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Are Short Sellers Informed? Evidence from REITs

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Abstract

This paper uses intraday short sale data to examine whether short sellers of Real Estate Investment Trusts (REITs) are informed. We find strong evidence that short selling predicts future returns of REITs. Heavily shorted REITs significantly underperform lightly shorted REITs by approximately 1% over the following 20 trading days. This predictive relation holds for both small and large trades, but is stronger for large short trades. We also document a positive relation between shorting activity and volatility. Our results are consistent with the

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view that short sellers of REITs are informed and contribute to market efficiency by impounding information into prices.

Keywords: short selling, informed trading, REIT

JEL Classifications: G14, G19

1. Introduction

The relation between short selling and security returns is a regular point of contention between regulators and academics. Recently, fearing that short sellers feed on volatility and exacerbate downward stock price movements, the U.S. Securities and Exchange Commission (SEC) has put considerable effort into adjusting short sale regulations.[1] In contrast, academics generally view short sellers as sophisticated and informed investors who enhance market efficiency. Recent studies find short sellers anticipate negative news (Karpoff and Lou, 2010), predict future returns (Boehmer, Jones and Zhang, 2008; Diether, Lee and Werner, 2009), and contribute to market efficiency (Boehmer and Wu, 2010; Saffi and Sigurdsson, 2011).

However, existing studies of short selling typically limit their samples to common stocks. This raises a natural question as to whether the informational content of short selling varies across asset classes. The purpose of this paper is to test for the existence of informed short selling in Real Estate Investment Trusts (REITs). It is important to study the information content of REIT short selling for several reasons. First, REITs are an important asset class that has grown rapidly. According to CRSP, the REIT sector has grown from just over $2 billion in 1980 to nearly $400 billion in 2010.[2] Second, as evidenced by the recent financial crisis, the real estate market can have a profound impact on the economy. Shiller (2008), for example, argues that the ultimate cause of the 2007–2008 financial crisis was the real estate bubble. As such, understanding the ability of investors to incorporate negative information into real estate asset prices (and hedge against exposure to them) is important for both academics and policy makers. Third, REITs lack alternate mechanisms for constructing synthetic shorts, for example, put options.[3] Therefore, compared to common equities, informed traders of REITs who possess negative information are more likely to short. Finally, evidence of informed REIT shorting would contribute to our understanding

[1] The SEC eliminated Rule 10a-1 in July of 2007 to remove price-test rules for short trading. During the "financial crisis" the SEC temporarily banned short selling in certain financial stocks in July and September of 2008. Following much debate, the SEC approved a new "up-tick" rule (Rule 201) which imposes price tests when stocks experience rapid price declines (greater than 10% in one day).

[2] The total market capitalization of all securities in CRSP with share codes of 18 or 48 is $2.4 billion at the end of 1980 and $384.3 billion at the end of 2010.

[3] Using option data obtained from *DeltaNeutral*, we find that 33% of REITS in our sample have listed options while 66% of a matched sample of common stocks has listed options.

of the role of short selling in capital markets and would be of great interest to analysts, managers and traders of real estate security portfolios.

SEC Regulation SHO (RegSHO) required U.S. stock exchanges to disclose all short sales made between January 2005 and June 2007. We use this transaction-level data to analyze the short selling of 242 REITs that have at least one short sale trade during this period. Our results indicate that short selling is a large component of daily REIT trading volume, accounting for an average of 27.12% (23.63%) of transactions (shares traded).[4] Constructing portfolios sorted by total shorting, we find that REITs with high shorting underperform those with low shorting by up to 1.04% on a risk-adjusted basis over the following month. Cross-sectional regressions controlling for firm characteristics reveal the same relation. A one-standard-deviation increase in shorting predicts a decrease in returns of up to 0.55% over the following month. Both portfolio sorting and regression results hold across all four measures of short selling utilized.

In addition to examining short sellers as a group, we investigate whether the informativeness of short selling varies by trade size. Intuitively, one might expect informed short sellers to use large transactions to capitalize on their superior information (Easley and O'Hara, 1987). Therefore, we would expect that large short trades are more informative than small trades in predicting subsequent returns.[5] Alternatively, informed short sellers might split their trades in order to hide information (e.g., Barclay and Warner, 1993; Chakravarty, 2001; Hansch and Choe, 2007). Our empirical results show the inverse relation between shorting activity and subsequent returns holds for both small and large short trades; the heavily shorted REIT portfolio underperforms lightly shorted REIT portfolio by up to 0.96% for small trades and 1.2% for large trades over the next month. Using a cross-sectional regression approach, we find large short trades have an economically stronger negative relation than small short trades. Overall, we find that both small and large shorting trades are informative, while large trades appear to be more informed.

We also analyze REIT short selling by examining the relation between shorting activity and volatility. Following the volume-volatility literature, which generally interprets a positive relationship between trades/volume and volatility as evidence of informed trading (e.g., Jones, Kaul and Lipson, 1994; Andersen, 1996; Chan and Fong, 2000), we find a significant positive relationship between short selling activity and volatility. This relationship varies in strength across shorting measures, but holds across two volatility models. To the extent that price movements are caused primarily by the arrival of new information, our volatility evidence reinforces our cross-sectional and portfolio sorting results that short sales of REITs are informed.

[4] The corresponding numbers for common stock are 27.29% and 25.11%, respectively.

[5] This argument is consistent with the empirical findings of common stock short selling research. Boehmer, Jones and Zhang (2008) find the informativeness of short trades increases in trade size.

In a concurrent paper, Blau, Hill and Wang (2011) contrast REIT short selling against a matched sample of common stocks and conclude REIT short selling is less informed than common stock short selling. Our paper differs from theirs in several important ways. First, while Blau, Hill and Wang (2011) focus on comparing REIT shorting to common stock shorting, we are more interested in whether REIT short selling is informed in absolute terms. Second, Blau, Hill, and Wang's sample is smaller because they only include NYSE REITs and short sales made on the NYSE. We analyze all REITs traded and shorted on all nine U.S. exchanges.[6] Third, we look at returns further into the future. While Blau, Hill and Wang (2011) look at the relation between shorting and returns up to three days in the future, we follow Boehmer, Jones and Zhang (2008) and look at returns over the subsequent month.[7] Finally, we conduct a more comprehensive analysis by also testing the relationship between shorting and volatility.

2. Relevant literature

2.1. The information content of short selling

Short selling is the act of borrowing a stock not currently owned and selling it. At some point in the future the borrower (short seller) reacquires the stock and returns it to the original lender. Short sellers profit from a fall in the stock's price if they reacquire the stock at a price lower than the original short sale price. If the stock price rises in value the short seller loses money. The various reasons for selling short include a belief that the stock is going to decline in value, the desire to create liquidity, and the need to hedge an offsetting long position in a related convertible security or option.

Diamond and Verrechia (1987) argue that the high costs of shorting limits its appeal to liquidity traders. SEC regulations require proceeds from shorting to be held in a collateral account until the short position is closed. While the collateral account accrues interest to the short seller at a minimal rate, typically the Fed Funds or LIBOR rate, the shorting broker charges a loan fee to the short seller for the borrowed stock for the duration of the short period. The rebate rate, that is, collateral interest rate minus the loan rate, is often negative. In addition, short sellers pay any cash dividend

[6] Looking at just NYSE listed REITs during 2005 and 2006 (the sample period of Blau, Hill and Wang 2011) we find that 88% of those REITs' shares shorted were shorted on the NYSE. While that is a large majority of short selling, it still leaves a considerable portion of shorting out of the sample. This inclusion of all shorts on all exchanges becomes more important during our sample, as during 2005 and 2006 as the NYSE rolled out its Hybrid Market platform and trades began to be automatically routed to different exchanges with better prices. For further discussion of the importance of including all U.S. exchanges in short sale research see Diether, Lee and Werner (2009) and Yu, Lynch, Nikolic and Yan (2011).

