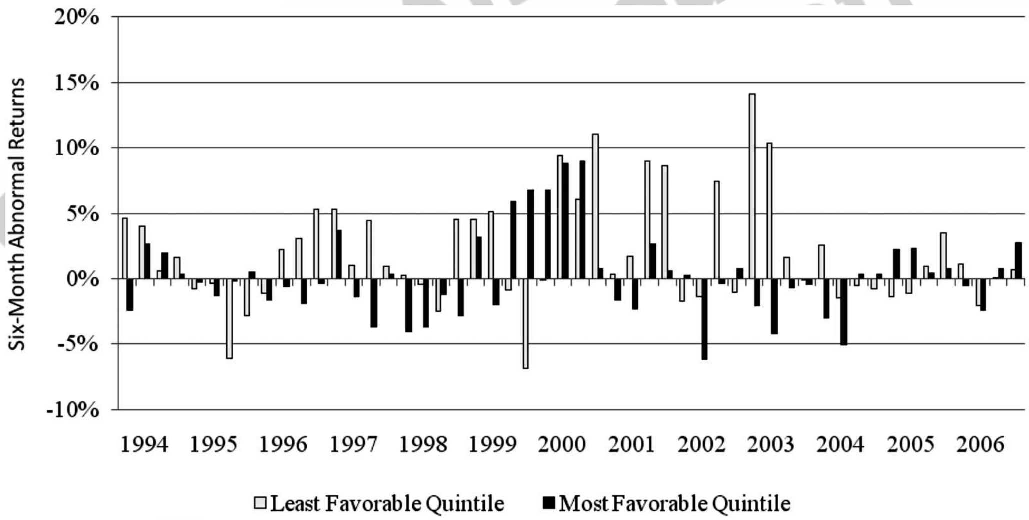
17 The Jegadeesh and Titman (1993) methodology avoids statistical problems associated with serial correlation induced by overlapping return accumulation periods. We thank an anonymous reviewer for suggesting this approach.

18 In a later section, we discuss the sensitivity of the results to a shorter return window of one month and the use of a four-factor model, which controls for the Fama-French risk factors and momentum.

We form our portfolios using all firm-month observations with available data for analyst recommendations, short interest levels, and stock returns. Thus, we drop the requirement that data are available for the 11 predictor variables, and we include every month (not just the last month of each quarter, as in our first set of analyses). These changes increase the sample size to 564,101 firm-month observations and, as a result, increase the extent to which we can generalize results.[19] We report results for the full time period, 1994 to 2006, and for three sub-periods because documenting the stability of abnormal returns to a particular trading strategy over time is critical to the evaluation of the strategy. The first sub-period consists of the five-year period from 1994 to 1998, which overlaps the 1985 to 1998 time period investigated by JKKL, and corresponds to a strong bull market. The second sub-period consists of the subsequent five years, from 1999 to 2003, which includes the precipitous decline in the NASDAQ index, the adoption of Regulation Fair Disclosure, and the Global Settlement agreement reached between the SEC, NASD, NYSE, and ten of the largest investment firms. The final sub-period consists of the most recent years in our sample, 2004 to 2006.

In Figure 1, we display six-month abnormal quarterly returns over the full test period for

FIGURE 1
Comparison of Six-Month Abnormal Returns to the Most and Least Favorable Recommendations



Consensus recommendations as of the last month of calendar quarter *t* are sorted into quintiles, with the highest quintile designated the most favorable portfolio and the lowest quintile the least favorable portfolio. Portfolios are reformed each calendar quarter and we report abnormal buy-and-hold returns for the six months beginning the first day of quarter *t*+1.

[19] In a robustness test (untabulated), we find that inferences from our trading strategies are unchanged when we restrict the sample to include firms *with* available data for the 11 predictor variables.

stocks in the least favorable recommendation quintile and for those in the most favorable recommendation quintile. Our first observation is that the variability of the absolute value of the abnormal returns differs considerably among the three sub-periods. The variability is much higher in the 1999–2003 sub-period than in the preceding 1994–1998 sub-period; return variability then drops precipitously and remains relatively low throughout the 2004–2006 sub-period. Our second observation is that analyst recommendations are not very reliable as a predictor of future returns. In fact, stocks in the least favorable recommendation quintile earn greater returns than those in the most favorable quintile in 35 of the 72 quarters. So, flipping a coin appears to be just as predictive.

