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*Real Estate Economics*, Vol. 49, No. 1 (Spring 2021): 332-389. [DOI](https://doi.org/10.1111/1540-6229.12256). This article is © Wiley and permission has been granted for this version to appear in [e-Publications@Marquette](http://epublications.marquette.edu/). Wiley does not grant permission for this article to be further copied/distributed or hosted elsewhere without the express permission from Wiley.

Option Trading and REIT Returns

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# Abstract

This article examines the relation between option trading volume and real estate investment trust (REIT) market performance. Specifically, we find that option volume increases are followed by decreases in returns. Furthermore, the portion of option volume that is orthogonal to REIT characteristics drives the observed return predictability relation, thereby suggesting that the return predictability of option trading is (at least partially) attributable to information-based explanations. Finally, consistent with informed traders favoring option market activities due to short-sale costs and/or constraints, we find option based return predictability is more evident within REITs than non-REITs, even though firms within this industry are generally viewed as informationally transparent.

# Introduction

This article examines the relation between option trading volume and real estate investment trust (REIT) market performance. Specifically, we find that option volume increases are followed by decreases in returns. Furthermore, the portion of option volume that is orthogonal to REIT characteristics drives the observed return predictability relation, thereby suggesting that the return predictability of option trading is (at least partially) attributable to information‐based explanations. Finally, consistent with informed traders favoring option market activities due to short‐sale costs and/or constraints, we find option based return predictability is more evident within REITs than non‐REITs, even though firms within this industry are generally viewed as informationally transparent.

Over the past two decades, a rich and robust literature has emerged examining linkages between equity markets and their related derivative securities. While early work in this area posited that derivatives were essentially redundant securities, a consensus soon emerged suggesting options help complete markets and facilitate price discovery. More explicitly, to the extent option markets allow traders to capitalize on private information effectively, option markets stimulate price discovery and foster greater informational efficiency. Within this context, the field has quickly and naturally progressed to explore potential associations between option market characteristics and return predictability.

Conceptually, informed traders can profit in either the equity or option markets. In practice, however, informed investors generally prefer the implicit leverage provided by options, so long as the option market is sufficiently liquid with respect to trade execution to allow them to profitably capitalize on their (real or perceived) informational advantage. Consistent with this broad paradigm, Johnson and So (2012) find evidence that option volume is indeed related to future stock returns, and further conclude that this relation is strongest when market conditions provide incentives for informed traders to operate within the option market. Furthermore, they suggest this observed return predictability provides a direct "indication of the sign of private information." Of note, these incentives are particularly strong for investors with negative information about the firm's future prospects, as short‐selling exposes investors to risks and costs not borne by option market transactions. For example, short selling exposes investors to unlimited downside risk, dividend fulfillment obligations, short squeezes and buy‐in losses. Additionally, short‐sale transactions are often characterized by high opportunity costs given margin interest requirements, as well as the high mandatory initial margin and minimum maintenance requirements. Finally, as just noted above, short sellers are responsible for compensating lenders for missed dividend payments. By construction, real estate investment trusts (REITs) exhibit high dividend payout ratios, and thus traders' preferences for option market transactions should be particularly strong within this market sector.

Surprisingly, however, neither Johnson and So (2012) nor the subsequent literature conclusively demonstrate whether option volume predictability is fully independent of firm characteristics, or alternatively, whether option volume predictability is disproportionately and systematically concentrated within a subset of firms with similar attributes and characteristics. This latter scenario gives rise to the possibility that relative option volume may serve as a proxy for firm risk.[1]

The current investigation attempts to fill this void by exploring the ability of option volume to predict future REIT returns, as well as potential mechanisms that give rise to this relation. Given the tangible nature of REITs' underlying assets, as well as their unique regulatory environment, this market sector provides noteworthy contrasts to the existing literature. First, with respect to the firm's asset base, REITs tend to hold highly recognizable, tangible assets. While the assets tend to be readily identifiable and informationally transparent, their typical scale and geographic specificity generally renders them relatively illiquid. Moreover, the liquidity of REIT assets is further reduced by regulatory restrictions against holding property for resale (also known as the Dealer Rule), as well as limitations on the fraction of assets that a firm may dispose of during any given year.[2] As such, firms within this industry are typically characterized by a relatively transparent and stable asset base.

Finally, the 90% regulatory mandated distribution requirements also mitigate information asymmetries within the REIT market, thereby further reducing the potential for return predictability. These mandatory distribution requirements are important to, and facilitate, REIT market valuation for multiple reasons. For example, the disgorgement of free cash flows effectively serves to mitigate potential agency problems associated with empire building.[3] Additionally, given the scale of typical commercial real estate projects, these restrictions effectively prohibit firms from retaining sufficient cash flows to internally fund capital expansion activities. Thus, the regulations force firms (and/or their managers) with growth ambitions to continually return to the capital markets for financing, where financial transparency is rewarded with lower capital acquisition costs, and thereby subjects REITs to enhanced market discipline.[4] Interestingly, while transparency is of tremendous value to potential capital providers, it may also reduce the number (or intensity) of privately informed traders within this industry, which in turn, may mitigate relations between the option market and the equity market.[5] On the other hand, evidence of return predictability within this highly transparent sector of the market would provide strong evidence and support regarding the value relevance of derivative market transactions to underlying equity market returns. Moreover, by focusing on a single industry, we also reduce extraneous variation across firm operational parameters and objectives, thus providing a cleaner test of our focal hypotheses.

Somewhat surprisingly, while the REIT option market has grown rapidly over the last two decades, and the above arguments clearly suggest it is a compelling laboratory within which to examine economic questions, its development, growth and operations have received relatively scant attention within the academic literature. Among the limited investigations exploring REIT option markets, Diavatopoulos *et al*. (2010) demonstrate that volatility observed in the option market is related to future equity volatility. Additionally, Diavatopoulos *et al*. (2011) examine the impact of REIT option introductions, and find REITs exhibit a similar reaction to option introduction as do non‐REIT equities. Finally, in the work most closely related to the current investigation, Chung *et al*. (2016) examine the predictive power of implied volatility in the option market, with a particular emphasis on changes in observed relations during the financial crisis of 2007–2009. They find option implied (1) positively predicts future stock return volatility, (2) negatively predicts contemporaneous stock returns and (3) negatively predicts future stock returns. They also document that these relations are significantly more pronounced during the crisis period. Building upon this prior literature, and focusing on the relative option volume metrics introduced by Johnson and So (2012), the current investigation seeks to provide further insights into both the return predictability of options trading, as well as explore whether and how the presence of informed traders in the option market contributes to this observed return predictability.

Previewing our results, we find strong evidence of REIT return predictability. Specifically, higher relative option volumes consistently forecast negative future equity returns for the underlying REIT. Additionally, we find REIT characteristics exhibit only a limited ability to predict option volume. Moreover, the portion of option trading that is orthogonal to REIT characteristics drives the observed return predictability. Taken together, these findings suggest option trading contributes to price discovery in the REIT market. We also find return predictability is concentrated in smaller, more illiquid and more informationally opaque REITs. That said, even after controlling for these potentially confounding effects, option volume continues to exhibit predictive power. Thus, our findings suggest that informed traders are present in the option market, and further, that the return predictability of our option market metrics is at least partially attributable to their presence. As such, we conclude REIT option trading provides value relevant, incremental information to market participants beyond what is already contained in observable REIT firm characteristics and company disclosures.

Finally, we examine whether the negative return predictability observed in REIT markets is the result of informed traders facing short‐sale constraints in the corresponding equity market, and present evidence documenting the return predictability is not entirely due to short‐sale levels or constraints. Potentially, when informed traders possess negative information about a company they heed the advice typically attributed to John Maynard Keynes: "The market can stay irrational longer than you can stay solvent." More directly, when informed investors are transacting based upon negative information, they may well prefer the option market as there is no guarantee regarding when the market will incorporate the negative information and see prices return to their fundamental values. While shorting requires the investor to lock up a significant amount of capital and leaves them subject to margin calls, the option market often requires less capital initially and can even be cash flow positive.[6] As such, our results suggest options and short‐sale markets may well serve complementary functions in completing financial markets and facilitating price discovery.

The remainder of this article is organized as follows. The section "Literature Review" reviews the relevant literature on option trading, with particular emphasis given to previous studies of both return predictability and applications to real estate markets. The "Data and Methodology" section then outlines the data and methodological approaches we employ to examine our focal hypotheses. Continuing, the "Option Trading and REIT Returns" section presents the empirical results of our main analysis, further tests into the heterogeneity of the observed effects across time, option moneyness and the possible confounding effects of short‐sale constraints, as well as a series of robustness tests evaluating the stability and consistency of our results. Finally, the "Summary and Conclusion" section summarizes and reviews our major findings, highlights their implications and concludes the article.

# Literature Review

The central question addressed by this investigation, as noted in the preceding section, is does option trading contribute meaningfully to price discovery in publicly traded REIT markets. Turning to the previous literature, the Black and Scholes (1973) option pricing model implicitly suggests option volumes should play no role in underlying asset valuation. In practice, however, the existing empirical evidence suggests option volume can, and often does, predict future market returns. Specifically, various measures of option market trading activity have been shown to help improve the price discovery process for underlying assets. For example, Chakravarty, Gulen and Mayhew (2004), Pan and Poteshman (2006), Johnson and So (2012) and Hu (2014, 2018) all find options order flow contains important, value relevant information regarding the underlying firm's equity value.

While there are multiple dimensions across which to examine and compare the informativeness of derivative market transactions, much of the existing literature focuses on return metrics. Of note, a large stream of research explicitly examines whether option volume predicts either activities or outcomes in the underlying equity market. Among the early studies in this area, Amin and Lee (1997), Easley, O'Hara and Srinivas (1998) and Cao, Chen and Griffin (2005) all document that trading imbalances within the option market exhibit predictive power over subsequent equity returns. Along this same dimension, using proprietary data obtained from the Chicago Board of Options Exchange, Pan and Poteshman (2006) estimate the put–call (P/C) ratio of sample firms, defined as buyer‐initiated put volume scaled by total option (both put and call) volume, and show that daily P/C ratios are negatively related to next‐day returns.

More recently, Roll, Schwartz, and Subrahmanyam (2010) introduce relative option volume, hereinafter O/S and defined as the ratio of option volume to stock volume, as an indicator of the relative intensity of option market trading. They further demonstrate O/S is systematically related to observable firm attributes. Applying this tool to examine equity market returns, Johnson and So (2012) find empirical support for the notion O/S predicts future (negative) stock returns, and further conclude the strength of the O/S signal is contingent upon financial market conditions.[7] Similarly, Choy and Wei (2012) use the ratio of option volume to option open interest in examining the relation between option market activity and stock returns surrounding earnings announcements. Once again, they find unexpected changes in option trading volume predict subsequent returns to underlying equity positions.[8] Continuing, Hu (2014) investigates intraday equity option‐induced trading and finds option‐induced imbalances significantly predict future stock returns in the cross‐section. Finally, both the aforementioned Easley, O'Hara, and Srinivas (1998) paper and An *et al*. (2014) find evidence that not only do stock prices follow option trading, but option trading also follows stock price changes. Taken together, these previous results indicate option trading plays an important role in price discovery, and further, option traders appear to be informed traders. The current article extends this existing literature by examining option trading and return predictability within the context of REIT markets.

With respect to REIT option markets, relatively little empirical work has been published to date. Among those limited investigations, Diavatopoulos *et al*. (2011) examine the impact of REIT option introductions. Despite the relatively transparent nature of both REITs and REIT assets, the authors find firms within this industry exhibit a similar reaction to option introductions as do non‐REIT equities. Additionally, Borochin *et al*. (2017) examine whether and how option market liquidity predicts REIT leverage changes. They find overall firm leverage is less likely to increase when REITs have higher historical volatility, or lower option market liquidity. Of more direct relevance to the current investigation, Diavatopoulos *et al*. (2010) examine both realized and implied volatility, and find that both of these option market metrics predict volatility within the underlying REIT equity market. Finally, in the work most closely related to the current investigation, Chung *et al*. (2016) examine the predictive power of REIT‐implied volatility, with a particular emphasis on changes in observed relations during the financial crisis of 2007–2009. They find option implied volatility: (1) positively predicts future stock return volatility, (2) negatively predicts contemporaneous stock returns and (3) negatively predicts future stock returns. They also document that these relations are significantly more pronounced during their focal crisis period. Building upon the findings of this prior literature, the current investigation seeks to examine the previously unexplored relation between relative option trading volume and subsequent REIT equity returns.