[7] The primary motivation for looking at returns at least one week in the future stems from Diether (2008), which finds the median holding period for short positions to be seven days, implying short sellers are concerned with stock returns at least one week in the future.

on the stock into the short account, so the net cost of carrying a short position is generally positive. It would be atypical, according to Diamond and Verrechia (1987), to see traders utilizing short selling unless they have some preconceived perception that the stock will either decrease in value or underperform an offsetting investment.

Empirical research on short selling tends to be consistent with Diamond and Verrechia (1987). Dechow, Hutton, Meulbroek and Sloan (2001) and Asquith, Pathak and Ritter (2005) find an inverse relationship between a stock's short interest and its future returns. Using shorting costs as a proxy for shorting, Cohen, Diether and Malloy (2007) find the same inverse relationship with future returns. Boehmer, Jones and Zhang (2008) use transactions data on NYSE stocks for 2000–2004 and find a negative relationship between daily shorting and subsequent returns.[8] The availability of intraday shorting data from mandatory exchange disclosures by SEC RegSHO allows for broad-based analysis. Researchers are now able to directly measure shorting activity across the universe of exchange traded stocks over a two and a half year time span from January 2005 to June 2007. For example, Diether, Lee and Werner (2009) identify a strong negative relationship between daily shorting and the following day's returns using RegSHO data for 2005.[9] Overall, the evidence presented in these papers suggests short selling of common stocks is informed.

2.2. The information content of REIT shorting

Blau, Hill and Wang (2011) argue that the inherent transparency of REITs makes gathering private information about them difficult. In order to maintain their tax pass through status, REITs must hold almost exclusively real estate assets and distribute 90% of their income as dividends. Therefore, REIT assets are very transparent (i.e., vacancy rates, rents). Also, high dividends force REITs to seek external capital for growth, triggering regular external monitoring by the capital markets, which reduces private information (Fama, 1980; Hardin and Hill, 2008). These two characteristics, according to Blau, Hill and Wang (2011), imply that REIT short selling should either be uninformed or, at most, less informed than common stock shorting.

However, while gathering private information about REITs may be difficult, there are several reasons to expect shorting of REITs to be informed. First, REITs have low shorting costs. Nagel (2005) identifies institutional ownership as a large source of shorting liquidity. Institutions are usually willing to lend shares because of the high loan rate associated with lending. Holding large blocks of stock, institutional investors provide extensive liquidity to the shorting of any company in which

[8] Studies that find evidence of informed short selling also include Asquith and Meulbroek (1995), Aitken, Frino, McCorry and Swan (1998), Desai, Ramesh, Thiagarajan and Balachandran (2002), Christophe, Ferri and Angel (2004) and Desai, Krishnamurthy and Venkataramaran (2006).

[9] Other current papers using transaction level data and finding evidence for informed short selling include Christophe, Ferri and Hsieh (2010) and Engelberg, Reed and Ringgenberg (2010).

they invest. REITs are a popular investment with institutional investors (Ciochetti, Craft and Shilling, 2003). In fact, Chan, Erickson and Wang (2002) find institutions hold 39% of an average REIT's outstanding shares, compared to 31% of the average firm's outstanding common stock. Therefore, REITs should have considerable shorting liquidity. Second, informed REIT traders with negative information have few alternatives for capitalizing on that information. During our sample period, only 32.9% of REITs have listed options.[10] Considering most informed REIT traders are limited to long and short equity positions, it is very likely that negative information will be traded on with short sales.

Empirical research on REIT short selling is limited. Li and Yung (2004) find high REIT short interest is associated with future underperformance, suggesting REIT short sellers may be informed. Blau, Hill and Wang (2011) use transaction-level data and find that short sellers of REITs are less informed than those of common stocks.

2.3. The information/volatility relationship

An extensive body of volume-volatility literature suggests informed trading drives the positive relation between trading volume and return volatility (Jones, Kaul and Lipson, 1994). More recently, Durnev, Morck, Yeung and Zarowin (2003) provide evidence that higher idiosyncratic volatility implies more informed trading. The implication is that the existence of a greater number of informed traders injects firm-specific information into the market and leads to an increase in idiosyncratic volatility. Piotroski and Roulstone (2004) apply this framework to several classes of informed investors (analysts, institutions, and insiders) and find they are associated with higher firm return variation. Brockman and Yan (2009) extend this test to blockholders and idiosyncratic volatility, finding blockholders have a positive impact on both return variation and idiosyncratic volatility. Overall, the literature strongly suggests that informed trading should be positively related to volatility.

3. Data and summary statistics

3.1. Data and variables

We obtain our sample of REITs from the CRSP database. We identify REITs as those securities with a CRSP share code of 18 or 48. We then collect all short trades disclosed under RegSHO by the Amex, Archipelago (ARCA), Boston (BSE), Chicago (CHX), NASD, Nasdaq, National (NSX), NYSE, and Philadelphia (PHLX)

[10] In comparison, 66.1% of a matched sample of common stocks (matched on market capitalization and monthly trading volume) has listed options. The REITs that do have options are also less actively traded, with approximately one-fifth the open interest and daily volume of their matched common stocks. The above statistics are based on historical daily options data from *DeltaNeutral*.

exchanges between January 3, 2005 and June 29, 2007.[11] We calculate daily summaries of this intraday data and match them to daily summaries calculated for the same period from the Trade and Quote (TAQ) database and remove REITs with no short trades during our sample period. We also collect relevant security-specific information from CRSP and book-to-market ratios calculated through balance sheet data acquired from COMPUSTAT. Kenneth French's Web site provides Fama-French factors.[12] The final data set consists of 242 REITs with 124,268 REIT-day observations.

We construct the following four measures of short selling for each REIT for each trading day:[13]

- total number of shares shorted (*svolume*)
- total number of short trades (*strade*)
- percentage of share volume shorted (*vshare*) – *svolume* divided by total shares traded
- percentage of trades shorted (*tshare*) – *strade* divided by total number of trades

The final two measures are scaled versions of the first two measures. They are more orthogonal to our other control variables than the first two measures and provide cleaner analysis when used in our cross-sectional and volatility regressions.

3.2. Summary statistics

Table 1 presents summary statistics of the REIT data. Panel A shows the basic characteristics of the four measures of shorting. In line with the recent shorting literature, REIT shorting is quite prevalent. Shorting makes up 23.63% and 27.12% of the total daily trading volume and trades, respectively.

Panel B provides contemporaneous correlations. As expected, *svolume* and *strade* are highly positively correlated with each other (0.871), as are *vshare* and *tshare* (0.854). The aggregate measures are less correlated with their scaled counterparts, all with correlations less than 0.328. We expect the shorting measures to be positively correlated with contemporaneous returns because short selling tends to

[11] RegSHO data from the NYSE are acquired through the TAQ database. Data from all other exchanges is acquired directly from each exchange. For further examination of the RegSHO data and breakdown of short selling across the exchanges see Yu, Lynch, Nikolic and Yan (2011).

[12] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html, generated in accordance with Fama and French (1996).