Returns for Portfolios Based on Analyst Recommendations or Short Interest

Table 5, Panel A reports average monthly abnormal returns based on analyst recommendations. The portfolios cover the 52 calendar quarters from 1994 to 2006. If analyst recommendations provide value to investors, then returns should be higher for more highly recommended stocks. That is, returns for stocks in the quintile with the highest average recommendation should exceed returns for lower recommendation quintiles. Consistent with the results previously presented in Table 4 (which indicate that analysts improperly incorporate value-relevant information into their forecasts), we find the opposite relation. We find that the mean abnormal returns generally *decrease* as the recommendation level increases. When we calculate returns from investing long in firms classified in the most favorable recommendation quintile and taking an offsetting short position in firms in the least favorable recommendation quintile, we obtain a *modestly negative* return of 26 monthly basis points ($t = -2.03$; $p < 0.01$).

Table 6, Panel A summarizes returns by recommendation quintile for each of the three sub-periods and provides statistical tests. The investment results vary considerably among the three sub-periods. However, the most favorable recommendation quintile does not perform better than fourth among the quintiles (see ranks in the right-most column). Two statistically significant portfolios fall in the 1999–2003 period, when returns are positive for the lowest recommendation quintiles. We also find that the hedge portfolio trading strategy (buying firms in the highest recommendation quintile and selling short those in the lowest recommendation quintile) yields a statistically significant return only in the 1999–2003 sub-period, and that return is a *negative* 48 monthly basis points. Overall, following the consensus analyst recommendation does not generate positive abnormal returns for investors and, in some periods, can actually generate significantly negative returns. While perhaps counterintuitive, this result is consistent with Barniv et al. (2009), who find that analysts' recommendations relate negatively to residual income valuation models, and with Seybert and Wang (2009), who find that firms with more optimistic recommendations earn lower future returns in periods of high investor sentiment.[20]

Table 5, Panel B reports average monthly abnormal returns from portfolios formed using short interest levels. We find that the average abnormal return across the quintiles declines monotonically from lowest to highest short interest. A trading strategy that invests long (short) in firms that are in the lowest (highest) short interest quintile provides an average monthly abnormal return of 56 basis points, which is both economically and statistically significant ($t = 2.46$; $p < 0.01$). Interestingly, 29 basis points of that return are earned because short sellers avoid sizable positions in stocks that yield positive future returns. Thus, not only are short sellers able to identify stocks that are likely to fall in price, but they successfully avoid stocks that are likely to realize price

[20] Relative to JKKL, we find a more negative relation between analyst recommendations (both levels and changes) and future returns. Our sub-period analysis suggests that an important factor driving this result is the different time periods examined across the two studies.

TABLE 5

Abnormal Returns to Portfolios Based on Analyst Recommendations and Short Interest 1994–2006

Panel A: Average Monthly Abnormal Returns Based on Recommendation Levels

	Performance 1994 to 2006		
Quintile Portfolios	**Mean Return**	**t-stat**	**Quintile Rank by Return**
Most Favorable Recommendations	−0.10%	−1.37	5 (Worst)
	0.01%	0.13	4
	0.11%	2.32**	3
	0.19%	3.64***	1 (Best)
Least Favorable Recommendations	0.16%	2.15**	2
Most Favorable – Least Favorable	−0.26%	−2.03**	

Panel B: Average Monthly Abnormal Returns Based on Short Interest

	Performance 1994 to 2006		
Quintile Portfolios	**Mean Return**	**t-stat**	**Quintile Rank by Return**
Lowest Short Interest	0.29%	3.19***	1
	0.20%	3.64***	2
	0.12%	2.70***	3
	0.04%	0.63	4
Highest Short Interest	−0.27%	−1.79*	5
Lowest SI – Highest SI	0.56%	2.46**	

*, **, *** Indicate statistical significance at the α = 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test.

n = 564,101 firm-months.