# Data and Methodology

In constructing our data set, we begin by obtaining daily option trading data from the OptionMetrics's Ivy DB U.S. database for the period 1996 through 2014. Next, we identify and collect daily data on all equity REITs from the ZIMAN REIT—Center for Research in Security Prices (CRSP) database. We then merge the available option trading data with these stock trading data. Examining this unrestricted sample reveals a clear pattern of strong and rapid growth in the REIT option market over the past decade. For example, Figure 1 illustrates the percentage of publicly held REITs with exchange‐traded options from 1996 through 2014. During this 19‐year period, the fraction of the equity REITs with exchange‐traded options increased dramatically, from just over 5% (10 out of 197) of firms in 1996 to nearly 90% (152 out of 169) of firms by 2014. These numbers both mirror and extend the trends noted by Diavatopoulos *et al*. (2010), who report the fraction of REITs with exchange‐traded options grew from only 5% in the mid‐1990s to approximately 35% by 2006. Interestingly, their study concluded immediately prior to a period of rapid growth and expansion within the REIT option market, as the number of equity REITs with liquid options trading more than doubled (from 62 firms in 2006 to 152 firms by year‐end 2014) in the eight years immediately following the conclusion of their sample period. Further illustrating this rampant growth in the option market not captured in prior studies, the percentage of equity REITs with exchange‐traded options averaged 23% from 1996 to 2006, 67% during the financial crisis period of 2007–2009 and 86% from 2010 to the end of our sample observation period in 2014. As a point of comparison, the percentage on non‐REITs with exchange‐traded options also experienced strong growth during our sample period, from 23.3% in 1996 to 63.6% by year‐end 2014. While not as dramatic as the shift observed for REITs, the broader cross‐section of non‐REIT firms also exhibits nontrivial option coverage differences across the pre‐ and postfinancial crisis periods. Specifically, the percentage of non‐REIT firms with exchange‐traded options increased from an average of 34% in the precrisis interval (1996–2006), to 47% during the depths of the great recession in 2007–2009, and has further risen to an average of 59% in the postcrisis environment. Given, the extended sample interval offered by the current investigation relative to existing REIT option market studies, our results offer the potential for significant new insights into the rapidly evolving REIT option market.

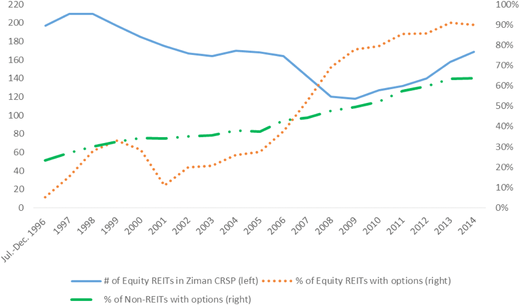


Figure 1. Equity REITs with traded options.

\*Based on the initial population, before we apply our data filters, with the exception of limiting to options with expirations within 5–35 trading days.

With respect to the current investigation, we note that we aggregate both end‐of‐day stock and option trading volumes to construct our weekly measures of relative volume for each firm. Specifically, following Johnson and So (2012), we use options (across all strike prices) expiring within the next 35 trading days.[9] Furthermore, in order to minimize mechanical issues associated with option trading volume associated with contract roll forward, we exclude options expiring within the next five trading days. Failure to account for the potential of option contracts being rolled forward would effectively lead to an overstatement of the level of unique option positions held against the underlying equity position. Additionally, to mitigate against potential problems associated with illiquidity in the option market, we require sample observations (*i.e*., firm‐weeks) to evidence a minimum of both 25 call and 25 put contracts traded per week in order to be retained as part of our estimation sample.[10] Continuing, as a number of our measures are constructed relative to their historical averages, we also require each observation to possess at least six months of both prior weekly stock and option volumes. Furthermore, to mitigate both small firm (micro‐REIT) and potential denominator effects, we exclude REITs with stock prices below $1.[11] Finally, the data necessary to construct additional control parameters, such as underlying stock characteristics and firm attributes, are obtained from Compustat‐Capital IQ (Compustat), CRSP, S&P Global Market Intelligence (formerly SNL Financial) and the Federal Reserve Economic Data database. After combining the relevant and available information from each of these databases and imposing the minimal data filters, screens and restrictions outlined above to ensure the accuracy of this information, our final estimation sample contains 14,608 (firm‐week) observations, obtained from 153 distinct equity REITS (representing an average of 42 unique equity REITs per year).

# Option Measures and Control Variables

## Option measures

While the patterns illustrated in Figure 1 clearly demonstrate that the breadth of REIT option trading has expanded markedly over the past decade, these patterns do not, nor are they intended to, measure the intensity of option trading with respect to any individual firm. Therefore, following Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012) and Ge, Lin, and Pearson (2016), we calculate the O/S ratio to measure firm‐level option trading intensity. Previous research demonstrates that while this O/S ratio tends to be highly skewed, the natural logarithm transformed O/S ratio seems to be well suited for linear regression.[12] As such, throughout this article we use logged values of the O/S ratio, and for simplicity refer to this transformed metric simply as the O/S ratio. More specifically, we define the options trading volume, stock trading volume and O/S ratio as follows:

 refers to the qualifying option contract volumes for REIT  in week  indicates the number of shares outstanding for REIT  in week  and  represents the total stock trading volume for REIT  in week . Because the base of every option contract is 100 shares of the underlying stock, multiplying the reported option contract volumes by 100 ensures more direct comparability to the reported equity volumes. Figure 2 illustrates the annual option and stock trading volumes over our sample period, while Figure 3 presents the annual O/S ratio over this same interval.[13] Of note, across our sample the annual average equity REIT option trading volume is 28,163.15 contracts (or approximately 2.816 million shares) per firm. As a point of comparison, the average equity REIT in our sample exhibits significantly higher annual equity trading volume at approximately 111.56 million shares.[14] Furthermore, we also note that across both equity REITs and non‐REIT firms, stock and option trading volumes have increased significantly over time, particularly during the interval surrounding the 2007–2009 financial crisis. This latter observation is entirely consistent with the notion that increased uncertainty and/or differences of opinion with respect to fundamental market valuation help drive trade. Additionally, building upon our previous analysis examining the significance of the financial crisis on REIT option market expansion, we also observe nontrivial differences in both equity REIT option volume and stock volume across time. Notably, both option and stock trading volumes increased markedly during the crisis period. While this growth has recently slowed, or even reversed, trading volumes have not receded to precrisis levels. Taken together, these patterns once again underscore the importance of more closely analyzing this rapidly growing derivative security marketplace.

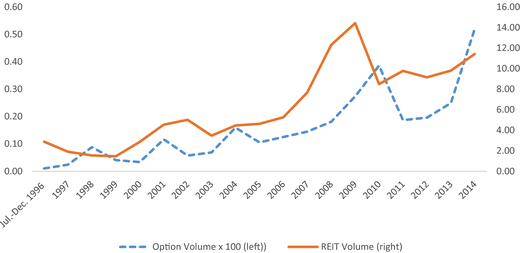


Figure 2. Equity REITs and option weekly trading volume (in millions).

\*Based on the sample used in our analysis.

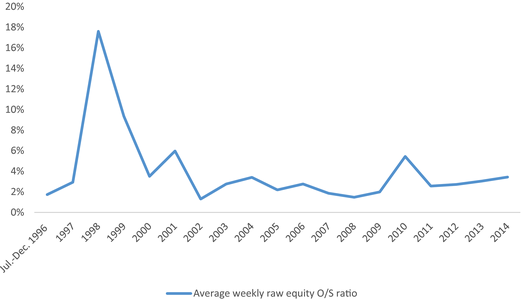


Figure 3. Weekly average raw equity O/S ratio.

\*Based on the sample used in our analysis.

\*\*Appendix A reports yearly descriptive statistics regarding the weekly O/S ratio.

Given the potential role and importance of historical average trading volume in future trading activities, we further decompose the O/S ratio into two component pieces: (1) the historical average O/S (AVG(O/S)) ratio and (2) the current period change, or innovation, in the O/S ratio (Δ(O/S)). Our historical average option measure, AVG(O/S), is calculated over the prior six months (*i.e*., 26 weeks), excluding weeks *w –* 1 through *w –* 6.[15] As alluded to above, the primary motivation for skipping six weeks is to ensure the historical average option measure does not include options that expire during our return measurement window, week . The option contracts included in our sample are further restricted to those expiring within 35 trading days beginning five days after the trade date, thus traded option contracts during weeks *w –* 7 through *w –* 26 would all expire prior to week . As such, no overlapping option contracts should exist across our current and historical option measures. Mathematically:

Finally, to account for nonsynchronous closing times between REIT equity and option markets, we follow Johnson and So (2012) and omit the Friday‐to‐Monday returns when calculating subsequent week returns. More specifically, weekly option measures are calculated based on calendar week *w*, while week  returns are calculated as cumulative daily returns from the close of markets on Monday in week  to the close of markets on the following Monday.[16] The complete time sequence for our weekly estimation sample may thus be illustrated as follows:

Firm attributes

The prior literature documents that a variety of firm characteristics may well be associated with future equity returns, while a related literature documents that stock characteristics are associated with trading activity. Therefore, to ensure that any observed relation between the weekly O/S ratio and subsequent REIT returns is not driven by multicollinearity, we follow Johnson and So (2012) and include past week stock returns (RET), firm size (SIZE), book‐to‐market (BM) ratios, momentum (MOM) and the historical average of Amihud's (2002) stock illiquidity measure (ILLIQ) as control variables. Specifically, RET is calculated as the cumulative, market‐adjusted stock return during the week (*w*). SIZE is computed as the natural logarithm of the firm's market capitalization (in millions of dollars) as of each firm's previous quarterly earnings announcement date. BM is constructed as the natural logarithm of the firm's BM equity ratio as of each firm's previous quarterly earnings announcement date. Finally, both MOM and ILLIQ are computed over the prior 26 weeks, skipping week *w –* 1 to ensure consistency with the previous literature.

Next, to account for the fact that hundreds of stock anomalies have been documented across the literature, we also include a composite metric (CM) to control for the aggregate impact of firm (*i.e*., REIT) characteristics.[17] CM was originally created by Stambaugh, Yu, and Yuan (2012), and is constructed using 11 stock return anomalies that persist after standard risk adjustments.[18] These anomalies (and their foundational underpinnings) include: (1) a financial distress metric (Campbell, Hilscher, and Szilagyi 2008); (2) Ohlson's O‐score bankruptcy probability (Ohlson 1980); (3) net stock issuances (Ritter (1991), Loughran and Ritter (1995), Fama and French (2008)); (4) composite equity issuances (Daniel and Titman (2006)); (5) total accruals (Sloan (1996)); (6) net operating assets (Hirshleifer *et al*. (2004)); (7) MOM (Jegadeesh and Titman (1993)); (8) gross profitability (Novy‐Marx (2013)); (9) asset growth (Cooper, Gulen, and Schill (2008)); (10) return on assets (Chen, Novy‐Marx, and Zhang (2011)) and (11) investment to assets (Titman, Wei and Xie 2004, Xing 2008, Chen, Novy‐Marx and Zhang 2011). In calculating this metric, stocks are first sorted into deciles based upon each of the 11 individual return anomalies. Higher ranks are assigned to stocks with expectations of higher future stock returns based on the given anomaly, with lower ranks assigned to stocks with expectations of lower future stock returns. We then take an equally weighted average of each decile rank to arrive at our CM score for each firm. Thus, by construction, higher CM scores imply higher expectations of future stock return potential. As such, we interpret REITs with high CM scores as being relatively cheap, while REITs with low CM scores are viewed as relatively expensive.