[13] To account for heterogeneity in prices we also construct two alternate measures of short selling, total dollar volume of shares shorted (*dvolume*) and total dollar volume of shares shorted divided by dollar volume of all shares traded (*dshare*). The *dvolume* measure produces similar results to *svolume*, while *dshare* produces nearly identical results to *vshare*. Both alternate measures support the conclusion that REIT short sellers are informed. For brevity, we do not report these results in the paper.

Table 1

Summary statistics

Daily summaries of shorting activity are generated from tick-level mandatory disclosures by the NYSE, Nasdaq, Amex, ARCA, NSX, NASD, PHLX, BSE and CHX due to SEC RegSHO from January 3, 2005 through June 29, 2007 and are matched to daily trading summaries generated from the TAQ database for the same period. Other firm specific variables are collected from CRSP and COMPUSTAT. REITs are identified from the entire sample by CRSP SHRCDs 18 and 48. There are 242 REITs included in this sample, 147 of which trade for the duration of that sample, with 130,308 firm-year observations. Panel A reports summary statistics of our four shorting measures. *svolume* is the aggregate number of shares shorted for each stock each day, *strade* is the aggregate number of short trades made for each stock each day, *vshare* is the percentage of total shares traded which were shorts for each stock each day and *tshare* is the percentage of total trades which were shorts for each stock each day. Panel B reports contemporaneous correlations between REIT returns and all four shorting measures. Numbers in parentheses are *p*-values. Panel C reports summary statistics of firm specific control variables.

	Number of shares shorted daily (*svolume*)	Number of short trades daily (*strade*)	Percentage of total volume shorted (*vshare*)	Percentage of total trades shorted (*tshare*)
Panel A: Summary of shorting measures				
Mean	83,340	282	23.63%	27.12%
Cross-sectional σ	144,481	343	15.23%	14.51%
25th percentile	10,459	48	13.37%	17.87%
50th percentile	40,211	179	21.98%	26.29%
75th percentile	97,407	388	31.92%	35.34%
Average sample size	208	208	208	208
	$svolume_t$	$strade_t$	$vshare_t$	$tshare_t$
Panel B: Correlations				
$return_t$	0.047 (0.01)	0.046 (0.01)	0.139 (0.01)	0.152 (0.01)
$svolume_t$		0.871 (0.01)	0.239 (0.01)	0.229 (0.01)
$strade_t$			0.279 (0.01)	0.328 (0.01)
$vshare_t$				0.854 (0.01)

	Number of daily shares traded	Number of daily trades	Daily share turnover	Mktcap (in millions)	Daily return volatility (ann'd)	B/M
Panel C: Summary of control variables						
Mean	359,991	1,013	0.57%	2,010	23.87%	0.75
Cross-sectional σ	608,448	115	0.80%	3,163	15.17%	0.63
25th percentile	56,919	216	0.24%	312	16.99%	0.45
50th percentile	194,595	710	0.41%	910	20.66%	0.62
75th percentile	424,525	1,377	0.65%	2,170	26.10%	0.85

increase after upward price movements (Diether, Lee and Werner, 2009). As evidence of this, all the shorting measures have a positive correlation with returns, although the *vshare* and *tshare* scaled measures have greater correlation (0.139 and 0.152, respectively) than the *svolume* and *strade* measures (0.047 and 0.046, respectively).

Panel C presents summary statistics of other control variables used throughout the paper. We find the average market capitalization for our sample of REITs is approximately 2 billion dollars and the average book-to-market ratio is 0.75.

4. Methods and results

4.1. Portfolio sorting

As suggested by Boehmer, Jones and Zhang (2008), there may be underlying nonlinearities in the relationship between shorting and future returns. Therefore, a portfolio approach seems like the appropriate starting point. Following Boehmer, Jones and Zhang (2008) we sort the REIT sample into quintile portfolios each day by the previous five day's average shorting (days −1 to −5). After skipping the event day (day 0) and the following day (day +1) each portfolio is held for 20 trading days (days +2 through +21) to simulate an approximate month long holding period. We construct both equal-weighted and value-weighted portfolios (weighted by lagged monthly market capitalization). This yields portfolios with overlapping return periods (see Jegadeesh and Titman, 1993). To account for this overlap, we compute the return on each portfolio using the average of the 20 daily portfolios, effectively rebalancing 1/20th of the portfolio every day.[14] Following Boehmer, Jones and Zhang (2008), we multiply the daily returns by 20 to represent monthly returns.

We then estimate risk-adjusted returns in a manner similar to Fama and French (1996) as the intercept of the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p1} * REITRF_t + \beta_{p2} * MKTRF_t + \beta_{p3} * SMB_t + \beta_{p4} * HML_t + \varepsilon_t, \quad (1)$$

where R_{pt}, is the return of each value-weighted portfolio, $REITRF_t$ is a daily index of cross-sectional average returns of all REITs in our sample minus the daily T-bill rate and $MKTRF_t$, SMB_t and HML_t are the traditional Fama-French factors defined as the market risk premium, small-minus-big and high-minus-low variables. Hartzell, Muhlhofer and Titman (2010) find an REIT index can explain a considerable portion of the variation in REIT returns, so our inclusion of REITRF is important for risk adjustment.[15] For ease of exposition, we call the intercept of regression Equation (1) the Fama-French alpha.

Table 2 shows the characteristics and returns of the portfolios sorted on each of the shorting measures. We find that *svolume* and *strade* are positively correlated with daily share turnover and firm market capitalization. This relationship is expected since firms with higher market capitalizations and more liquid stock should have greater shorting volume. The two scaled measures *vshare* and *tshare* do not share this

[14] For a more detailed description of the process, please see Boehmer, Jones and Zhang (2008).

[15] We find similar results using exogenously constructed REIT index returns (NAREIT/FTSE, MSCI, and SNL). These results are not reported but are available on request.

Table 2

Portfolio sorting analysis

We obtain transaction-level short sale data for 242 REITs traded on NYSE and Nasdaq from these exchanges under the SEC RegSHO for the period from January 3, 2005 through June 29, 2007. Daily Return Volatility is the standard deviation of the stock's daily returns over the previous 20 trading days, annualized. Market Capitalization is daily price multiplied by shares outstanding. Book to market is defined as Total Assets − Total Liabilities − Total Preferred Stock + Deferred Taxes + Convertible Debt divided by Current Market Capitalization, calculated with data provided through COMPUSTAT. Portfolios are formed based on the average amount of shorting over the previous five days and then held for the periods $t + 2$ through $t + 21$, with 1/20 of the portfolio rebalanced daily. Both equal-weighted and value-weighted portfolios are formed. Value-weighted portfolios are weighted using the previous month's logged market capitalization. Fama-French alphas are generated through a modified three factor model discussed in the paper from the value-weighted portfolios. $R_t - r_f = \beta_1$ reitrf $+ \beta_2$ mktrf $+ \beta_3$ smb $+ \beta_4$ hml, where R_t is the portfolio return, r_f, mktrf, smb and hml defined as in Fama and French (1993, 1996) and reitrf is a daily index formed from the average cross-sectional daily return of all REITs in the sample. Differences are reported as the lowest ranked portfolio returns subtracted from either the fourth or fifth ranked portfolio, with associated t-statistics reported in parentheses.