We report mean monthly abnormal returns adjusted for firm size, book-to-market ratio, and past returns (Daniel et al. 1997) for portfolios based on analyst recommendations or short interest. Using the methodology in Jegadeesh and Titman (1993), we construct portfolios monthly based on the quintile rank of analyst recommendations or short interest selected in the current month and in each of the past five months (six-month holding period).

TABLE 6

Abnormal Returns to Portfolios Based on Analyst Recommendations or Short Interest for Sub-Periods

Panel A: Average Monthly Abnormal Returns Based on Recommendation Levels

	Performance 1994 to 1998			**Performance 1999 to 2003**			**Performance 2004 to 2006**		
Quintile Portfolios	**Mean Return**	**t-stat**	**Rank by Return**	**Mean Return**	**t-stat**	**Rank by Return**	**Mean Return**	**t-stat**	**Rank by Return**
Most Favorable Recommendations	−0.16%	−1.53	5	−0.17%	−1.22	5	0.02%	0.26	4
	−0.07%	−0.58	4	0.03%	0.23	4	0.05%	0.75	3
	0.11%	1.68*	2	0.15%	1.53	3	0.06%	1.00	1
	0.10%	1.52	3	0.40%	3.93***	1	0.06%	0.80	2
Least Favorable Recommendations	0.13%	1.16	1	0.31%	2.11**	2	−0.06%	−0.63	5
Most Favorable – Least Favorable	−0.29%	−1.58		−0.48%	−1.93*		0.09%	0.55	

Panel B: Average Monthly Abnormal Returns Based on Short Interest

	Performance 1994 to 1998			**Performance 1999 to 2003**			**Performance 2004 to 2006**		
Quintile Portfolios	**Mean Return**	**t-stat**	**Rank by Return**	**Mean Return**	**t-stat**	**Rank by Return**	**Mean Return**	**t-stat**	**Rank by Return**
Lowest Short Interest	0.22%	1.72*	1	0.30%	1.69*	1	0.30%	2.74***	1
	0.17%	2.09**	2	0.27%	2.52**	2	0.11%	1.61	2
	0.05%	0.93	3	0.19%	2.17**	3	0.05%	0.79	3
	0.01%	0.10	4	0.18%	1.31	4	−0.08%	−0.97	4
Highest Short Interest	−0.30%	−1.43	5	−0.24%	−0.80	5	−0.24%	−1.59	5
Lowest SI – Highest SI	0.52%	1.63		0.54%	1.20		0.54%	2.43***	

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test.

n = 564,101 firm-months.

We report mean monthly abnormal returns adjusted for firm size, book-to-market ratio, and past returns (Daniel et al. 1997) for portfolios based on analyst recommendations or short interest. Using the methodology in Jegadeesh and Titman (1993), we construct portfolios monthly based on the quintile rank of analyst recommendations or short interest selected in the current month and in each of the past five months (six-month holding period).

increases. This finding is consistent with concurrent research by Boehmer et al. (2010), who also find that the positive signals from low short interest can be equal to or greater in absolute magnitude than the negative signal from high short interest.

Table 6, Panel B presents returns from trading on short interest levels for each of the three sub-periods. A monotonic pattern of decreasing returns occurs within each of the three sub-periods as one reads down the table from lowest to highest short interest, with several of the individual quintiles statistically significant. Over the 2004–2006 sub-period, the zero-investment hedge strategy produces a statistically significant abnormal return of 54 monthly basis points. The monthly hedge returns are similar for the other sub-periods but are not statistically significant. Thus, while larger abnormal returns can be earned by trading on the level of short interest rather than on analysts' recommendations, the hedge strategy results are not of sufficient magnitude to be statistically significant in each sub-period. Interestingly, the returns to buying stocks in the lowest short interest quintile are more likely to be statistically significant than are the returns to selling short the stocks in the high short interest quintile. Overall, short interest provides a more reliable signal about which stocks to *buy* than about which stocks should be sold short.