In addition to these firm characteristics, and motivated by the findings of Aguilar, Boudry, and Connolly (2018) that higher (active) institutional ownership levels are associated with increased pricing efficiency within REIT markets, we also control for the level of institutional ownership. Specifically, following Roll, Schwartz, and Subrahmanyam (2010), and using institutional holdings data obtained from Thomson Financial, we calculate the percentage of shares outstanding held by institutions as of December of each sample year. Finally, Diavatopoulos *et al*. (2010) demonstrate that implied volatility is related to future realized volatility, while An *et al*. (2014) show that changes in implied volatility predict cross‐sectional common stock returns. Therefore, we control for implied volatility with two different measures used in the prior literature. The first, ΔIV, is constructed by taking the difference between the current and historical average implied volatility for each sample firm. Daily implied volatility is obtained directly from OptionMetrics, while weekly implied volatility is calculated as the option volume‐weighted average of daily implied volatility for REIT *i* in week *w*. Following Chung *et al*. (2016), our second IV metric is calculated in a similar fashion but employs vega weights. Across both metrics, the historical average implied volatility is computed using the past six months of data, while once again skipping weeks *w –* 1 to *w –* 6 to ensure an independent estimation window devoid of measurement concerns surrounding overlapping option contracts and expirations. In general, both metrics yield qualitatively similar results. As such, for ease of presentation throughout our analyses below, we tabulate results exclusively from the original weighting metric, and note any rare exception where vega weights lead to significantly different results. A detailed explanation of all variables employed throughout the empirical portion of this analysis is presented in Appendix B.

### Descriptive Statistics

Descriptive statistics for both our focal option market metrics and underlying firm characteristics are presented in Table 1. We note that to facilitate interpretations of these results, all values are presented in their raw format without log transformations.[19] Examining the data, we find that on average REIT weekly option volume represents slightly more than 3% of REIT trading volume. There is considerable variation along this dimension, with the 5th through 95th percentile range spanning from 0.14% to 9.66%. Similar values and ranges are reported with respect to our historical average O/S metric, while a comparison of our change metrics (both Δ(O/S) and ΔIV) to the previous finance literature suggests REIT option markets may exhibit similar mean values, though considerably wider variation, along these same dimensions.[20]

1 Table. Descriptive statistics

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Observations** | **Mean** | **Median** | **SD** | **5th Percentile** | **25th Percentile** | **75th Percentile** | **95th Percentile** |
| O/S | 14,608 | 0.030 | 0.010 | 0.125 | 0.001 | 0.004 | 0.025 | 0.097 |
| Δ(O/S) | 14,608 | −0.067 | −0.104 | 1.238 | −1.987 | −0.841 | 0.659 | 2.057 |
| AVG(O/S) | 14,608 | 0.025 | 0.011 | 0.042 | 0.001 | 0.005 | 0.027 | 0.096 |
| ΔIV | 14,608 | 0.015 | −0.008 | 0.207 | −0.231 | −0.065 | 0.067 | 0.334 |
| RET | 14,608 | 0.000 | 0.000 | 0.060 | −0.076 | −0.022 | 0.021 | 0.072 |
| SIZE ($millions) | 14,608 | 7,635 | 4,578 | 8,115 | 739 | 2,043 | 11,228 | 21,501 |
| BM | 14,608 | 0.528 | 0.419 | 0.522 | 0.087 | 0.277 | 0.643 | 1.210 |
| MOM | 14,608 | 0.073 | 0.077 | 0.320 | −0.417 | −0.065 | 0.193 | 0.502 |
| ILLIQ | 14,608 | 0.934 | 0.338 | 2.536 | 0.067 | 0.148 | 0.793 | 3.449 |
| CM | 14,608 | 4.346 | 4.300 | 0.859 | 3.000 | 3.800 | 4.900 | 5.818 |
| Inst.Own. (%) | 14,608 | 78.629 | 84.150 | 25.030 | 21.480 | 69.189 | 95.493 | 108.055 |

*Notes*: This table provides descriptive statistics (sample size, mean, median, standard deviation as well as 5th, 25th, 75th and 95th percentiles) for the variables considered in the analysis. Appendix B provides a detailed description and definition of each variable.

With respect to firm characteristics, not surprisingly, the average REIT's market adjusted return is near 0. Turning to firm size, the average REIT in our sample possesses a market capitalization in excess of $7.6 billion (median = $4.6 billion), ranging from a low of $93 million for First Industrial Realty Trust Inc. in March of 2009, to a high of over $50 billion for Simon Property Group Inc. across multiple observation windows. These numbers are somewhat larger than would be observed for the entire universe of publicly traded REITs in the United States, with the disparity driven by the relative paucity of small and micro‐REITs with liquid option listings.[21] An additional notable difference between our sample firms and the broader universe of REITs is with respect to growth prospects, as REITs with listed options exhibit considerably lower BM ratios, and hence higher perceived growth prospects, than peer firms lacking derivative coverage. Both our MOM and composite firm characteristics (CM) controls exhibit similar means and wider variation than found in previous studies of non‐REIT option markets, while results for Amihud's (2002) illiquidity ratio suggests REITs may well be more liquid than their non‐REIT peers. Finally, consistent with prior studies, sample firms exhibit relatively high (78.6%) average levels of institutional ownership.[22]

Continuing, Table 2 reports Pearson correlation coefficients for each of our sample attributes. Given our relatively large sample, many of the reported correlations exhibit strong statistical significance. That said, the magnitude for the majority of these relations is quite low. Of note, while each of our three focal O/S metrics (O/S, Δ(O/S) and AVG(O/S)) unsurprisingly exhibit strong correlations with one another, across Table 2 only two additional Pearson correlation coefficients exhibit an absolute value greater than 0.4. Highlighting these stronger relations across firm characteristics, we note that REIT size appears to be positively correlated with both firm liquidity (lower illiquidity ratios), as well as with growth prospects (lower BM ratios).[23] Additionally, Panel B provides variance inflation factors (VIFs) and Tolerances (= 1/VIF) for those characteristics included in our core empirical models. Based upon traditional rules of thumb (*e.g*., VIF > 10 or Tolerance < 0.10 merit further consideration), these estimated VIF and Tolerance values are quite modest, suggesting our independent variables are unlikely to be linear combinations of one another. Rather, they appear to represent independent metrics.

2 Table. Correlation matrix and VIFs

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel A: Correlation Matrix** |  |  |  |  |  |  |  |  |  |  |
|  | **O/S** | **Δ(O/S)** | **AVG(O/S)** | **ΔIV** | **RET** | **SIZE** | **BM** | **MOM** | **ILLIQ** | **CM** |
| Δ(O/S) | 0.4889 |  |  |  |  |  |  |  |  |  |
|  | (<0.0001) |  |  |  |  |  |  |  |  |  |
| AVG(O/S) | 0.5452 | −0.4648 |  |  |  |  |  |  |  |  |
|  | (<0.0001) | (<.0001) |  |  |  |  |  |  |  |  |
| ΔIV | −0.0861 | 0.2181 | −0.2970 |  |  |  |  |  |  |  |
|  | (<0.0001) | (<0.0001) | (<0.0001) |  |  |  |  |  |  |  |
| RET | 0.0166 | 0.0118 | 0.0055 | −0.0339 |  |  |  |  |  |  |
|  | (0.0455) | (0.1558) | (0.5055) | (<.0001) |  |  |  |  |  |  |
| SIZE | 0.2023 | −0.1949 | 0.3927 | −0.1644 | −0.0081 |  |  |  |  |  |
|  | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (0.3292) |  |  |  |  |  |
| BM | −0.1828 | 0.0621 | −0.2453 | 0.0261 | 0.0460 | −0.5086 |  |  |  |  |
|  | (<0.0001) | (<0.0001) | (<0.0001) | (0.0016) | (<0.0001) | (<0.0001) |  |  |  |  |
| MOM | 0.0805 | −0.0377 | 0.1179 | −0.2352 | −0.0183 | 0.0719 | −0.0936 |  |  |  |
|  | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (0.0268) | (<0.0001) | (<0.0001) |  |  |  |
| ILLIQ | −0.0005 | 0.0998 | −0.0963 | 0.1514 | 0.0287 | −0.4971 | 0.3419 | −0.0349 |  |  |
|  | (0.9556) | (<0.0001) | (<0.0001) | (<0.0001) | (0.0005) | (<0.0001) | (<0.0001) | (<0.0001) |  |  |
| CM | 0.1148 | −0.0759 | 0.1894 | −0.0393 | 0.0076 | 0.3634 | −0.3425 | 0.0488 | −0.1827 |  |
|  | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (0.3598) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) |  |
| Inst.Own. (%) | −0.0476 | −0.0648 | 0.0140 | −0.0967 | 0.0043 | 0.2268 | −0.1813 | 0.0657 | −0.2177 | 0.0815 |
|  | (<0.0001) | (<0.0001) | (0.0914) | (<0.0001) | (0.6032) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) | (<0.0001) |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel B: VIF and Tolerance Levels** |  |  |  |  |  |  |  |  |
| **Variable** | **VIF** | **SQRT VIF** | **Tolerance** | **R2** | **VIF** | **SQRT VIF** | **Tolerance** | **R2** |
| O/S | 1.09 | 1.04 | 0.92 | 0.08 |  |  |  |  |
| Δ(O/S) |  |  |  |  | 1.31 | 1.14 | 0.77 | 0.23 |
| AVG(O/S) |  |  |  |  | 1.60 | 1.26 | 0.63 | 0.37 |
| ΔIV | 1.11 | 1.05 | 0.90 | 0.10 | 1.20 | 1.10 | 0.83 | 0.17 |
| RET | 1.01 | 1.00 | 0.99 | 0.01 | 1.01 | 1.00 | 0.99 | 0.01 |
| SIZE | 1.78 | 1.33 | 0.56 | 0.44 | 1.92 | 1.39 | 0.52 | 0.48 |
| BM | 1.47 | 1.21 | 0.68 | 0.32 | 1.47 | 1.21 | 0.68 | 0.32 |
| MOM | 1.07 | 1.04 | 0.93 | 0.07 | 1.07 | 1.04 | 0.93 | 0.07 |
| ILLIQ | 1.40 | 1.18 | 0.71 | 0.29 | 1.41 | 1.19 | 0.71 | 0.29 |
| CM | 1.20 | 1.10 | 0.83 | 0.17 | 1.20 | 1.10 | 0.83 | 0.17 |
| Inst.Own. (%) | 1.09 | 1.04 | 0.92 | 0.08 | 1.09 | 1.05 | 0.91 | 0.09 |
| Average | 1.25 | 1.11 | 0.83 | 0.17 | 1.33 | 1.15 | 0.78 | 0.22 |

*Notes*: Panel A reports Pearson correlation coefficients associated with our various firm attributes. All numbers are based on our sample of 14,608 firm‐week observations. Panel B reports VIF and Tolerance scores for each of our firm attributes. Columns 2–5 present the scores for our first specification, where we use the O/S ratio directly. Columns 6–9 present the scores for the model specification that decomposes O/S into its changes and average values. A detailed definition for each characteristic is provided in Appendix B.

## Option Trading and REIT Returns

### Quintile Portfolios

Having outlined and explored our sample, we proceed to a more formal, four‐stage analysis of the return predictability of REIT option measures. In stage one, we sort our observations into quintile portfolios based upon each of our focal option market measures. We then apply a variety of pricing models to each portfolio and compare (high minus low) alphas across quintiles. If option volume is predictive of future stock performance, we would expect to observe significant negative alphas accruing to our high minus low portfolios.