	(1) Shares shorted (*svolume*)	(2) Short trades (*strade*)	(3) % of volume (*vshare*)	(4) % of trades (*tshare*)	(5) Daily turn (%)	(6) Daily ret σ (ann'd) (%)	(7) Mkt cap (mill)	(8) B/M	(9) Equal-weighted return (%)	(10) Value-weighted return (%)	(11) Risk-adjusted PF5-PF1 (t-stat)
Portfolios sorted by Number of Shares Shorted (*svolume*)											
1 Least	3,131	11	19.37	20.80	0.21	25.61	192	1.09	1.18	1.30	
2	20,439	89	22.24	26.14	0.44	23.50	608	0.75	1.05	1.27	
3	51,055	215	23.58	27.68	0.56	22.03	1,428	0.64	1.16	1.37	
4	91,488	360	25.63	29.80	0.66	22.31	2,301	0.63	1.11	1.34	
5 Most	251,082	740	27.45	31.29	0.97	26.11	5,553	0.65	0.56	1.22	−0.52 (−2.80)
Portfolios sorted by Number of Shares Trades (*strade*)											
1 Least	3,763	9	19.01	20.26	0.22	26.50	169	1.13	1.12	1.18	
2	22,048	84	21.80	25.80	0.45	23.43	567	0.77	0.94	1.18	
3	53,429	203	23.55	27.63	0.59	22.77	1,256	0.66	1.16	1.36	
4	93,473	356	25.61	29.70	0.67	22.28	2,236	0.62	1.15	1.30	
5 Most	244,468	762	28.31	32.32	0.91	24.57	5,857	0.59	0.68	1.26	−0.48 (−2.68)

(*Continued*)

Table 2 (*continued*)

Portfolio sorting analysis

	(1) Shares shorted (*svolume*)	(2) Short trades (*strade*)	(3) % of volume (*vshare*)	(4) % of trades (*tshare*)	(5) Daily turn (%)	(6) Daily ret σ (ann'd) (%)	(7) Mkt cap (mill)	(8) B/M	(9) Equal-weighted return (%)	(10) Value-weighted return (%)	(11) Risk-adjusted PF5-PF1 (t-stat)
Portfolios sorted by Percentage of Total Volume Shorted (*vshare*)											
1 Least	37,269	114	14.15	17.27	0.54	24.48	1,010	0.94	1.27	1.87	
2	73,280	245	19.98	23.50	0.57	23.78	1,999	0.78	1.10	1.44	
3	89,885	311	23.43	27.06	0.57	23.61	2,383	0.72	1.04	1.22	
4	104,239	360	27.49	31.07	0.58	23.37	2,532	0.67	0.82	1.12	
5 Most	111,632	383	33.20	36.81	0.59	24.28	2,136	0.67	0.83	1.03	−1.04 (−6.19)
Portfolios sorted by Percentage of Total Trades Shorted (*tshare*)											
1 Least	35,870	110	14.73	16.52	0.49	25.21	1,066	0.98	1.18	1.85	
2	75,231	250	19.89	22.90	0.59	23.41	2,170	0.76	1.17	1.43	
3	90,961	310	23.56	26.93	0.59	23.62	2,348	0.71	0.89	1.07	
4	105,107	358	27.32	31.25	0.60	23.59	2,368	0.67	0.91	1.03	
5 Most	109,107	385	32.75	38.11	0.57	23.69	2,108	0.65	1.01	1.27	−0.75 (−4.60)

correlation. This is one reason Diether, Lee and Werner (2009) advocate for the use of these scaled measures. They are more orthogonal to control variables, and thus more reliable when used in regressions.

Columns 9 through 11 report the portfolio returns. Looking just at the raw portfolio returns (either equal or value weighted) we see a weakly inverse relation between shorting and future returns. However, when we examine risk-adjusted returns we identify a strong negative relation across all four shorting measures.[16] Column 11 reports the risk-adjusted returns to the highest shorted portfolio minus the lowest shorted portfolio. In economic terms, this inverse relationship is very strong; the highest shorted REITs underperform the lowest shorted REITs by 0.52% and 0.48% over the following month for *svolume* and *strade*, respectively. The relation is twice as strong when using our scaled measures. *vshare* (*tshare*) predicts future underperformance of 1.04 (0.75) percent. These results are consistent with Boehmer, Jones and Zhang (2008), which find that heavily shorted common stocks underperform lightly shorted common stocks, and suggest that REIT shorting is informed.[17]

4.2. Cross-sectional regressions

Our shorting measures are correlated with other firm-specific characteristics such as market capitalization and turnover. We therefore move to a cross-sectional multivariate setting in order to account for multiple return determinants simultaneously. We adopt the cross-sectional approach used by Boehmer, Jones and Zhang (2008) and estimate daily cross-sectional regressions. These regressions use each of the previously defined four shorting measures calculated using the five day lag averages:

$$\begin{aligned} Return_{i,t+2,t+21} = {} & \alpha + \delta * Short_{i,t} + \beta * \ln(ME)_{i,t} \\ & + \gamma * B/M_{i,t} + \theta * \sigma(Ret)_{i,t} + \varphi * Turn_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where ln(*ME*) is logged monthly market capitalization, *B/M* is monthly book to market, σ(*Ret*) is the monthly standard deviation of daily returns and *Turn* is monthly share volume turnover. The dependent variable *Return* is either the raw or risk-adjusted 20 day cumulative stock return. To compute this return we use a procedure similar to that previously explained for the daily portfolios, skipping days 0 and +1 and computing returns from day +2 to +21. We construct risk-adjusted returns as follows. We first estimate factor loadings on *REITRF*, *MKTRF*, *SMB*, and *HML* using

[16] We acknowledge that raw returns, particularly those on the short side, are more instructive about the profitability of short sale trades. Results in Table 2, however, reveal no evidence that realized returns for heavily shorted stocks are negative. This finding is similar to Boehmer, Jones and Zhang (2008) and Diether, Lee and Werner (2009). Our use of risk-adjusted returns and focus on the return spread between heavily and lightly shorted REITs are consistent with prior literature.

[17] As a robustness test we sort REITs first by market capitalization (into quintiles) and then by shorting. We find REITs with high shorting underperform those with low shorting in all but the smallest size quintile.

the previous quarter's data.[18] We then use these estimated factor loadings to compute risk-adjusted returns for the period from day +2 to +21 based on Equation (1). Because the factor loadings are estimated using only data prior to day 0, the risk-adjusted returns computed from these factor loadings can be interpreted as being achievable.[19] To counter a small amount of drift in the aggregate levels of short selling over the sample period and to provide for more uniform interpretation, we standardize all explanatory variables daily to have a zero cross-sectional mean and unit standard deviation. Coefficients in the table are time series averages of the daily regressions, using Newey-West corrected standard errors to compute *t*-statistics with 20 lags.

Table 3 reports our regression results. For each measure we estimate two models, one simple regression of returns on the shorting variable and the other regressing returns on shorting as well as control variables. We estimate our regressions for both raw and risk-adjusted returns. These results reinforce our conclusion from Table 2. Panel A reports regression results using raw returns, and, unlike Table 2, we find a strong inverse relationship. When controlling for REIT characteristics, all four shorting measures predict REITs with higher shorting will underperform in the following month. Specifically, a one-standard-deviation increase in *svolume* predicts a decrease in return of 0.41%. Turning to Panel B, using risk-adjusted returns, all eight regressions show a statistically and economically significant negative relation between shorting and future returns. For example, looking at *svolume* we find a one-standard-deviation increase in shorting predicts a 0.55 (0.40) percent decrease in the following months risk-adjusted returns with (without) control variables. Combined with our portfolio sorting analysis, this is strong evidence that REIT short sellers are informed.