Returns for Portfolios Combining Analyst Recommendations and Short Interest Levels

The evidence presented to this point indicates that none of the signals in isolation produce consistent results across each sub-period. In this section, we investigate whether combining the signals from analysts and short sellers can improve upon this investment performance. We consider trading strategies that are based on concurring and conflicting signals from analysts and short sellers. To conduct our analysis, we independently sort analysts' recommendations and short interest into quintiles and merge these quintile rankings to form 25 different portfolios. Since the sorts are independent, the average number of stocks across portfolios is not equal. Nevertheless, as reported in Table 7, the sample is broadly distributed across the 25 different portfolios, ranging from an average number of firms per portfolio of 492 to 950. This suggests that analysts and short sellers are just as likely to disagree as they are to agree on the future prospects of any one firm.

Table 7 presents abnormal returns for portfolios formed using both analyst recommendations and short interest. Reading down each recommendation column in Table 7, Panel A shows that abnormal returns tend to decline as the level of short interest increases. Notably, the decline is monotonic for the three quintiles with the most favorable recommendations. In addition, reading across each short interest row from left to right shows a general tendency for abnormal returns to decrease as the recommendation becomes more favorable. The combined effect is that the lowest returns occur in the lower right quadrant and the highest in the upper left quadrant.

Table 7, Panel B reports returns for two zero-investment trading strategies. The first strategy is to trade when short sellers and analysts strongly concur about a company's prospects. The specific trade is to buy firms in the portfolio with the most favorable recommendations and lowest short interest, and to sell short firms with the worst recommendations and highest short interest. The upper half of Panel B reports the returns and t-statistics from this strategy. The sample period return is 36 monthly basis points, which is not statistically significant ($t = 1.25$; $p = 0.21$). Examining sub-periods, a positive abnormal return occurs in each sub-period; however, the return is only statistically significant during the 2004 to 2006 time period (at the 10 percent level). We also note that the returns in each sub-period are less than the returns available to investors by trading only on the level of short interest (see Table 6, Panel B).

The second strategy is to trade when short sellers and analysts strongly conflict about a company's prospects. The strategy is to follow the short sellers by buying firms in the portfolio with the least favorable recommendations but the lowest short interest level, while selling short firms with the best recommendations but the highest short interest. The combined return reported in Panel B is 111 monthly basis points (40 + 71 from the corner cells in Panel A), which is both

TABLE 7

Abnormal Returns to Portfolios Formed Using Recommendations and Short Interest 1994–2006

Panel A: Average Monthly Returns (Portfolio Sample Size in Parentheses) for Cross-Tabulation of Recommendation Levels and Short Interest

	Analyst Recommendation Quintiles, 1994–2006				
Short Interest Quintiles	**Least Favorable**				**Most Favorable**
Lowest Short Interest	0.40%***	0.19%	0.31%***	0.29%**	0.24%**
	(950)	(492)	(757)	(601)	(932)
	0.19%*	0.27%***	0.30%***	0.11%	0.14%*
	(799)	(691)	(820)	(691)	(788)
	0.20%*	0.20%***	0.23%***	0.03%	−0.07%
	(723)	(829)	(844)	(765)	(696)
	0.16%	0.26%***	0.00%	−0.03%	−0.18%
	(700)	(874)	(835)	(821)	(665)
Highest Short Interest	−0.12%	0.06%	−0.19%	−0.32%*	−0.71%***
	(667)	(795)	(781)	(874)	(728)

(continued on next page)

Panel B: Average Monthly Hedge Portfolio Returns

	When Short Interest and Analyst Recommendations Strongly Concur							
	1994–1998		**1999–2003**		**2004–2006**		**Sample Period 1994–2006**	
	Mean	**t-stat**	**Mean**	**t-stat**	**Mean**	**t-stat**	**Mean**	**t-stat**
Firms with lowest short interest and most favorable analyst recommendation = Buy	0.01%	0.04	0.25%	1.04	0.39%	2.51**	0.24%	2.12**
Firms with highest short interest and least favorable analyst recommendation = Sell	−0.31%	−1.14	0.12%	0.24	−0.11%	−0.49	−0.12%	−0.55
Buy–Sell	0.30%	0.88	0.13%	0.22	0.50%	1.74*	0.36%	1.25
When Short Interest Strongly Conflicts with Analyst Recommendations								
Firms with lowest short interest but least favorable analyst recommendation = Buy	0.42%	1.95*	0.39%	1.45	0.25%	1.45	0.40%	2.81***
Firms with highest short interest but most favorable analyst recommendation = Sell	−0.68%	−2.68***	−0.91%	−2.95**	−0.46%	−2.11**	−0.71%	−4.27***
Buy – Sell	1.10%	2.58**	1.30%	2.62**	0.71%	2.20**	1.11%	4.09***

*, **, *** Indicate statistical significance at the $\alpha = 0.10$, 0.05, and 0.01 levels, respectively, using a two-tailed test.

n = 564,101 firm-months.