Table 3 presents descriptive statistics (Panel A) regarding our various alpha estimates, as well as the average alphas generated from our quintile portfolios (Panels B–D). In Panels B–D, column 1 presents the average alpha resulting from the Fama–French three‐factor model. The alphas reported in column 2 are derived using the Fama–French four‐factor model (*i.e*., the Fama–French three‐factor model plus a MOM factor), while column 3 relies on the Fama–French four‐factor model plus an illiquidity factor. Following Chen, Downs, and Patterson (2012), column 4 relies on the Fama–French four‐factor model plus a REIT factor. Finally, the results presented in column 5 are derived from the Stambaugh and Yuan (2017) pricing model. This model includes market, size and mispricing factors.[24]

3 Table. Quintile portfolios

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel A: Summary Statistics of Risk‐Adjusted Returns** |  |  |  |  |  |  |  |
| **Variable** | **Mean** | **Median** | **SD** | **5th Percentile** | **25th Percentile** | **75th Percentile** | **95th Percentile** |
| Fama–French 3 | 0.09 | 0.04 | 5.00 | −6.67 | −1.96 | 2.02 | 6.66 |
| Fama–French 4 | 0.10 | 0.05 | 5.02 | −6.63 | −1.96 | 2.05 | 6.68 |
| Fama–French 4 and illiquid | 0.17 | 0.07 | 5.01 | −6.50 | −1.94 | 2.11 | 6.77 |
| Chen, Downs and Patterson (2012) | 0.07 | −0.01 | 5.07 | −6.55 | −1.92 | 1.87 | 6.75 |
| Stambaugh and Yuan (2017) | 0.09 | 0.01 | 5.03 | −6.53 | −1.96 | 2.06 | 6.66 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Panel B: O/S Quintile Portfolios** |  |  |  |  |  |
|  | **FF3** | **FF4** | **FF4+I** | **CD&P** | **S&Y** |
| Low | 0.1609 | 0.1673 | 0.1712 | 0.1507 | 0.1853 |
|  | (1.19) | (1.25) | (1.27) | (1.18) | (1.36) |
| 2 | 0.1369 | 0.1409 | 0.1442 | 0.1302 | 0.1456 |
|  | (1.11) | (1.15) | (1.18) | (1.09) | (1.15) |
| 3 | 0.0852 | 0.0884 | 0.0937 | 0.0771 | 0.0805 |
|  | (0.66) | (0.69) | (0.73) | (0.61) | (0.61) |
| 4 | 0.0575 | 0.0615 | 0.0645 | 0.0480 | 0.0499 |
|  | (0.48) | (0.52) | (0.54) | (0.42) | (0.41) |
| High | −0.23110001 | −0.22740001 | −0.22530001 | −0.24040001 | −0.2209 |
|  | (−1.75) | (−1.73) | (−1.72) | (−1.91) | (−1.63) |
| High – Low | −0.39200001 | −0.39470001 | −0.39650001 | −0.39110001 | −0.40620001 |
|  | (−3.19) | (−3.19) | (−3.18) | (−3.15) | (−3.23) |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Panel C: Δ(O/S) Quintile Portfolios** |  |  |  |  |  |
|  | **FF3** | **FF4** | **FF4+I** | **CD&P** | **S&Y** |
| Low | 0.26010001 | 0.26660001 | 0.27090001 | 0.25840001 | 0.28040001 |
|  | (1.90) | (1.97) | (2.01) | (1.94) | (2.02) |
| 2 | 0.0845 | 0.0868 | 0.0912 | 0.0752 | 0.0645 |
|  | (0.69) | (0.70) | (0.75) | (0.63) | (0.51) |
| 3 | −0.0034 | 0.0003 | 0.0052 | −0.0112 | 0.0066 |
|  | (−0.03) | (0.00) | (0.04) | (−0.10) | (0.05) |
| 4 | −0.0275 | −0.0230 | −0.0209 | −0.0385 | −0.0100 |
|  | (−0.21) | (−0.17) | (−0.16) | (−0.31) | (−0.07) |
| High | −0.0841 | −0.0805 | −0.0790 | −0.0991 | −0.0863 |
|  | (−0.66) | (−0.64) | (−0.63) | (−0.85) | (−0.68) |
| High – Low | −0.34410001 | −0.34710001 | −0.34990001 | −0.35750001 | −0.36670001 |
|  | (−3.11) | (−3.14) | (−3.16) | (−3.30) | (−3.28) |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Panel D: Average (O/S) Quintile Portfolios** |  |  |  |  |  |
|  | **FF3** | **FF4** | **FF4+I** | **CD&P** | **S&Y** |
| Low | 0.1114 | 0.1175 | 0.1198 | 0.0980 | 0.1325 |
|  | (0.80) | (0.86) | (0.87) | (0.77) | (0.95) |
| 2 | −0.0246 | −0.0207 | −0.0168 | −0.0354 | −0.0192 |
|  | (−0.20) | (−0.17) | (−0.14) | (−0.30) | (−0.15) |
| 3 | 0.1393 | 0.1425 | 0.1461 | 0.1320 | 0.1383 |
|  | (1.16) | (1.19) | (1.22) | (1.13) | (1.14) |
| 4 | 0.0612 | 0.0644 | 0.0685 | 0.0534 | 0.0577 |
|  | (0.51) | (0.54) | (0.57) | (0.46) | (0.46) |
| High | −0.0684 | −0.0638 | −0.0603 | −0.0736 | −0.0639 |
|  | (−0.49) | (−0.46) | (−0.44) | (−0.55) | (−0.45) |
| High – Low | −0.1798 | −0.1813 | −0.1801 | −0.1716 | −0.1964 |
|  | (−1.34) | (−1.34) | (−1.33) | (−1.29) | (−1.45) |

*Notes*: Panel A presents descriptive statistics regarding the various weekly risk‐adjusted returns (in percentages) used in this analysis. Panels B–D present quintile portfolio performance, where portfolios are created based on the O/S ratio (Panel B), Δ(O/S) (Panel C) and AVG(O/S) (Panel D). The results represent alphas generated by each quintile portfolio based on our various pricing models. All returns are shown as percentages. The results presented in column 1 are based on the Fama–French three‐factor model. The pricing model used in column 2 is the Fama–French four‐factor model, while column 3 relies on the Fama–French four‐factor model plus an illiquidity factor. Column 4 uses the pricing model of Chen, Downs and Patterson (2012), which augments the Fama–French four‐factor model to include a REIT factor. Column 5 relies on the Stambaugh and Yuan (2017) four‐factor pricing model, which includes market, size and mispricing factors. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively.

In Panel B, quintile portfolios are based upon observed levels of the O/S ratio. Zero‐cost portfolios that are long the highest quintile of O/S ratio securities, and short the lowest quintile of such firms, are then constructed with returns to these long–short portfolios presented. The results are quite striking, as across all five pricing models high O/S portfolios consistently earn significantly lower future returns than their low O/S counterparts.[25] Panel C presents corresponding results when quintiles are based on changes in O/S, rather than O/S levels. Once again, results from this alternative specification are consistent with option volume predicting future returns, as significant negative returns accrue to zero‐cost portfolios that are long REITs with the highest changes in relative option volumes (Δ(O/S)) and short REITs with the lowest changes. Similarly, Panel D employs six‐month historical average O/S levels as the basis for portfolio formation. Interestingly, while we again observe negative returns accruing to our long–short portfolios, the returns are no longer statistically significant at conventionally accepted levels. Taken together, these high minus low portfolio alphas reported across Table 3 provide evidence of significant, options based (negative) return predictability in U.S. REIT markets. As such, these results strongly imply option traders, and particularly innovations or changes in observable option market activity, provide value‐relevant information to broader market participants.

### Panel Regressions of REIT Returns on Option Measures

Given these findings, stage two of our analysis attempts to provide more structure to the investigation, and further explores the return predictability of option volume by estimating a series of panel regressions. The dependent variable across each specification presented in Table 4 is the following week's Chen, Downs, and Patterson (2012) risk‐adjusted returns ().[26] Model 1 regresses these returns against our set of firm characteristics, excluding any measure of option volume. Results from this specification reveal that smaller firms and cheap stocks (as measured by our composite firm attribute control, CM) both exhibit significantly higher returns than their counterparts. Furthermore, value stocks (as measured by higher BM ratios) and REITs characterized by low MOM exhibit marginally higher returns. In columns 2 and 3, we expand the model to include relative option trading volume. Consistent with our previous analysis, we again find evidence that option volume is strongly and negatively related to future REIT returns. Specifically, model 2 indicates that a one‐standard‐deviation increase in O/S is associated with a 0.16% drop in subsequent returns.[27] Additionally, to make our results comparable to the prior literature, in untabulated analyses we replace our O/S measure with the decile ranking used by Johnson and So (2012). They report a 0.23% per week difference between firms in the highest and lowest deciles, for REITs we find this difference is considerably higher at 0.43% per week. Model 3 further refines this analysis by decomposing the O/S ratio into its six‐month historical average (AVG(O/S)), and the deviation from this historical average (Δ(O/S)). Interestingly, and in contrast to the findings in Panel C of Table 3, these results suggest that the return predictability of the O/S ratio is attributable, in part, to both component pieces. While both the average O/S and the change in O/S exhibit some predictive ability, the fact that changes in O/S are associated with future REIT returns suggests O/S predictability is at least partially due to the presence of informed traders within the option market who dynamically alter their positions in response to changing firm conditions.

4 Table. Current option volumes and next week's risk‐adjusted returns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** |
| O/S |  | −0.11900001 |  |  | −0.12330001 |  |
|  |  | (−3.06) |  |  | (−3.20) |  |
| Δ(O/S) |  |  | −0.11430001 |  |  | −0.12200001 |
|  |  |  | (−2.93) |  |  | (−3.16) |
| AVG(O/S) |  |  | −0.13850001 |  |  | −0.12830001 |
|  |  |  | (−2.25) |  |  | (−2.08) |
| ΔIV |  |  |  | 0.1743 | 0.2192 | 0.2136 |
|  |  |  |  | (0.81) | (1.02) | (0.98) |
| RET | 1.1867 | 1.2282 | 1.2250 | 1.2231 | 1.2756 | 1.2735 |
|  | (0.34) | (0.35) | (0.35) | (0.35) | (0.37) | (0.37) |
| SIZE | −0.48480001 | −0.45430001 | −0.44490001 | −0.47790001 | −0.44450001 | −0.44230001 |
|  | (−2.74) | (−2.59) | (−2.48) | (−2.72) | (−2.54) | (−2.47) |
| BM | 1.00520001 | 1.03670001 | 1.05070001 | 1.01290001 | 1.04760001 | 1.05100001 |
|  | (1.87) | (1.89) | (1.93) | (1.89) | (1.91) | (1.93) |
| MOM | −0.39990001 | −0.38500001 | −0.38530001 | −0.40180001 | −0.38690001 | −0.38690001 |
|  | (−1.94) | (−1.85) | (−1.85) | (−1.95) | (−1.86) | (−1.86) |
| ILLIQ | −0.0185 | −0.0197 | −0.0188 | −0.0228 | −0.0251 | −0.0248 |
|  | (−0.34) | (−0.36) | (−0.34) | (−0.41) | (−0.45) | (−0.44) |
| CM | 0.20550001 | 0.20660001 | 0.20740001 | 0.20460001 | 0.20550001 | 0.20580001 |
|  | (3.18) | (3.24) | (3.26) | (3.22) | (3.29) | (3.29) |
| Inst.Own. (%) | 0.0042 | 0.0041 | 0.0042 | 0.0043 | 0.0042 | 0.0042 |
|  | (1.45) | (1.46) | (1.49) | (1.48) | (1.49) | (1.50) |
| Intercept | 2.95880001 | 2.0801 | 1.8819 | 2.4798 | 1.4458 | 1.4102 |
|  | (1.95) | (1.30) | (1.11) | (1.60) | (0.88) | (0.82) |
| Property‐type fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,608 | 14,608 | 14,608 | 14,608 | 14,608 | 14,608 |
| Adjusted‐R2 | 0.351 | 0.352 | 0.352 | 0.351 | 0.352 | 0.352 |

*Notes*: This table examines the ability of option volume to predict future risk‐adjusted returns. The dependent variable is the REIT's subsequent week alpha from the Chen, Downs and Patterson (2012) risk‐adjusted return model. All standard errors are robust to heteroskedasticity, and clustered by firm. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a definition for all variables employed in the analysis.

Additionally, as the prior literature documents implied option volatility exhibits predictive power among non‐REIT firms, in models 4 through 6, we replicate our earlier analyses controlling for implied volatility. While all three of our option metrics remain robust to the inclusion of this additional control, in contrast to the previous literature we find no evidence that changes in implied volatility (ΔIV) are predictive of future REIT returns at conventionally accepted levels of statistical significance.[28]

### Heterogeneity in Return Predictability

#### Double sorts

Having presented evidence that relative option volume is able to predict subsequent REIT returns, we next explore whether this return predictability is concentrated within a particular subset of REITs. We do this by creating double‐sorted portfolios, where observations are sorted into terciles based on their underlying REIT characteristic, and independently into terciles based on their relative option trading volumes. This double‐sorting procedure results in nine different portfolios for each attribute examined. Table 5 presents average subsequent week Chen, Downs, and Patterson (2012) risk‐adjusted returns for these nine portfolios, across seven different REIT characteristics. Highlighting the key takeaways, we find evidence that return predictability tends to be concentrated in those firms that are smaller, more illiquid, relatively expensive, exhibit low MOM and/or are characterized by low to moderate levels of institutional ownership.[29] Taken together, these results suggest that option volume's return predictability is concentrated in REITs that are more informationally opaque, which is once again consistent with the notion that option trading is driven, at least in part, by informed investors.