4.3. Trade size

All trades are not created equal. Kyle (1985) provides a theoretical foundation for the optimal trade size and Easley and O'Hara (1987) extend that analysis to argue that informed traders have an incentive to make trades as large as possible given trading costs. Boehmer, Jones and Zhang (2008) find evidence consistent with these theories in common stock short traders. When they break their sample into five trade-size segments, the subsamples with larger transaction sizes are significantly more informed in terms of predicting future returns. As REIT short trades are considerably smaller than the average common stock trade (either long or short), we are unable to divide our sample into several subsamples like Boehmer, Jones and Zhang (2008). Instead we divide our sample into categories: small trades of less than 500 shares and

[18] The previous quarter is defined as the most recent full calendar quarter prior to time *t*.

[19] We thank an anonymous referee for pointing this out. We note, however, that our risk-adjusted returns do not take into account transaction costs or shorting costs.

Table 3

Cross-sectional regressions

We obtain transaction-level short sale data for 242 REITs traded on NYSE and Nasdaq from these exchanges under the SEC RegSHO for the period from January 3, 2005 through June 29, 2007. Each day we run a cross-sectional regression of one-month-ahead returns on short activity. Shorting is measured in one of four manners as defined in Table 1. Log(mkt), B/M, Ret σ and Turnover, Logged Market Capitalization, Book to Market Ratio, Return Volatility and Monthly Stock Turnover are all calculated using data from the previous month. The dependent variable is either raw returns or modified Fama-French alphas, cumulative from $t+2$ to $t+21$. Panel A reports regressions using raw returns as the dependent variable. Panel B reports regressions using Fama-French alphas as the dependent variable. The modified Fama-French model used is $R_t - r_f = \beta_1$ reitrf $+ \beta_2$ mktrf $+ \beta_3$ smb $+ \beta_4$ hml, where R_t is the stock's return, r_f, mktrf, smb and hml defined as in Fama and French (1993, 1996) and reitrf is a daily index formed from the average cross-sectional daily return of all REITs in the sample. Factor loadings are generated from the most recent full calendar quarter prior to day t. All explanatory variables are normalized to have a zero mean and unit standard deviation. Standard errors are generated using a Newey-West procedure with 20 lags. Reported coefficients are time series averages of the daily cross-sectional coefficients with t-statistics reported below.

Dependent	Short	Log(mkt)	B/M	Ret σ	Ret$_{t-1}$	Turnover	Adj R^2
Panel A: Raw returns							
Number of	−0.223						0.011
shares	−1.83						
shorted	−0.407	0.426	0.168	−0.211	0.257	−0.133	0.121
(*svolume*)	−3.19	3.16	1.07	−1.08	1.45	−0.62	
Number of	−0.140						0.010
short trades	−1.24						
(*strade*)	−0.247	0.193	0.126	−0.180	0.294	−0.276	0.117
	−2.45	1.89	0.80	−0.88	1.62	−1.12	
Percent of	−0.191						0.003
shares	−2.98						
shorted	−0.176	0.287	0.278	0.359	0.369	−0.061	0.117
(*vshare*)	−3.09	1.81	1.81	−1.77	1.76	−0.26	
Percent of	−0.134						0.002
trades	−2.36						
shorted	−0.111	−0.014	0.227	−0.334	0.409	−0.256	0.116
(*tshare*)	−2.25	−0.12	1.46	−1.58	1.88	−0.98	
Panel B: Risk-adjusted returns							
Number of	−0.396						0.013
shares	−3.11						
shorted	−0.546	0.364	0.151	−0.216	0.270	−0.193	0.116
(*svolume*)	−4.05	3.39	0.97	−1.08	1.50	−0.82	
Number of	−0.372						0.008
short trades	−3.60						
(*strade*)	−0.454	0.186	0.129	−0.183	0.292	−0.274	0.113
	−4.29	1.81	0.82	−0.89	1.62	−1.11	
Percent of	−0.25						0.001
shares	−4.24						
shorted	−0.196	0.295	0.253	−0.364	0.389	−0.096	0.111
(*vshare*)	−3.40	2.10	1.65	−1.74	1.83	−0.38	
Percent of	−0.201						0.001
trades	−3.13						
shorted	−0.134	−0.021	0.230	−0.336	0.409	−0.258	0.111
(*tshare*)	−2.02	−0.19	1.49	−1.59	1.89	−0.99	

Table 4

Summary statistics of shorting measures categorized by trade size

Daily summaries of shorting activity are generated from tick-level mandatory disclosures by the NYSE and Nasdaq due to SEC RegSHO from January 3, 2005 through June 29, 2007 and are matched to daily trading summaries generated from the TAQ database for the same period. Other firm specific variables are collected from CRSP and COMPUSTAT. REITs are identified from the entire sample by CRSP SHRCDs 18 and 48. There are 242 REITs included in this sample, 147 of which trade for the duration of that sample, with 130,308 firm-year observations. Panel A reports summary statistics of our four shorting measures. *svolume* is the aggregate number of shares shorted for each stock each day, *strade* is the aggregate number of short trades made for each stock each day, *vshare* is the percentage of total shares traded which were shorts for each stock each day and *tshare* is the percentage of total trades which were shorts for each stock each day. A trade is classified as small if it is under 500 shares and as a large trade if it is greater than or equal to 500 shares.

	Number of shares shorted daily (*svolume*)		Number of short trades daily (*strade*)		Percentage of total volume shorted (*vshare*)		Percentage of total trades shorted (*tshare*)	
	Small	Large	Small	Large	Small	Large	Small	Large
Mean	38,291	45,049	245	37	13.23%	10.41%	23.45%	3.67%
Cross-sectional σ	46,951	107,235	286	68	10.54%	10.34%	13.26%	4.69%
25th percentile	6,020	2,831	43	3	6.34%	3.55%	15.18%	11.75%
50th percentile	23,757	13,643	160	14	11.55%	8.04%	22.37%	2.59%
75th percentile	53,011	42,743	344	41	17.90%	14.36%	30.72%	4.74%
Average sample size	208	208	208	208	208	208	208	208

large trades of 500 or more shares.[20,21] Table 4 presents a summary of the shorting measures for small and large trades. As we expect, large trades make up a very small percentage of short transactions but nearly an equal number of shares shorted.

Analogous to Table 2, we repeat the portfolio sorting for both trade size subsamples and report the results in Table 5. We report the difference between the highest shorted portfolio and the least shorted portfolio with corresponding *t*-statistics to the right. Panel A provides the results for the small trade subsample and shows a uniformly negative relation across all shorting measures. Panel B provides the same analysis for the large short trade subsample, which again shows clear negative differences for both value- and equal-weighted portfolio risk-adjusted returns. In contrast to Boehmer, Jones and Zhang (2008) we find evidence of informed shorting

[20] The stealth trading literature, in general, considers small trades to be between 100 and 499 shares, medium trades to be 500–9,999 shares, and large trades to be greater than 10,000 shares. Across our two and a half year sample, we have only a handful of REIT short trades greater than 1,000. This is not a surprise, given smaller REIT market capitalizations and lower mean REIT volume. Given the relatively small size of REIT short trades, we lose much statistical power when we attempt to divide our sample into more than two trade size subsamples, and so our analysis is restricted to small and large trades.

[21] We also conduct these analyses using a cut-off of 1,000 shares, instead of 500, and find similar results.