We report mean monthly abnormal returns adjusted for firm size, book-to-market ratio, and past returns (Daniel et al. 1997) for portfolios based on analyst recommendations and short interest. In parentheses, we report the average number of firms per month in each portfolio. Using the methodology in Jegadeesh and Titman (1993), we construct portfolios monthly based on the quintile rank of analyst recommendations and short interest selected in the current month and in each of the past five months (six-month holding period).

sizable and statistically significant ($t = 4.09$; $p < 0.01$). Positive returns accrue on both the long and short side, and the combined return is about double the return of 54 basis points available from trading only on the level of short interest (see Table 5, Panel B). This trading strategy also produces statistically significant returns of 110 basis points in 1994–1998, 130 basis points in 1999–2003, and 71 basis points in 2004–2006, providing evidence of the stability of this strategy over time. Note that the highest return occurs in the 1999–2003 time period when analyst recommendations are most misleading and produce a negative return of −48 monthly basis points (Table 6, Panel A).

In sum, we find that combining investment signals from analysts and short sellers yields incrementally greater future returns than trading strategies that use only one of the signals. Consistent with the results presented in Table 4, the most profitable investment strategy is when an investor trades in firms about which analysts and short sellers strongly disagree, and the investor takes the buy or sell position indicated by the short interest signal.

Robustness Tests

In this section, we report the results of several robustness tests (all untabulated). We begin by examining the sensitivity of the results to using the I/B/E/S provided consensus recommendation, rather than our self-constructed consensus. We find that our sample size increases slightly (to 86,592 firm-quarter observations) with all results qualitatively the same as those reported.

Next, we use an alternative short interest variable. Recall that for our main analyses, we use the short interest ratio (open short interest divided by shares outstanding). As an alternative deflator, we scale open short interest by the previous month's trading volume and label this variable *SIVOL*. We find that *SIVOL* is highly correlated with the short interest ratio ($\rho = 0.74$). When we regress the quintile assignment of *SIVOL* on the 11 predictive variables, we again find that all 11 variables are statistically significant in the expected direction, which is consistent with the results using the short interest ratio.

Our remaining robustness tests reexamine the profitability of the trading strategies that use information from both analysts and short sellers. First, we examine whether our results are robust to monthly rebalancing of the portfolio and using a holding period of one month. Consistent with our main results, we find that the most profitable strategy is to follow the short sellers when the signals from analysts and short sellers strongly conflict (100 monthly basis points; $t = 3.39$; $p < 0.01$). The alternative strategy, which trades when analyst and short seller signals strongly concur, remains less profitable although it improves from 36 monthly basis points ($t = 1.25$; $p = 0.21$) to 75 basis points ($t = 2.14$; $p < 0.01$).

Second, we examine whether the returns to our hedge portfolios become more profitable when we use a finer partition to form portfolios. Each month, we sort firms into deciles (instead of quintiles) based on the consensus analyst recommendation and/or the level of short interest. We intersect the recommendation and short interest deciles to produce 100 portfolios and the strategies take positions in the four most extreme portfolios using a six-month holding period. We find that the more refined stock selection yields greater hedge portfolio returns (140 monthly basis points; $t = 3.35$; $p < 0.01$).

Finally, we estimate the returns to our trading strategies using calendar-time portfolios, as an alternative method for estimating abnormal returns. Specifically, we assess the profitability of the strategies by estimating alphas from a regression of each portfolio's time-series of excess returns on the Fama-French risk factors and momentum (Fama and French 1993; Carhart 1997). We find that all hedge portfolio returns maintain statistical significance, which is consistent with the main results that calculate abnormal returns using characteristic portfolio matching (Daniel et al. 1997). We again find that the most profitable strategy is to follow the short sellers when their positions conflict with analyst recommendations.