5 Table. Double‐sorted portfolio returns

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | **O/S** |  |  |  |
|  |  | **L** | **M** | **H** | **H – L** |
| RET | L | 0.00310001 | 0.0007 | −0.0006 | −0.00370001 |
|  |  | (2.26) | (0.51) | (−0.42) | (−1.89) |
|  |  | 1,533 | 1,576 | 1,449 |  |
|  | M | −0.0003 | 0.0006 | 0.0011 | 0.0014 |
|  |  | (−0.22) | (0.61) | (1.12) | (0.89) |
|  |  | 1,475 | 1,949 | 1,757 |  |
|  | H | 0.00300001 | 0.0006 | −0.00220001 | −0.00520001 |
|  |  | (1.94) | (0.51) | (−1.76) | (−2.61) |
|  |  | 1,550 | 1,656 | 1,663 |  |
|  | H – L | –0.0001 | −0.0001 | −0.0016 |  |
|  |  | (−0.05) | (−0.04) | (−0.85) |  |
| SIZE | L | 0.0020 | −0.0003 | −0.0016 | −0.00360001 |
|  |  | (1.56) | (−0.24) | (−0.92) | (−1.70) |
|  |  | 1,714 | 1,672 | 1,172 |  |
|  | M | 0.0021 | 0.0003 | −0.0002 | −0.0023 |
|  |  | (1.54) | (0.33) | (−0.15) | (−1.26) |
|  |  | 1,745 | 1,922 | 1,514 |  |
|  | H | 0.0017 | 0.00200001 | −0.0001 | −0.0019 |
|  |  | (1.12) | (1.85) | (−0.16) | (−1.05) |
|  |  | 1,099 | 1,587 | 2,183 |  |
|  | H – L | −0.0003 | 0.0024 | 0.0014 |  |
|  |  | (−0.13) | (1.32) | (0.73) |  |
| BM | L | 0.0016 | 0.001 | 0.0000 | −0.0016 |
|  |  | (0.94) | (0.93) | (−0.03) | (−0.84) |
|  |  | 997 | 1,533 | 2,028 |  |
|  | M | 0.0011 | 0.0015 | −0.0010 | −0.0021 |
|  |  | (0.96) | (1.48) | (−0.84) | (−1.27) |
|  |  | 1,528 | 1,968 | 1,685 |  |
|  | H | 0.00290001 | −0.0006 | −0.0007 | −0.0035 |
|  |  | (2.09) | (−0.43) | (−0.37) | (−1.57) |
|  |  | 2,033 | 1,680 | 1,156 |  |
|  | H−L | 0.0013 | −0.0016 | −0.0006 |  |
|  |  | (0.61) | (−0.89) | (−0.32) |  |
| MOM | L | 0.00480001 | −0.0008 | −0.0015 | −0.00630001 |
|  |  | (2.70) | (−0.54) | (−0.90) | (−2.59) |
|  |  | 1,554 | 1,574 | 1,430 |  |
|  | M | 0.0011 | 0.0002 | −0.0006 | −0.0017 |
|  |  | (0.93) | (0.20) | (−0.61) | (−1.11) |
|  |  | 1,512 | 1,913 | 1,756 |  |
|  | H | 0.0000 | 0.00250001 | 0.0004 | 0.0005 |
|  |  | (−0.04) | (2.33) | (0.41) | (0.31) |
|  |  | 1,492 | 1,694 | 1,683 |  |
|  | H – L | −0.00480001 | 0.00330001 | 0.0019 |  |
|  |  | (−2.31) | (1.79) | (0.98) |  |
| ILLQ | L | 0.0026 | 0.0013 | 0.0002 | −0.0024 |
|  |  | (1.51) | (1.15) | (0.23) | (−1.24) |
|  |  | 915 | 1,465 | 2,178 |  |
|  | M | 0.0014 | 0.0003 | 0.0009 | −0.0005 |
|  |  | (1.1) | (0.26) | (0.67) | (−0.27) |
|  |  | 1,860 | 1,805 | 1,410 |  |
|  | H | 0.00230001 | 0.0004 | −0.00320001 | −0.00550001 |
|  |  | (1.73) | (0.38) | (−2.07) | (−2.70) |
|  |  | 1,783 | 1,911 | 1,281 |  |
|  | H – L | −0.0004 | −0.0010 | −0.00350001 |  |
|  |  | (−0.17) | (−0.58) | (−1.91) |  |
| CM | L | 0.00370001 | −0.0017 | −0.0026 | −0.00630001 |
|  |  | (2.31) | (−1.2) | (−1.48) | (−2.65) |
|  |  | 1,637 | 1,659 | 1,326 |  |
|  | M | 0.0015 | 0.0003 | −0.0004 | −0.0019 |
|  |  | (1.32) | (0.29) | (−0.39) | (−1.22) |
|  |  | 1,776 | 1,855 | 1,521 |  |
|  | H | 0.0003 | 0.00330001 | 0.0009 | 0.0005 |
|  |  | (0.23) | (3.29) | (0.99) | (0.31) |
|  |  | 1,145 | 1,667 | 2,022 |  |
|  | H – L | −0.0034 | 0.00500001 | 0.00350001 |  |
|  |  | (−1.56) | (2.89) | (1.77) |  |
| Inst.Own. (%) | L | 0.0022 | −0.00200001 | −0.0023 | −0.00450001 |
|  |  | (1.3) | (−1.69) | (−1.58) | (−2.01) |
|  |  | 1,275 | 1,705 | 1,578 |  |
|  | M | 0.0020 | 0.00300001 | −0.0013 | −0.00330001 |
|  |  | (1.58) | (2.46) | (−1.40) | (−2.11) |
|  |  | 1,626 | 1,854 | 1,701 |  |
|  | H | 0.0018 | 0.0008 | 0.00210001 | 0.0003 |
|  |  | (1.39) | (0.68) | (1.72) | (0.14) |
|  |  | 1,657 | 1,622 | 1,590 |  |
|  | H – L | −0.0004 | 0.00280001 | 0.00440001 |  |
|  |  | (−0.16) | (1.70) | (2.32) |  |

*Notes*: This table presents average next week portfolio alphas from the Chen, Downs and Patterson (2012) risk‐adjusted return model. Portfolios are created by independently sorting our sample into terciles based on the O/S ratio, and across various firm characteristics. This double sorting creates the nine portfolios, whose average returns are presented below for each firm attribute. \*\*\*, \*\* and \* indicates statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a detail description of the variables employed in this analysis.

#### Short‐sale markets

The results of the double sorts offer compelling insights into the driving factors behind the observed return predictability in REIT markets. Of note, the findings suggest that informational opacity considerations may inhibit the rapid and effective price adjustment of REITs to new information. While such information barriers could hinder the speed of adjustment with respect to either positive or negative information, Johnson and So (2012) contend that short‐sale costs may drive negatively informed investors toward the option market. As such, and combined with previous empirical evidence suggesting short sellers are indeed informed, we would anticipate our return predictability results should be relatively more pronounced within those REITs it is most difficult to sell short.

To elaborate, both short‐sale and option markets offer potential venues for privately informed investors to transact and profit on their negative information regarding future firm prospects. Thus, the finding that option market activities are inversely related to subsequent market returns implies a link between the option market and short selling. In sum, investors appear to use the option market when transacting based on negative information and shorting allows another means of profiting on negative information. Moreover, numerous previous studies document significant return predictability attributable to various dimensions of short‐sale activity across broad financial markets.[31] With respect to real estate markets, French, Lynch, and Yan (2012) document heavily shorted REITs slightly underperform their lightly shorted counterparts (by ≈ 1% over four weeks). Similarly, Chen, Downs, and Patterson (2012) affirm the information content of REIT short interest, though this result is observed exclusively across the less transparent firms within their data set.

Conceptually, these findings are entirely consistent with Johnson and So (2012), who contend that the inverse relation we observe is driven by equity short‐sale costs that lead informed agents to trade options more frequently for negative signals than positive ones. Under such a scenario, the return predictability we previously documented may well be tied to potential short‐sale costs and constraints within REIT markets. Along this same dimension, Wong, Lai, and Deng (2017) argue that direct real estate markets are less complete than indirect, securitized real estate markets. As it is difficult if not impossible to short direct property investments, key (negative) information signals are missing from this sector of the market, leading market participants to "learn" about negative private information by observing short sales (and other information) in the indirect real estate market. Consistent with this notion, Brounen, Ling, and Prado (2013) conclude REIT short‐sale constraints lead to overvaluation, and further, may explain approximately one‐third of the variation in REIT NAV premia across their sample period (June 2006–September 2008).

On the other hand, Gentry, Jones, and Mayer (2004) suggest that "trading costs and short‐sale constraints are not prohibitive" within REIT markets. Additionally, consistent with increased informational transparency within this market sector, Blau, Hill, and Wang (2011) find REITs are shorted less than their non‐REIT counterparts. They further demonstrate that such transactions are less informative with respect to future returns within this sector than in broader markets, while Devos *et al*. (2014) conclude that naked short selling did not contribute significantly to REIT losses during the global financial crisis. Given these latter findings, we view the relative role and importance of short‐sale markets to REIT prices and return predictability as an open empirical question.

To further explore the potential significance and confounding influences of REIT short‐sale markets on our previously documented return predictability, we begin by identifying a subset of REITs for which short‐sale constraints are most likely to be binding. Conceptually, following Asquith, Pathak, and Ritter (2005), we identify short‐sale constrained firms using a combination of high demand for, and low supply of, available shares to short. With respect to the current investigation, REITs whose ratio of total outstanding short interest to shares outstanding falls within the highest 5% of firms within a given week are deemed to exhibit high short demand. As observed short demand is inherently an equilibrium construct, to proxy for the supply of available shares to short we use institutional ownership levels. More specifically, REITs within the highest (lowest) tercile of institutional ownership within a given week are deemed to exhibit a high (low) supply of available short shares. REITs exhibiting a high demand for short selling, and low available supply, are considered short‐sale constrained.

After identifying those firms for which short‐sale constraints are most likely to be binding, we compare subsequent risk‐adjusted returns across portfolios independently double‐sorted by our short‐sale constrained indicator and relative option volume metrics. The results of this procedure are presented in Panel A of Table 6. Examining the results, we find no evidence that short‐sale constraints materially influence the predictability of the option market. Nevertheless, we also examine the influence of short‐sale constraints in a multivariate setting. Specifically, we next augment our base model specifications to include measures of both changes in the level of short interest outstanding, as well as identifiers for those firms that are most likely to be short‐sale constrained. The results of these analyses are presented in Panel B of Table 6.