Table 5

Portfolios sorting by trade size

We obtain transaction-level short sale data for 242 REITs traded on NYSE and Nasdaq from these exchanges under the SEC RegSHO for the period from January 3, 2005 through June 29, 2007. Shorting is measured in one of four manners, as defined in Table 1. Portfolios are formed from the average amount of shorting over the previous five days and then held for the periods $t + 2$ through $t + 21$, with 1/20 of the portfolio rebalanced daily. Both equal-weighted and value-weighted portfolios are formed. Value-weighted portfolios are weighted using the previous month's logged market capitalization. Fama-French alphas are generated through a modified three factor model discussed in the paper from the value-weighted portfolios. $R_t - r_f = \beta_1$ reitrf $+ \beta_2$ mktrf $+ \beta_3$ smb $+ \beta_4$ hml, where R_t is the portfolio return, r_f, mktrf, smb and hml defined as in Fama and French (1993, 1996) and reitrf is a daily index formed from the average cross-sectional daily return of all REITs in the sample. Only the differences are reported here (analogous to those reported in Table 2) and are the highest ranked portfolio returns minus the lowest ranked portfolio, with associated t-statistics reported to the right. Panel A reports the results from the portfolio sorting analysis conducted using only small trades (less than 500 shares in a transaction) while Panel B reports the results from the portfolio sorting analysis conducted using only large trades (greater than or equal to 500 shares in a transaction).

	FF value weighted	*t*-stat	FF equal weighted	*t*-stat
Panel A: Portfolio sorting: small trades				
Number of shares shorted daily (*svolume*)	−0.74	−2.44	−1.51	−4.28
Number of short trades daily (*strade*)	−0.66	−2.23	−1.47	−4.23
Percentage of total volume shorted (*vshare*)	−0.71	−2.01	−0.51	−1.39
Percentage of total trades shorted (*tshare*)	−0.96	−3.65	−0.76	−2.63
Panel B: Portfolio sorting: large trades				
Number of shares shorted daily (*svolume*)	−0.64	−2.27	−1.54	−3.94
Number of short trades daily (*strade*)	−0.68	−2.39	−1.58	−4.14
Percentage of total volume shorted (*vshare*)	−1.20	−5.34	−1.43	−4.18
Percentage of total trades shorted (*tshare*)	−1.06	−4.06	−1.30	−3.29

for both small and large short trades. However, consistent with Boehmer, Jones and Zhang, we find that large shorts do have, on average, a slightly more economically significant relation with future returns.

We also repeat our cross-sectional analysis for both small and large trade subsamples and report the results in Table 6. Panel A presents the results for raw returns and Panel B presents the results for risk-adjusted returns. The small and large trade columns of both panels report the coefficients for the shorting variable as described in Table 3, with and without controls. These regressions show a larger dichotomy between the informativeness of small and large trades than our portfolio sorting analysis. The first column shows that less than half of the coefficients on small short trades are negative and statistically significant. Moreover, none of the coefficients is statistically significant for our preferred scaled shorting measures. However, the third column, reporting the coefficients using large short trades, is unambiguous in showing a statistically and economically significantly negative relationship between shorting and future returns across all four shorting measures using both raw

Table 6

Cross-sectional regressions by trade size

We obtain transaction-level short sale data for 242 REITs traded on NYSE and Nasdaq from these exchanges under the SEC RegSHO for the period from January 3, 2005 through June 29, 2007. Each day we run a cross-sectional regression of one-month-ahead returns on short activity using both small trade and large trade subsamples, as defined in Table 4. Shorting is measured in one of four manners as defined in Table 1. Control variables used, but not reported, include Log(mkt), B/M, Ret σ and Turnover, Logged Market Capitalization, Book to Market Ratio, Return Volatility and Monthly Stock Turnover, and are all calculated using data from the previous month. The dependent variable is either raw returns or Fama-French alphas, cumulative from $t+2$ to $t+21$. The modified Fama-French model used is $R_t - r_f = \beta_1\text{reitrf} + \beta_2\text{mktrf} + \beta_3\text{smb} + \beta_4\text{hml}$, where R_t is the stock's return, r_f, mktrf, smb and hml defined as in Fama and French (1993, 1996) and reitrf is a daily index formed from the average cross-sectional daily return of all REITs in the sample. Factor loadings are generated from the most recent full calendar quarter prior to day t. All explanatory variables are normalized to have a zero mean and unit standard deviation. Standard errors are generated using a Newey-West procedure with five lags. Reported coefficients are time series averages of the daily cross-sectional coefficients with t-statistics reported below. Only the short measure coefficients are reported, with t-statistics reported in parentheses and R^2 for the each regression reported to the right. Panel A reports regression results using raw returns as the dependent variable while Panel B reports regression results using Fama-French adjusted returns.

		Small trades		Large trades	
		Coef.	R^2	Coef.	R^2
Panel A: Raw returns					
Number of shares shorted daily (*svolume*)	Simple	−0.120	0.009	−0.252	0.014
		(−1.08)		(−1.83)	
	W/Controls	−0.228	0.117	−0.423	0.123
		(−2.27)		(−2.92)	
Number of short trades daily (*strade*)	Simple	−0.001	0.009	−0.251	0.014
		(−0.91)		(−1.81)	
	W/Controls	−0.184	0.117	−0.414	0.122
		(−1.93)		(−3.03)	
Percentage of total volume shorted (*vshare*)	Simple	0.031	0.011	−0.301	0.014
		(0.25)		(−2.31)	
	W/Controls	0.000	0.119	−0.369	0.122
		(0.05)		(−3.18)	
Percentage of total trades shorted (*tshare*)	Simple	−0.064	0.004	−0.227	0.023
		(−0.85)		(−1.32)	
	W/Controls	−0.059	0.116	−0.214	0.126
		(−1.06)		(−1.91)	
Panel B: Risk-adjusted returns					
Number of shares shorted daily (*svolume*)	Simple	−0.355	0.006	−0.388	0.017
		(−3.55)		(−2.60)	
	W/Controls	−0.446	0.112	−0.518	0.118
		(−4.30)		(−3.35)	
Number of short trades daily (*strade*)	Simple	−0.340	0.006	−0.433	0.017
		(−3.46)		(−2.94)	
	W/Controls	−0.390	0.112	−0.556	0.117
		(−3.81)		(−3.91)	

(*Continued*)

Table 6 (*continued*)

Cross-sectional regressions by trade size

		Small trades		Large trades	
		Coef.	R^2	Coef.	R^2
Percentage of total volume shorted (*vshare*)	Simple	−0.015	0.008	−0.351	0.013
		(−0.12)		(−2.84)	
	W/Controls	−0.014	0.113	−0.295	0.117
		(−0.16)		(−3.46)	
Percentage of total trades shorted (*tshare*)	Simple	−0.139	0.003	−0.227	0.022
		(−1.58)		(−1.33)	
	W/Controls	−0.092	0.112	−0.197	0.120
		(−1.16)		(−1.76)	

and risk-adjusted returns. The economic significance of this relationship using large short trades is considerable for most of these regressions. For example, the model regressing risk-adjusted returns on *strade* and controls predicts a decrease in return of 0.52% over the following month (6.40% annualized). To summarize, we find the informativeness of REIT shorting, like common stock shorting, is increasing in trade size.

5. Volatility

In the previous sections we investigate, as much of the shorting literature, the predictive power of short selling for future returns. To shed additional light on whether REIT short sellers are informed we examine the relation between short selling and return volatility. From a market microstructure perspective, price movements are caused primarily by the arrival of new information (e.g., Kyle, 1985). As such, a positive relation between short selling activity and price volatility would be consistent with short sellers revealing private information to the market and, therefore, demonstrating they are informed. We employ two models. The first is a classic two-step regression model and the second is a GARCH model.