V. CONCLUSION

We contribute new findings on the characteristics of stocks favored by short sellers, about how those characteristics differ from those used by analysts in developing buy-hold-sell recommendations, and on the value relevance of short interest data to investors. By so doing, we expand upon the results of Dechow et al. (2001) and other studies that examine information used by short sellers.[21] First, we find that analysts and short sellers use publicly available information differently. Analysts over-recommend stocks with high growth, high accruals, and low book-to-market ratios, even though prior research shows these characteristics are negatively related to future returns. In contrast, short sellers incorporate into their investment decisions the future return implications of all 11 accounting and market variables considered in this study. Second, we find that short interest provides information about future returns beyond that provided in the 11 items of information that prior research shows to be predictive of future returns. Analysts' recommendations also provide incremental information, but a negative coefficient suggests trading against the analysts. Third, based on these results, we show that a highly profitable trading strategy is one where investors trade with the short sellers when the short interest signal strongly conflicts with the consensus analyst recommendation. In fact, the value of short interest in choosing stocks to buy or sell is greater when conditioned on a conflicting consensus recommendation than when used by itself to trade stocks.

Our study contributes to the stream of academic literature documenting market inefficiencies. The debate over market efficiency has shifted from simple yes-or-no questions to issues such as the types of information incorporated into prices with a delay, the speed of price adjustment, and factors that facilitate or impede price discovery. We consider fundamental and other predictive information that prior research has shown to be incorporated into prices with a delay. We show that analysts' recommendations can impede price discovery of this information, but short selling facilitates price discovery. A frequent criticism of research documenting a delayed reaction to information is that a relation between information and future returns found to exist in the past may not recur in the future. That is, while some stocks are always misvalued, the characteristics of those stocks change over time, reducing the effectiveness of any system that places fixed weights on information. This criticism is less likely to be true for our approach, which identifies misvalued stocks based on a (strong) difference of opinion between analysts and short sellers. The characteristics of misvalued stocks can change over time, as long as short sellers and analysts disagree about valuation and the current stock price under-weights the views of short sellers. The extent of disagreement is also likely to be greatest in periods of high return volatility, and this is the type of market environment in which investors want stock-picking guidance. Consistent with this conjecture, we find the highest returns during the 1999–2003 sub-period.

Our study is timely in light of recent actions in the U.S. and other countries to further regulate short selling. For example, SEC Release No. 34-58591 (SEC 2008) requires institutional managers with at least $100 million under management to report detailed information about daily short sales in new Form SH. The rationale in Release No. 34-58591 is that "sudden and unexplained declines in the prices of securities … can give rise to questions about the underlying financial condition of an issuer, which in turn can create a crisis of confidence without a fundamental underlying basis."[22] While our evidence does not include the specific time period referred to in this quote, any new regulations are likely to extend to more normal periods of market activity. An important implication of our study is that regulations that restrict or increase the cost of short selling run the

[21] Two concurrent working papers consider aspects of short seller information use (Cao et al. 2007; Seybert and Wang 2009).

[22] In SEC Release No. 58724 (October 2, 2008), the SEC states the daily short selling information reported on Form SH will not be publicly available, in part, because it could give rise to imitative short selling.

risk of limiting a potentially important source of information for investors about future equity values. In this regard, the SEC has recently taken actions to increase the public availability of short interest positions. On March 6, 2007, the SEC approved rule changes that increase the frequency of short interest reporting from monthly to twice a month, effective September 2007. More timely reporting of short interest data to the public should further increase the role of short sellers as an information intermediary.

APPENDIX
QUANTITATIVE INVESTMENT SIGNALS

The last month of each calendar quarter is labeled quarter t. On this date, we measure our stock recommendation and short interest variables. Relative to this date, we label as quarter q the most recent fiscal quarter for which an earnings announcement is made at least two months prior to the end of quarter t and no more than four quarters prior to the end of quarter t.