6 Table. Short‐sale constrained

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Panel A** |  |  |  |  |  |
|  |  | **O/S** |  |  |  |
|  |  | **L** | **M** | **H** | **H – L** |
| Short‐sale constrained | 0 | 0.0014 | 0.0011 | 0.0007 | −0.0008 |
|  |  | (1.42) | (1.22) | (0.78) | (−0.58) |
|  |  | 3,300 | 3,523 | 3,428 |  |
|  | 1 | 0.0081 | 0.0052 | 0.0078 | −0.0003 |
|  |  | (1.24) | (1.05) | (1.4) | (−0.03) |
|  |  | 55 | 82 | 53 |  |
|  | 1 ‐ 0 | 0.0067 | 0.0041 | 0.0071 |  |
|  |  | (1.01) | (0.82) | (1.27) |  |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel B** |  |  |  |  |  |  |  |  |
|  | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
| O/S | −0.09900001 |  | −0.09740001 |  | −0.09710001 |  | −0.09300001 |  |
| . | (−2.07) |  | (−2.03) |  | (−2.34) |  | (−2.22) |  |
| Δ(O/S) |  | −0.10110001 |  | −0.09910001 |  | −0.10030001 |  | −0.09580001 |
|  |  | (−2.08) |  | (−2.02) |  | (−2.34) |  | (−2.22) |
| AVG(O/S) |  | −0.0896 |  | −0.0898 |  | −0.0824 |  | −0.0783 |
|  |  | (−1.26) |  | (−1.27) |  | (−1.31) |  | (−1.24) |
| O/S 0001 ΔSISO |  |  | −0.0674 |  |  |  |  |  |
|  |  |  | (−1.31) |  |  |  |  |  |
| Δ(O/S) 0001 ΔSISO |  |  |  | −0.0634 |  |  |  |  |
|  |  |  |  | (−1.08) |  |  |  |  |
| AVG(O/S) 0001 ΔSISO |  |  |  | −0.0711 |  |  |  |  |
|  |  |  |  | (−1.16) |  |  |  |  |
| O/S 0001 high\_siso\_95\_low\_io |  |  |  |  |  |  | −0.2205 |  |
|  |  |  |  |  |  |  | (−0.85) |  |
| Δ(O/S) 0001 high\_ siso \_95\_low\_io |  |  |  |  |  |  |  | −0.2459 |
|  |  |  |  |  |  |  |  | (−0.83) |
| AVG(O/S) 0001 high\_ siso \_95\_low\_io |  |  |  |  |  |  |  | −0.1970 |
|  |  |  |  |  |  |  |  | (−0.66) |
| ΔSI | −0.0691 | −0.0689 | −0.4199 | −0.4356 |  |  |  |  |
|  | (−0.75) | (−0.74) | (−1.40) | (−1.28) |  |  |  |  |
| Lag1\_ siso | 0.0102 | 0.0099 | 0.0097 | 0.0094 |  |  |  |  |
|  | (0.92) | (0.87) | (0.89) | (0.84) |  |  |  |  |
| high\_ siso \_95\_low\_io |  |  |  |  | 0.66660001 | 0.67200001 | −0.3363 | −0.2096 |
|  |  |  |  |  | (1.90) | (1.92) | (−0.27) | (−0.15) |
| Lag1\_ SISO |  |  |  |  | 0.0046 | 0.0040 | 0.0042 | 0.0037 |
|  |  |  |  |  | (0.29) | (0.26) | (0.27) | (0.24) |
| REIT characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Property‐type fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,424 | 10,424 | 10,424 | 10,424 | 10,424 | 10,424 | 10,424 | 10,424 |
| Adjusted‐R2 | 0.402 | 0.402 | 0.402 | 0.402 | 0.402 | 0.402 | 0.402 | 0.402 |

*Notes*: This table presents the results of our analysis examining the effects of short‐sale constraints on the return predictability of option volume. Panel A presents subsequent week portfolio alphas based on Chen, Downs and Patterson's (2012) risk‐adjusted return model. Portfolios are created by independently sorting our sample into terciles based on the O/S ratio, and firms classified as either short‐sale constrained or not. We classify observations as short constrained when their total outstanding short interest to shares outstanding is in the highest 5% in a given week, and their institutional ownership is in the bottom tercile. Panel B presents the results of the multivariate analysis of short‐sale constraints and option volume predictability. The dependent variable is the REIT's subsequent week alpha from the Chen, Downs and Patterson (2012) five‐factor model. All standard errors are robust to heteroskedasticity, and clustered by firm. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a definition for all variables employed in the analysis.

In columns 1 through 4, we augment our original specifications to include lagged values of REIT‐specific short interest levels, current period changes (or innovations) in short interest outstanding and interactions terms designed to capture the differential impact of relative option volume across differing levels of short‐sale activity. Similarly, in columns 5 through 8, we alter our original specifications to include lagged values of REIT‐specific short interest levels, an indicator flag for potentially short‐sale constrained firms, and interaction terms designed to capture the potentially contingent nature of short‐sale constraints and relative option volume on REIT return predictability. Exploring the results, we find little to no evidence that either changes in short interest levels or potential short‐sale constraints materially influence or mitigate our previously observed relations between option market metrics and return predictability. More specifically, our focal O/S and Δ(O/S) relative option volume parameters retain their previously observed predictive capacity, while none of the potential interaction effects approach statistical significance at conventionally accepted levels.[32] In sum, the previously reported return predictability we attribute to relative option volume metrics appears robust to the consideration and inclusion of potential short‐sale constraints.

Additionally, in untabulated analyses we examine the effect of the SEC's short‐sale moratorium in the fall of 2008 in response to the financial crisis. More specifically, the SEC temporarily banned shorting on certain financial stocks, including 14 REITs. Of these, 10 are equity REITs, with options, which are included in our sample.[33] Having identified these firms, we explore whether the short selling ban strengthened option return predictability. Somewhat surprisingly, we find no evidence that option predictability differs between firms included in the short‐sale ban versus those where shorting was allowed to continue. That said, the findings of no significant differences in return predictability are broadly consistent with Blau, Hill, and Wang's (2011) conclusion that short sales are not particularly informative with respect to REIT markets. They are also consistent with Devaney (2012), who reports the short‐sale ban did not result in abnormal (positive or negative) returns in the cross‐section of REITs.[34]

An alternative explanation for our inability to find a relation between short‐sale constraints and option predictability in the REIT market is that the costs associated with shorting are sufficiently high, and the option market now sufficiently developed, as to make the option market the dominate means of transacting based upon negative information. Indeed, options are relatively cheap compared to shorting, which requires an initial capital outlay of 50% of the total position (not to mention potential expenses related to maintenance requirements, margin shortfalls, etc.). The purchasing of puts is generally significantly cheaper as these initial outlays may be avoided, while the alternative of selling call options would further reduce the upfront cost and generate an initial capital inflow. Finally, options have limited risk exposure compared to the potential unlimited downside associated with shorting the stock directly. Taken together, these factors may well contribute to enhanced investor preferences for option markets over short‐sale markets when transacting upon negative information.

#### Option moneyness

Having found evidence that option volume predictability is concentrated within REITs exhibiting specific characteristics, we next examine whether trading in alternative types of options is differentially predictive. While the preceding analysis grouped all option contracts together, here we differentiate between: in‐the‐money (ITM) options, at‐the‐money (ATM) options and out‐of‐the money (OTM) options. Trading in these different levels of options potentially conveys materially different signals to the market.[35] For example, OTM options require security price movements in order for purchasers to earn positive returns. As such, it is entirely plausible that enhanced volume with respect to OTM options provides a stronger information signal to market participants than would be offered by ITM or ATM offerings. Figure 4 illustrates the relative distribution of option moneyness over time, as well as a news sentiment index. This sentiment index is derived using the RavenPack news database that specializes in identifying positive and negative words and phrases in articles. The scores of the sentiment index can take the values of 0, 50 or 100 indicating negative, neutral or positive sentiment, respectively. Not surprisingly, sentiment scores for sample REITs declined precipitously during the depths of the financial crisis, and have risen steadily ever since.[36] Similarly, consistent with enhanced uncertainty or volatility in REIT values, we also observe a slight increase in the OTM option market share both during and after the crisis period.

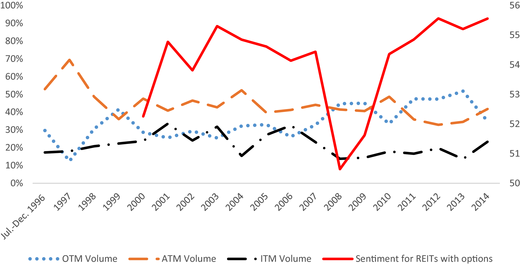


Figure 4. Equity REITs option moneyness and news sentiment.

\*Based on the sample used in our analysis.

More importantly, to examine the relative predictive power of trading within these different levels of options moneyness, we redefine our relative option volume measures to include only those options that meet specific moneyness criteria. More specifically, in constructing our option moneyness indicators, when delta is available, we follow Bollen and Whaley (2004) and define an option as:

OTM if |delta| ≤ 0.4,

ATM if 0.4 < |delta| ≤ 0.6 and

ITM if 0.6 < |delta|.

If delta is unavailable but option trading volume and open interest are available, we define call options as:

ATM if |(strike price – stock price)| ≤ 0.1 \* strike price,

OTM if |(strike price – stock price)| > 0.1 \* strike price and strike price > stock price and

ITM if |(strike price – stock price)| > 0.1 \* strike price and strike price < stock price.

Similarly, we define put options as:

ATM if |(strike price – stock price)| ≤ 0.1 \* strike price,

OTM if |(strike price – stock price)| > 0.1 \* strike price and strike price < stock price and

ITM if |(strike price – stock price)| > 0.1 \* strike price and strike price > stock price. [37]

The results of this examination are presented in Table 7 and consistent with *a priori* expectations. Specifically, we find that OTM option volume is more predictive of subsequent risk‐adjusted returns than either ITM or ATM option volume. Additionally, in untabulated analyses, we find qualitatively similar results when our alternative option market metrics Δ(O/S) and AVG(O/S) are employed, as well as across all five risk‐adjusted return models previously examined. The findings from these additional tests are available directly from the authors upon request. Finally, we note that while REIT characteristics are included throughout these analyses, their coefficient estimates have been suppressed for ease of presentation.

7 Table. Option moneyness and next week's risk‐adjusted return

|  |  |  |  |
| --- | --- | --- | --- |
|  | **1** | **2** | **3** |
| OTM O/S | −0.09340001 |  |  |
|  | (−2.53) |  |  |
| ATM O/S |  | −0.0162 |  |
|  |  | (−0.63) |  |
| ITM O/S |  |  | −0.0243 |
|  |  |  | (−0.74) |
| Equity REIT characteristics | Yes | Yes | Yes |
| Property‐type fixed effects | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes |
| Observations | 11,812 | 11,812 | 11,812 |
| Adjusted‐R2 | 0.382 | 0.381 | 0.381 |

*Notes*: This table explores whether the trading of options at different moneyness levels are predictive of future risk‐adjusted returns. The dependent variable is the REIT's subsequent week alpha from the Chen, Downs and Patterson (2012) five‐factor model. Column 1 examines the predictive power of the relative volume of trades involving out‐of‐the money options. Column 2 looks at the relative volume of at‐the‐money options, while column 3 examines in‐the‐money options. All standard errors are robust to heteroskedasticity, and clustered by firm. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a definition for all variables employed in the analysis.

#### Intertemporal variation

As previously documented, the REIT option market experienced unprecedented growth during our sample period. As such, we next investigate whether option volume predictability is influenced by this rapid growth. In doing so, we create three period indicators: precrisis (1996–2006), crisis (2007–2009) and postcrisis (2010–2014). We then include these indicator variables directly in our base model specification, along with the interaction of these terms with our relative option volume metrics. The results of these analyses are present in Table 8.[38] Panel A presents the results from interacting our precrisis indicator variable with our relative option volume metrics. Examining the results, we observe that the interaction term between our precrisis indicator and our option volume metrics are statistically insignificant, while our relative option volume main effect terms remain significantly negative. This suggests return predictability was not differentially more, or less, pronounced in the precrisis era versus later periods. Turning to Panel B, when examining the actual crisis period, we find evidence that return predictability was significantly more pronounced from 2007 to 2009 than in either the pre‐ or postcrisis intervals. Finally, Panel C presents the results of our postcrisis examination. During this era, where REIT option markets enjoy significantly enhanced market breadth and depth, while relative option trading volume continues to significantly forecast future returns, the magnitude of the relation is lower than in the earlier portion of our sample period. That said, we note tests of the joint significance of our focal O/S metrics and their interaction terms reveal the combined effects remain significantly negative, and hence continue to evidence return predictability during this more recent interval. Taken together, while the magnitude of our observed return predictability is shown to vary across time, the underlying economic relation appears to be persistent.