5.1. Two-step regression model

Following the empirical methodology of Schwert (1990), Jones, Kaul and Lipson (1994) and Chan and Fong (2000) we specify a two-step model incorporating volatility as follows:

$$Return_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} Day_{k,t} + \sum_{k=1}^{5} \beta_{i,k} Return_{i,t-k} + \sum_{k=0}^{5} \gamma_{i,t-k} Short_{i,t-k} + \varepsilon_{i,t} \tag{3}$$

$$|\varepsilon_{i,t}| = \tau_i + \psi_t Monday_t + \sum_{k=1}^{5} \rho_{i,k} |\varepsilon_{i,t-k}| + \varphi Volume_{i,t} + \sum_{k=0}^{5} \delta_{i,t-k} Short_{i,t-k} + \eta_{i,t}, \tag{4}$$

where *Return* is the return on stock i at time t, *Day* is a collection of dummy variables for the day of the week, *Monday* is a dummy variable for Monday, *Short* is defined as each of the four previously discussed shorting measures, and *Volume* is dependent on the shorting measure used, where volume is total shares traded (where the *svolume* or *vshare* measures are used) or total number of trades (where the *strade* or *tshare* measures are used). The absolute value of residual from Equation (3), $\varepsilon_{i,t}$, represents volatility.

Table 7 shows the cross-sectional averages of the time series coefficients. Panel A of Table 7 presents the results from the first equation of the model (Equation (3)). Because our cross-sectional analysis demonstrates a significant relationship between past shorting and future returns, we include five lags of shorting in the model to generate more accurate residuals. We find that both lagged returns and lagged shorting have significant explanatory power over current returns, with the majority of shorting coefficients being negative. While lagged shorting is generally insignificant when the aggregate shorting measures are used, they are quite strong when the scaled shorting measures are used. Contemporaneous shorting is positive and significant for all short measures, consistent with Diether, Lee and Werner (2009).

Panel B reports the results for the second (volatility) equation, which is of primary interest. The Monday effect is positive and significant, suggesting that returns are more volatile on Monday. The positive coefficients on trading volume and number of trades are consistent with prior literature (e.g., see Lamoureux and Lestrapes, 1990, for share volume and Jones, Kaul and Lipson, 1994, for number of trades). Short selling has a significant and positive relationship with volatility for all four measures of shorting. Following Durnev, Morck, Yeung and Zarowin (2003), we interpret this as evidence of informed short trading as short sellers impact REIT prices by injecting new information into prices.

5.2. GARCH(1,1)

Our second model is the following standard GARCH(1,1) model:

$$\begin{aligned} Return_{i,t} = {} & \sum_{k=1}^{5} \alpha_{i,k} Day_{k,t} + \sum_{k=1}^{5} \beta_{i,k} Return_{i,t-k} + \sum_{k=0}^{5} \gamma_{i,t-k} Short_{i,t-k} \\ & + \varepsilon_{i,t} \;\; \varepsilon_{i,t} \sim N\left(0, \sigma_{i,t}^2\right) \end{aligned} \tag{5}$$

$$\sigma_{i,t}^2 = \omega_i + \rho_i \varepsilon_{i,t-1}^2 + \psi_i \sigma_{i,t-1}^{+2} + \varphi Volume_{i,t} + \sum_{k=0}^{5} \delta_{i,t-k} Short_{i,t-k}, \tag{6}$$

Table 7

Volatility—two-step model

Model is specified as follows:
Equation (3):

$$Return_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} Day_{k,t} + \sum_{k=1}^{5} \beta_{i,k} Return_{i,t-k} + \sum_{k=0}^{5} \gamma_{i,t-k} Short_{i,t-k} + \varepsilon_{i,t}$$

Equation (4):

$$|\varepsilon_{i,t}| = \tau_i + \psi_t Monday_t + \sum_{k=1}^{5} \rho_{i,k} |\varepsilon_{i,t-k}| + \varphi Volume_{i,t} + \sum_{k=0}^{5} \delta_{i,t-k} Short_{i,t-k} + \eta_{i,t}$$

The dependent variable for Equation (3) is daily return. *Day* includes five dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. *Monday* is a dummy variable for Monday. *Short* is defined as either number of shares shorted (*svolume*), number of short trades (*strade*), percentages of shares shorted (*vshare*) or percentage of trades shorted (*tshare*). Where *svolume* or *vshare* are used *Volume* is defined as number of shares traded. Where *strade* or *tshare* are used *Volume* is defined as number of trades. Coefficients and *t*-statistics are reported for Equation (3) in Panel A and for Equation (4) in Panel B. Coefficients reported are the cross-sectional means of the company specific time series coefficients. Coefficients reported for Shorting in Panel A and for Intercept, Shorting, Volume and Monday in Panel B have been scaled by 100. Average *N* is the average number of observations in each time series regression.

Short measure	$Return_{t-1}$	$Return_{t-2}$	$Return_{t-3}$	$Return_{t-4}$	$Return_{t-5}$	$Short_t$	$Short_{t-1}$	$Short_{t-2}$	$Short_{t-3}$	$Short_{t-4}$	$Short_{t-5}$	Days
Panel A: Equation (3)												
Number of shares	−0.01664	−0.0389	−0.0410	−0.0098	−0.0111	0.9300	−0.0389	0.0148	0.0082	0.0672	0.0180	Yes
shorted (*svolume*)	−2.38	−8.80	−12.92	−2.75	−3.10	3.17	−0.67	0.22	0.15	0.85	0.34	
Number of short	−0.0138	−0.0378	−0.0387	−0.0090	−0.0108	0.0038	−0.0002	−0.0001	−0.0001	−0.0002	0.0003	Yes
trades (*strade*)	−1.96	−8.18	−11.89	−2.62	−3.02	3.66	−1.08	−0.71	−0.44	−0.50	1.02	
Percent of shares	−0.0157	−0.0393	−0.0379	−0.0110	−0.0143	0.1633	−0.0463	−0.0139	−0.0074	−0.0064	−0.0191	Yes
shorted (*vshare*)	−2.34	−9.06	−12.53	−3.38	−4.27	18.70	−9.05	−2.25	−1.43	−1.17	−4.13	
Percent of trades	−0.0158	−0.0382	−0.0399	−0.0116	−0.0129	0.2583	−0.0913	−0.0289	−0.0017	−0.0182	−0.0273	Yes
shorted (*tshare*)	−2.33	−8.74	−12.09	−3.45	−3.76	23.80	−14.09	−4.14	−0.25	−2.75	−5.37	

(*Continued*)

Table 7 (*continued*)