Variable	Description	Calculation Details	Normative correlation with subsequent returns
SUE	Unexpected earnings	Seasonally adjusted earnings scaled by price for fiscal quarter q, as calculated by: $\frac{EPS_q - EPS_{q-4}}{Price_q}$, where *EPS* = earnings per share before extraordinary items (DATA#19) divided by the split adjustment factor (DATA#17) [Compustat]; and *Price* = stock price (DATA#14) divided by the split adjustment factor (DATA#17) [Compustat].	Positive (Bernard and Thomas 1989)
TACCR	Total accruals	Earnings before extraordinary items and discontinued operations (DATA#76) minus cash flow from operations (DATA#108– DATA#78), scaled by average assets (DATA#44) as measured at the end of fiscal quarter q [Compustat]. Since Compustat reports cumulative (i.e., year-to-date) data for cash flow items, adjustments were made to arrive at total accruals for fiscal quarter q (see Collins and Hribar 2000).	Negative (Sloan 1996)
CAPEX	Capital expenditures	Rolling sum of the preceding four quarters of capital expenditures ending at fiscal quarter q divided by average total assets as calculated by: $\frac{\Sigma_{i=0}^{3} Capex_{q-i}}{(TA_q - TA_{q-4})/2}$, where *Capex* = capital expenditures (DATA#90); and *TA* = total Assets (DATA#44).	Negative (Beneish et al. 2001)
MVE	Market capitalization	Natural log of the market value of equity at the end of fiscal quarter q, as calculated by DATA#14 × DATA#61 [Compustat].	Negative (Fama and French 1992)
EP	Earnings-to-price ratio	Ratio of the rolling sum of earnings over the preceding four quarters divided by price at the end of fiscal quarter q, as calculated by: $\Sigma_{i=0}^{3} \frac{EPS_{q-i}}{Price_q}$, where *EPS* = earnings per share before extraordinary items (DATA#19) divided by the split adjustment factor (DATA#17) [Compustat]; and *Price* = stock price (DATA#14) divided by the split adjustment factor (DATA#17) [Compustat].	Positive (Fama and French 1992)
BTM	Book-to-market ratio	Ratio of the book value of equity to the market value of equity at the end of fiscal quarter q, as calculated by DATA#59/(DATA#14 × DATA#61) [Compustat].	Positive (Fama and French 1992)

(continued on next page)

Variable	Description	Calculation Details	Normative correlation with subsequent returns
TURN	Stock turnover	Average daily volume turnover ratio measured as the exchange-specific, percentile rank of: $\Sigma_{i=1}^{n} \frac{Daily\ Vol. / Shrout}{n}$, where *Daily Vol.* = daily stock volume [CRSP]; *Shrout* = shares outstanding [CRSP]; and n = the number of trading days for the six-month period ending on the last trading day of calendar quarter t.	Negative (Lee and Swaminathan 2000)
SG	Sales growth	Rolling sum of the preceding four quarters of sales ending at fiscal quarter q divided by the rolling sum of the preceding four quarters of sales ending on quarter $q-1$, as calculated by: $\frac{\Sigma_{i=0}^{3} Sales_{q-i}}{\Sigma_{i=0}^{3} Sales_{q\text{-}4-i}}$, where *Sales* = DATA#2 [Compustat].	Negative (Lakonishok et al. 1994)
LTG	Long-term growth forecast	Mean, consensus long-term earnings growth forecast at the end of calendar quarter t [I/B/E/S].	Negative (Lakonishok et al. 1994; La Porta 1996)
FREV	Forecast revision	Rolling sum of the preceding six-month earnings forecast revisions to price ratios, as calculated by: $\Sigma_{i=0}^{5} \frac{FEPS_{m-i} - FEPS_{m-i-1}}{Price_{m-i-1}}$, where *FEPS* = mean, consensus analyst forecast for one-year-ahead (FY1) earnings-per-share [I/B/E/S]; m = the last month of calendar quarter t; and *Price* = stock price just prior to the consensus measurement date [I/B/E/S].	Positive (Bernard and Thomas 1989; Chan et al. 1996)
MOM	Stock momentum	Buy-and-hold raw stock return for six-month period ending one month prior to the end of quarter t [CRSP].	Positive (Jegadeesh and Titman 1993)

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