8 Table. Panel regressions: Subsample periods

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Panel A** |  |  |  |  |
|  | **1** | **2** | **3** | **4** |
| O/S | −0.15550001 |  | −0.16610001 |  |
|  | (−4.18) |  | (−4.06) |  |
| Δ(O/S) |  | −0.16480001 |  | −0.17440001 |
|  |  | (−4.19) |  | (−3.92) |
| AVG(O/S) |  | −0.12330001 |  | −0.13510001 |
|  |  | (−2.36) |  | (−2.39) |
| O/S 0001 Year< = 2006 |  |  | 0.0781 |  |
|  |  |  | (1.35) |  |
| Δ(O/S) 0001 Year< = 2006 |  |  |  | 0.0736 |
|  |  |  |  | (1.12) |
| AVG(O/S) 0001 Year< = 2006 |  |  |  | 0.0920 |
|  |  |  |  | (1.17) |
| Year< = 2006 | −0.0169 | 0.0025 | 0.3300 | 0.4138 |
|  | (−0.11) | (0.02) | (1.10) | (1.09) |
| Equity REIT characteristics | Yes | Yes | Yes | Yes |
| Property‐type fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | No | No | No | No |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,608 | 14,608 | 14,608 | 14,608 |
| Adjusted‐R2 | 0.004 | 0.004 | 0.004 | 0.004 |
| F value | 9.68 | 6.37 | 6.61 | 4.20 |
| Prob. > F | 0.0001 | 0.0004 | 0.0003 | 0.0013 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Panel B** |  |  |  |  |
|  | **1** | **2** | **3** | **4** |
| O/S | −0.15970001 |  | −0.08070001 |  |
|  | (−4.17) |  | (−2.83) |  |
| Δ(O/S) |  | −0.16730001 |  | −0.09070001 |
|  |  | (−4.23) |  | (−3.08) |
| AVG(O/S) |  | −0.13250001 |  | −0.0570 |
|  |  | (−2.36) |  | (−1.22) |
| O/S 0001 Year2007∼2009 |  |  | −0.26530001 |  |
|  |  |  | (−2.94) |  |
| Δ(O/S) 0001 Year2007∼2009 |  |  |  | −0.25100001 |
|  |  |  |  | (−2.17) |
| AVG(O/S) 0001 Year2007∼2009 |  |  |  | −0.27870001 |
|  |  |  |  | (−2.87) |
| Year2007∼2009 | −0.1359 | −0.1280 | −1.37160001 | −1.42770001 |
|  | (−1.62) | (−1.50) | (−3.08) | (−3.04) |
| Equity REIT characteristics | Yes | Yes | Yes | Yes |
| Property‐type fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | No | No | No | No |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,608 | 14,608 | 14,608 | 14,608 |
| Adjusted‐R2 | 0.005 | 0.004 | 0.005 | 0.005 |
| F value | 8.97 | 6.22 | 5.93 | 5.56 |
| Prob. > F | 0.0002 | 0.0005 | 0.0008 | 0.0003 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Panel C** |  |  |  |  |
|  | **1** | **2** | **3** | **4** |
| O/S | −0.16180001 |  | −0.27280001 |  |
|  | (−4.31) |  | (−3.87) |  |
| Δ(O/S) |  | −0.16720001 |  | −0.27230001 |
|  |  | (−4.26) |  | (−3.46) |
| AVG(O/S) |  | −0.14080001 |  | −0.26300001 |
|  |  | (−2.63) |  | (−3.06) |
| O/S 0001 Year> = 2010 |  |  | 0.19640001 |  |
|  |  |  | (2.73) |  |
| Δ(O/S) 0001 Year> = 2010 |  |  |  | 0.18830001 |
|  |  |  |  | (2.19) |
| AVG(O/S) 0001 Year> = 2010 |  |  |  | 0.20380001 |
|  |  |  |  | (2.62) |
| Year> = 2010 | 0.16690001 | 0.15350001 | 1.06440001 | 1.08730001 |
|  | (1.84) | (1.76) | (3.17) | (3.16) |
| Equity REIT characteristics | Yes | Yes | Yes | Yes |
| Property‐type fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | No | No | No | No |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,608 | 14,608 | 14,608 | 14,608 |
| Adjusted‐R2 | 0.005 | 0.004 | 0.005 | 0.005 |
| F value | 11.26 | 7.48 | 7.17 | 5.17 |
| Prob. > F | 0.0000 | 0.0001 | 0.0002 | 0.0006 |

*Notes*: This table examine how the predictability of option volume on future risk adjust return varies through time. The dependent variable is the REIT's subsequent week alpha from the Chen, Downs and Patterson (2012) five‐factor model. Panel A examines differential return predictability during the precrisis (1996–2006) era. Panel B examines how return predictability changed during the financial crisis (2007–2009). Panel C examines differential return predictability following the financial crisis (2010–2014). All standard errors are robust to heteroskedasticity, and clustered by firm. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a definition for all variables employed in the analysis

### Robustness Tests

#### Informational advantage and firm characteristics

Our initial robustness tests are designed to explore whether the observed return predictability is driven by informational advantages accruing to option market traders and/or participants, or alternatively, whether the return predictability is systematically related to observable differences in underlying REIT characteristics. To examine these alternative drivers of return predictability, we perform a two‐stage analysis. First, we decompose our option measures into their predicted and residual components. This decomposition, which follows the methodology of both Chordia, Huh, and Subrahmanyam (2007) and Roll, Schwartz, and Subrahmanyam (2010), regresses our option metrics against lagged values of corresponding REIT characteristics. The second stage examines whether the predicted or residual components of our option metrics predict future returns.[39] Evidence that return predictability is primarily attributable to the predictable component of option volumes would favor a REIT characteristics based explanation of return predictability. Alternatively, evidence that the unexplained, residual portion of our option volume measures drives the observed return relations would favor an information asymmetry/advantage based explanation, as it would suggest market participants proactively alter their option market holdings to capitalize on anticipated movements in underlying equity prices.

While we do not explicitly report the results of the first‐stage analysis, we note that firm characteristics exhibit only a limited ability to predict either relative option volumes, or changes in those levels. With respect to relative levels of option volume (O/S), unreported stage one results reveal only prior returns (RET) and innovations in idiosyncratic volatility (ΔIV) exhibit even marginally significant predictive power. With respect to changes in relative option volumes (Δ(O/S)), while several model parameters exhibit statistical significance, their combined effect explains less than 20% of the variation in this metric. Moving on to the second stage of this analysis, whose results are presented in Table 9, we observe that return predictability is driven almost exclusively by the unexplained, residual components of our option measures. This finding is consistent across both relative option volume and changes in our option volume metrics. Once again, these findings are consistent with an information‐based mechanism or channel driving the observed return predictability relation.

9 Table. Information versus characteristics: what drives return predictability?

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **1** | **2** | **3** | **4** | **5** | **6** |
| Predicted O/S | −2.0632 |  | −2.0632 |  |  |  |
|  | (−1.42) |  | (−1.43) |  |  |  |
| Residual O/S |  | −0.11680001 | −0.11680001 |  |  |  |
|  |  | (−2.84) | (−2.74) |  |  |  |
| Predicted Δ (O/S) |  |  |  | −0.8589 |  | −0.9301 |
|  |  |  |  | (−0.86) |  | (−0.93) |
| Residual Δ (O/S) |  |  |  |  | −0.11100001 | −0.11770001 |
|  |  |  |  |  | (−2.70) | (−3.00) |
| AVG(O/S) |  |  |  | −0.0821 | −0.14170001 | −0.16170001 |
|  |  |  |  | (−1.62) | (−2.40) | (−2.83) |
| Property‐type fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
|  |  |  |  |  |  |  |
| Observations | 14,607 | 14,607 | 14,607 | 14,607 | 14,607 | 14,607 |
| Adjusted‐R2 | 0.350 | 0.350 | 0.351 | 0.350 | 0.350 | 0.350 |

*Notes*: This table presents the results of the second stage of our two‐stage analysis. The first stage, which is not reported, decomposes our O/S measure into its predicted and residual components. The dependent variable is the REIT's subsequent week alpha derived from the Chen, Downs and Patterson (2012) five‐factor model. All standard errors are robust to heteroskedasticity, and clustered by firm. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a definition for all variables employed in the analysis.

#### Does informed trading drive REIT return predictability?

Our second robustness test examines whether risk‐adjusted REIT returns are systematically related to our relative option volume measures. Employing the same core set of pricing models that informed our quintile portfolio sorted comparisons in Table 3, we estimate risk‐adjusted returns as follows:

where  refers to the model‐specific risk factors: RMRF, SMB, HML, UMD, ILLIQ, REIT factor and/or mispricing factors. In estimating the weekly factor loadings (), we follow Brennan, Chordia, and Subrahmanyam (1998) and employ a rolling two‐year (*i.e*., 104 week) historic window across all securities that had at least 26 weekly observations during the sample period. After estimating the weekly factor loadings and calculating risk‐adjusted returns, we then regress those risk‐adjusted returns against our relative option volume measures. As the risk‐adjustment process and subsequent controls should orthogonalize returns to both perceived risk factors and REIT characteristics, significant coefficient estimates on our relative option volume measures would once again be consistent with an information‐based explanation of informed option trading driving return predictability. The results of this analysis are presented in Table 10. Consistent with our previous findings, across all five model specifications we find strong evidence that relative option volume is significantly (negatively) related to future REIT risk‐adjusted returns. More specifically, on average across these five models, we find a one‐standard‐deviation increase in the relative O/S ratio is associated with a 16.1 bp reduction in subsequent week, risk‐adjusted REIT returns.[40]

10 Table. Risk model robustness check

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **FF3 Adjusted Returns** | **FF4 Adjusted Returns** | **FF4+ILLIQ Adjusted Returns** | **Chen, Down and Patterson (2012)** | **Stambaugh and Yuan (2017)** |
| **Dep. Var.** | **1** | **2** | **3** | **4** | **5** |
| O/S | −0.12640001 | −0.12590001 | −0.13010001 | −0.12330001 | −0.10730001 |
|  | (−3.26) | (−3.25) | (−3.47) | (−3.20) | (−2.85) |
| ΔIV | 0.0842 | 0.1053 | 0.0928 | 0.2192 | 0.0936 |
|  | (0.37) | (0.47) | (0.44) | (1.02) | (0.40) |
| RET | −1.2215 | −1.3020 | −0.9638 | 1.2756 | −0.5911 |
|  | (−0.34) | (−0.39) | (−0.31) | (0.37) | (−0.19) |
| SIZE | −0.49260001 | −0.45820001 | −0.33840001 | −0.44450001 | −0.52860001 |
|  | (−3.24) | (−2.71) | (−2.00) | (−2.54) | (−3.73) |
| BM | 1.07220001 | 0.8956 | 0.6653 | 1.04760001 | 1.04020001 |
|  | (1.90) | (1.47) | (1.08) | (1.91) | (1.84) |
| MOM | −0.3328 | −0.3376 | −0.39610001 | −0.38690001 | −0.3160 |
|  | (−1.52) | (−1.55) | (−1.82) | (−1.86) | (−1.43) |
| ILLIQ | −0.0159 | −0.0075 | −0.0298 | −0.0251 | −0.0087 |
|  | (−0.35) | (−0.17) | (−0.65) | (−0.45) | (−0.18) |
| CM | 0.17760001 | 0.17510001 | 0.13790001 | 0.20550001 | 0.14820001 |
|  | (2.80) | (2.72) | (2.08) | (3.29) | (2.35) |
| Inst.Own. (%) | 0.0050 | 0.0043 | 0.0019 | 0.0042 | 0.0054 |
|  | (1.55) | (1.38) | (0.56) | (1.49) | (1.62) |
| Intercept | 3.00230001 | 2.2815 | 1.9796 | 1.4458 | 3.06540001 |
|  | (2.07) | (1.53) | (1.29) | (0.88) | (2.18) |
| Property‐type fixed effects | Yes | Yes | Yes | Yes | Yes |
| Week fixed effects | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,608 | 14,608 | 14,608 | 14,608 | 14,608 |
| Adjusted‐R2 | 0.337 | 0.338 | 0.323 | 0.352 | 0.342 |

*Notes*: This table examines the relation between option volume and subsequent week risk‐adjusted returns across five different pricing models. While the dependent variable is next week's alpha, in each column the pricing model we use to calculate alpha changes. Specifically, in column 1 alphas are based on the Fama–French three‐factor model. The pricing model used in column 2 is the Fama–French plus Carhart four‐factor model, while column 3 relies on the Fama–French four‐factor model plus an illiquidity factor. Column 4 uses the pricing model of Chen, Downs and Patterson (2012), which is the Fama–French four‐factor model plus a REIT factor. Column 5 relies on the Stambaugh and Yuan (2017) four‐factor pricing model, which includes market, size and mispricing factors. All standard errors are robust to heteroskedasticity, and clustered by firm. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively. Appendix B provides a definition for all variables employed in the analysis

#### Additional tests

Finally, in rounding out the investigation, we conduct a number of additional tests to ensure the robustness of our results. While space limitations lead us to keep these results untabulated, we outline a number of the more notable findings below. First, it is entirely reasonable to wonder whether trading venue (*e.g*., NYSE vs. NASDAQ) is an important determinant of the information signal provided by relative option volume.[41] Indeed, the extant literature finds significant variation between exchange trading venues across various dimensions of liquidity, information asymmetry and trade execution costs.[42] With respect to the current investigation, these issues would appear to be largely mitigated, as the vast majority of equity REITs with liquid options are traded on the NYSE. Specifically, over 98% of our sample firm‐week observations trade on the NYSE. Nevertheless, to ensure our focal results are not materially influenced by such trading venue considerations, we re‐estimate our base models (1) explicitly controlling for exchange trading venue, (2) omitting those firm‐week observations attributable to NASDAQ firms and (3) exclusively on the subset of NASDAQ firms. Not surprisingly, given the paucity of NASDAQ‐related observations, our previously reported findings are robust to both the inclusion of trading venue controls, as well as the omission of NASDAQ traded firms. Moreover, while our NASDAQ only estimations lack statistical power, they reveal nothing that materially challenges our proffered focal relations.