Volatility—two-step model

Short measure	Short	Volume	Mon	Short_{t-1}	Short_{t-2}	Short_{t-3}	Short_{t-4}	Short_{t-5}	$\lvert\varepsilon_{t-1}\rvert$	$\lvert\varepsilon_{t-2}\rvert$	$\lvert\varepsilon_{t-3}\rvert$	$\lvert\varepsilon_{t-4}\rvert$	$\lvert\varepsilon_{t-5}\rvert$
Panel B: Equation (4)													
Number of shares	0.0383	0.0079	0.0466	−0.0153	0.0012	−0.007	−0.0008	−0.0071	0.0766	0.0378	0.0484	0.0386	0.0343
shorted (*svolume*)	2.69	3.71	5.74	−2.18	0.41	−1.98	−0.35	−2.16	14.14	10.07	13.24	9.57	12.06
Number of short	0.0125	0.007	0.0341	−0.0038	0.0012	−0.0018	−0.0015	−0.0015	0.0648	0.0335	0.0446	0.0385	0.0308
trades (*strade*)	4.33	3.47	4.21	−2.93	0.69	−2.45	−1.9	−3.12	10.35	9.05	13.22	10.78	10.62
Percent of shares	0.7455	0.0111	0.0403	0.1113	−0.0151	0.0508	0.0922	0.0422	0.0484	0.0177	0.0257	0.025	0.0235
shorted (*vshare*)	19.86	4.21	4.85	3.11	−0.44	1.6	2.93	1.22	8.25	4.43	7.13	6.96	7.06
Percent of trades	0.6648	0.0107	0.039	−0.0076	−0.0564	0.0098	0.1041	0.0018	0.0507	0.0191	0.0277	0.0281	0.0241
shorted (*tshare*)	16.09	4.16	4.69	−0.16	−1.64	0.31	2.8	0.04	8.25	5.09	7.55	8.28	7.75

Table 8

Volatility—GARCH model

Model is specified as follows:
Equation (5):

$$Return_{i,t} = \sum_{k=1}^{5} \alpha_{i,k} Day_{k,t} + \sum_{k=1}^{5} \beta_{i,k} Return_{i,t-k} + \sum_{k=0}^{5} \gamma_{i,t-k} Short_{i,t-k} + \varepsilon_{i,t} \; \varepsilon_{i,t} \sim N(0, \sigma_{i,t}^2)$$

Equation (6):

$$\sigma_{i,t}^2 = \omega_i + \rho_i \varepsilon_{i,t-1}^2 + \psi_i \sigma_{i,t-1}^{+2} + \varphi Volume_{i,t} + \sum_{k=0}^{5} \delta_{i,t-k} Short_{i,t-k}$$

We obtain transaction-level short sale data for 242 REITs traded on NYSE and Nasdaq from these exchanges under the SEC RegSHO for the period from January 3, 2005 through June 29, 2007. The dependent variable for Equation (5) is daily return. *Day* includes five dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. *Short* is defined as either number of shares shorted (*svolume*), number of short trades (*strade*), percentages of shares shorted (*vshare*) or percentage of trades shorted (*tshare*). Where *svolume* or *vshare* are used *Volume* is defined as number of shares traded. Where *strade* or *tshare* are used *Volume* is defined as number of trades. Coefficients and t-statistics for Equation (5) are reported in Panel A and for Equation (6) in Panel B. Coefficients reported are cross-sectional averages of the company specific coefficients generated by the time series regressions. Coefficients reported for the *Short* variables in Panel A have been scaled by ten. Coefficients reported for ω, *Volume* and *Short* in Panel B have been scaled by 100. Average N is the average number of observations in each time series regression. We report t-statistics below coefficient estimates.

Short measure	$Return_{t-1}$	$Return_{t-2}$	$Return_{t-3}$	$Return_{t-4}$	$Return_{t-5}$	$Short_t$	$Short_{t-1}$	$Short_{t-2}$	$Short_{t-3}$	$Short_{t-4}$	$Short_{t-5}$
Panel A: Equation (5)											
Number of shares shorted (*svolume*)	−0.0288	−0.042	−0.0421	−0.0207	−0.0048	0.0965	−0.0135	0.006	−0.0025	−0.0001	−0.0026
	−4.12	−9.15	−12.46	−5.67	−1.37	3.31	−1.33	1.24	−0.63	−0.03	−0.82
Number of short trades (*strade*)	−0.0407	−0.0445	−0.0403	−0.0198	−0.0057	0.0039	−0.0002	0.00001	0.00001	−0.0002	0.00001
	−7.07	−10.79	−11.76	−6.63	−3.55	21.8	−9.05	−2.30	−2.51	−0.32	−5.23
Percent of shares shorted (*vshare*)	−0.0451	−0.0489	−0.0377	−0.0199	−0.0102	0.1545	−0.0418	−0.0122	−0.0103	−0.0015	−0.0215
	−6.33	−9.99	−12.77	−6.60	−1.77	4.01	−0.63	0.06	0.10	−0.48	−0.05
Percent of trades shorted (*tshare*)	−0.0448	−0.0445	−0.0395	−0.0195	−0.0096	0.2393	−0.0842	−0.0296	−0.0036	−0.0132	−0.0296
	−7.21	−10.36	−10.54	−6.53	−3.20	25.21	−15.56	−4.86	−0.65	−2.67	−6.73

(*Continued*)

Table 8 (*continued*)

Volatility—GARCH model

Short measure	ω	${\varepsilon_{t-1}}^2$	${\sigma_{t-1}}^2$	Volume	Short_t	Short_{t-1}	Short_{t-2}	Short_{t-3}	Short_{t-4}	Short_{t-5}
Panel B: Equation (6)										
Number of shares shorted (*svolume*)	0.00003	0.0647	0.0043	0.0008	0.0316	0.0035	0.0135	0.0042	0.0116	0.0025
	2.12	5.43	1.96	3.29	2.22	4.96	1.57	18.97	1.47	12.05
Number of short trades (*strade*)	0.00004	0.1159	0.0296	0.0007	0.0085	0.0005	0.0012	0.0001	0.0007	0.00001
	7.62	11.5	3.81	3.56	2.70	1.44	1.07	1.75	1.03	2.92
Percent of shares shorted (*vshare*)	0.00002	0.1271	0.0256	0.0013	0.1357	0.0247	0.0132	0.0346	0.0392	0.0241
	4.18	7.45	3.68	3.28	6.52	5.20	4.73	1.52	3.46	5.04
Percent of trades shorted (*tshare*)	−0.0448	−0.0445	0.00003	0.1105	0.0185	0.0012	0.1088	0.02	0.0203	0.0143
	2.48	12.62	3.24	3.47	4.28	4.81	2.38	5.02	3.64	3.62

where $\sigma^2_{i,t}$ is the residual variance from Equation (5) and other variables are as previously defined (Bollerslev, 1986; Hansen and Lunde, 2005).

We estimate Equations (5) and (6) for each REIT in our sample and then report the cross-sectional average of time series coefficients in Table 8. The results in Panel A of Table 8 (Equation (5)) are similar to those of Panel A in Table 7 in that short selling is contemporaneously positively correlated with returns. Panel B reports results for Equation (6), which are consistent with our two-step volatility analysis results. We find that short selling significantly positively impacts volatility for all four of our shorting measures. Overall, we find robust evidence of a positive relation between short selling activity and price volatility.[22] To the extent that volatility is primarily driven by the arrival of new information, our evidence suggests that short sellers are informed.

6. Conclusions

We examine whether short sellers in the REIT market are informed. We choose REITs because they have been excluded from nearly all previous short selling research. We find strong evidence that short sellers of REITs are informed. The inverse predictive relationship between shorting and future returns is evident through portfolio sorting and cross-sectional regressions for all four shorting measures used. A one-standard-deviation increase in shorting predicts as much as a 54.6 basis point reduction in risk-adjusted returns over the following month. This informed shorting appears in both small and large short trades, but consistent with previous shorting research is stronger in large trades. Extending our analysis of REITs to volatility, we find a strong positive relation between shorting and volatility. According to the volume-volatility literature such a relation is consistent with informed trading. Overall, we find strong and robust evidence that REIT short selling is informed and, therefore, contributes to market efficiency.

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[22] In untabulated results we rerun both volatility models with the trade size subsamples and find a similar positive relation between shorting and volatility for both small and large trades, though the relation is stronger for large trades.

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