Second, to ensure that observations with extreme values are not materially driving our results, we re‐estimated our analyses both excluding and winsorizing, observations whose relative option trading metrics fall outside the 1–99% (and 5–95%) interval ranges. Reassuringly, we find qualitatively similar results when we examine these outlier controlled samples, as all three of our option volume measures continue to exhibit significant (and/or enhanced) return predictability after the application of such restrictions.

Third, while the current investigation has explored three alternative measures of relative option volume, these are far from the only possible measures that could have been employed along this dimension. The selection of O/S, ΔO/S and AVG(O/S) was designed to both enhance the tractability of our results, as well as to facilitate more direct comparisons to the work of Johnson and So (2012). That said, in unreported analyses we have explored a number of alternative metrics. For example, Borochin *et al*. (2017) employs both the number of call options, and the amount of open interest on call options, as alternative proxies for the types of option liquidity and information flow risk measures we wish to capture. Unfortunately, as noted above, given that our data do not allow us to differentiate between buyer‐ versus writer‐initiated transactions for either puts or calls, we are not able to unambiguously sign the expectation of what call versus put option volumes truly suggest from an information/pricing perspective, and are thus more comfortable relying upon metrics of total option market activity for our primary results.[43] That said, for readers more familiar with the approach of Borochin *et al*. (2017), we do note that in untabulated results our return predictability findings appear to be stronger for calls than for puts, but stronger for combined option volume than either puts or calls measured in isolation.

Finally, while our weekly return framework was chosen primarily to correspond with the approach of Johnson and So (2012), we readily acknowledge that alternative holding periods and/or estimation windows could produce divergent results. To explore this possibility, we have also conducted our analysis using alternative holding periods. Under these alternative frameworks, daily returns appear too noisy to consistently document the return predictability evident in our weekly estimations, while monthly returns generate findings that are qualitatively similar, but not as statistically robust, as those reported herein. Similarly, the choice of a 30‐day option expiry window (*i.e*., options maturing in days 5–35) to measure relative option volume is also somewhat arbitrary. Expanding this window to include options maturing within 60 days (*i.e*., *t* = 5–65), 90 days (*i.e*., *t* = 5–95), or simply eliminating this constraint entirely (*i.e*., *t* = 5 to *∞*) continues to yield measures that evidence significant return predictability.[44] On the other hand, return predictability dissipates rather quickly as the expected investment horizon increases. While current levels of relative option volume continue to strongly forecast two‐week returns, these effects dramatically weaken when the investment horizon is extended to three and four weeks, and provide little to no incremental value in forecasting values more than one month out.[45]

# Summary and Conclusion

Over the last decade, REIT option markets have experienced tremendous growth as evidenced by both the increasing number of REITs with exchange‐traded options, as well as the enhanced volume of trading across these derivative securities. Interestingly, however, there has been relatively little examination of the economic linkages between REIT option markets and their underlying REIT equity market counterparts. Moreover, while the general finance literature has explored the predictive power of various option market characteristics and measures in explaining future equity returns, the limited existing REIT studies in this area have focused primarily on the predictive power of option market volatility. In this article, we explore the predictive power of another potentially important characteristic of REIT option markets, relative trading volume. Summarizing our results, we find evidence that relative option trading volume metrics are significantly related to future REIT performance. Specifically, we find strong and consistent evidence that higher relative option volumes negatively forecast subsequent week returns accruing to the underlying REIT's equity shares. Furthermore, the observed return predictability holds across multiple option market measures, including the currently observed level of the O/S ratio, the historical (AVG(O/S)) ratio, and current period innovations in the average long‐run option to stock volume ratio (Δ(O/S)). Interestingly, while our focal results are robust to a variety of alternative model specifications and controls, we do find evidence that the return predictability findings are both: (1) driven by the components of option trading that are orthogonal to the REITs' underlying firm characteristics and (2) concentrated in REITs that are more informationally opaque. Notably, this latter set includes smaller REITs, those perceived to possess enhanced growth options, and those characterized by relatively low levels of institutional ownership. Importantly, these results are also robust to the potential effects of short‐sale opportunities and constraints. Finally, our empirical evidence also suggests the predictive ability of relative option trading volumes to forecast future equity returns is attributable, at least partially, to the presence of information asymmetries and/or informed traders in the option market. Taken together, our results suggest that even within the relatively transparent REIT market sector, option market trading activities facilitate price discovery and enhance overall market efficiency.

# Acknowledgments

*We thank Will Armstrong, Honghui Chen, Vladimir Gatchev, Jeffrey Mercer, Qinghai Wang and three anonymous referees for helpful comments and suggestions on a previous version of this manuscript. This article was the recipient of the 2017 American Real Estate Society (ARES) real estate portfolio management best paper award*.

# A Appendix Raw O/S Ratio by Year, Reported as Percentages

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Mean** | **Median** | **SD** | **5th Percentile** | **25th Percentile** | **75th Percentile** | **95th Percentile** |
| 1996 | 1.734 | 1.734 | 2.177 | 0.195 | 0.195 | 3.274 | 3.274 |
| 1997 | 2.941 | 1.475 | 3.444 | 0.152 | 0.951 | 3.674 | 14.256 |
| 1998 | 17.603 | 3.286 | 42.620 | 0.315 | 1.032 | 13.890 | 106.516 |
| 1999 | 9.349 | 1.726 | 18.124 | 0.424 | 0.881 | 6.872 | 63.239 |
| 2000 | 3.517 | 0.914 | 6.982 | 0.262 | 0.630 | 2.517 | 22.707 |
| 2001 | 5.982 | 1.351 | 13.380 | 0.162 | 0.498 | 4.366 | 32.919 |
| 2002 | 1.302 | 0.754 | 1.934 | 0.208 | 0.389 | 1.313 | 3.381 |
| 2003 | 2.767 | 0.896 | 7.998 | 0.214 | 0.484 | 1.740 | 11.427 |
| 2004 | 3.413 | 1.135 | 10.530 | 0.200 | 0.511 | 2.740 | 12.936 |
| 2005 | 2.187 | 1.255 | 3.681 | 0.230 | 0.560 | 2.562 | 6.397 |
| 2006 | 2.772 | 1.157 | 10.652 | 0.196 | 0.543 | 2.536 | 6.943 |
| 2007 | 1.862 | 0.875 | 5.028 | 0.143 | 0.431 | 1.893 | 5.171 |
| 2008 | 1.477 | 0.589 | 3.662 | 0.106 | 0.298 | 1.318 | 5.768 |
| 2009 | 1.988 | 0.803 | 4.410 | 0.112 | 0.336 | 2.025 | 6.820 |
| 2010 | 5.446 | 1.219 | 26.387 | 0.165 | 0.511 | 3.311 | 16.233 |
| 2011 | 2.559 | 0.972 | 6.894 | 0.124 | 0.387 | 2.235 | 8.862 |
| 2012 | 2.717 | 1.146 | 7.027 | 0.146 | 0.444 | 2.787 | 9.873 |
| 2013 | 3.046 | 1.415 | 9.429 | 0.156 | 0.505 | 3.309 | 10.627 |
| 2014 | 3.437 | 1.376 | 8.071 | 0.154 | 0.561 | 3.511 | 11.417 |
| All | 4.005 | 1.267 | 10.128 | 0.193 | 0.534 | 3.467 | 18.882 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Firm characteristics by tercile of O/S** |  |  |  |  |  |  |  |  |  |  |
| **Variable** | **ΔIV** | **RET** | **SIZE** | **BM** | **MOM** | **ILLIQ** | **CM** | **InstOwnership%** | **SIZE ($millions)** | **Unlogged BM** |
| Low | 0.048 | 0.000 | 8.222 | 0.430 | 0.076 | 0.926 | 4.213 | 81.082 | 5,724.480 | 0.596 |
| 2 | 0.043 | 0.000 | 8.343 | 0.389 | 0.066 | 1.044 | 4.359 | 77.233 | 6,868.860 | 0.527 |
| High | 0.036 | 0.001 | 8.674 | 0.347 | 0.076 | 0.825 | 4.457 | 77.819 | 10,238.150 | 0.464 |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Firm characteristics by decile of O/S** |  |  |  |  |  |  |  |  |  |  |
| **Variable** | **ΔIV** | **RET** | **SIZE** | **BM** | **MOM** | **ILLIQ** | **CM** | **InstOwnership%** | **SIZE ($millions)** | **Unlogged BM** |
| Low | 0.060 | −0.001 | 8.294 | 0.469 | 0.074 | 0.813 | 4.142 | 81.374 | 6,051.170 | 0.664 |
| 2 | 0.058 | 0.001 | 8.194 | 0.433 | 0.074 | 0.953 | 4.204 | 81.501 | 5,521.890 | 0.607 |
| 3 | 0.035 | 0.000 | 8.207 | 0.401 | 0.075 | 0.989 | 4.261 | 80.256 | 5,673.940 | 0.542 |
| 4 | 0.046 | −0.001 | 8.236 | 0.411 | 0.069 | 1.094 | 4.284 | 78.231 | 6,040.990 | 0.564 |
| 5 | 0.041 | 0.001 | 8.305 | 0.389 | 0.072 | 0.915 | 4.347 | 78.199 | 6,587.200 | 0.524 |
| 6 | 0.053 | 0.000 | 8.358 | 0.387 | 0.069 | 1.204 | 4.382 | 76.446 | 7,039.660 | 0.530 |
| 7 | 0.029 | −0.001 | 8.454 | 0.365 | 0.073 | 0.999 | 4.448 | 76.326 | 7,824.950 | 0.486 |
| 8 | 0.023 | 0.001 | 8.570 | 0.363 | 0.076 | 0.825 | 4.467 | 77.262 | 8,721.820 | 0.482 |
| 9 | 0.024 | 0.000 | 8.672 | 0.352 | 0.073 | 0.856 | 4.443 | 77.025 | 10,218.920 | 0.476 |
| High | 0.062 | 0.001 | 8.941 | 0.317 | 0.071 | 0.539 | 4.440 | 81.383 | 13,465.490 | 0.419 |

# B Appendix Variable Definitions

|  |  |
| --- | --- |
| **Variable Name** | **Definition** |
| O/S | Ratio of total option trading volume to stock trading volume, using options across all strike prices, and with five to 35 trading days remaining until expiration. |
| Δ(O/S) | Change in the option to stock volume ratio, defined as the difference between the total option trading volume to stock trading volume ratio (O/S) and the six‐month historical average of this ratio (AVG(O/S)). |
| AVG(O/S) | Historical average option volume to stock volume ratio, defined as the average O/S over the prior six months, skipping the first six weeks. |
| ΔIV | Historical average implied volatility, defined as the option volume‐weighted average implied volatility over the prior six months, skipping the first six weeks. |
| RET | Past week cumulative REIT returns adjusted by CRSP value‐weighted average market returns. |
| SIZE | Natural logarithm of market capitalization (as measured in millions of dollars) calculated as of the REIT's last quarterly earnings announcement date. |
| BM | Natural logarithm of the book value to market value of equity ratio, calculated as of the REIT's last quarterly earnings announcement date. |
| MOM | Momentum return is calculated as the underlying REIT's cumulative returns over the past six months, skipping week w – 1. |
| ILLIQ | Historical daily average Amihud (2002) illiquid ratio measured over the prior six months, skipping week w – 1. The value is multiplied by one billion for ease of presentation. |
| CM | Composite metric, defined as the equally weighted average of decile ranks of 11 stock anomalies. The 11 anomalies include financial distress, Ohlson's O‐score bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assets and investment‐to‐asset ratios. Higher CM scores imply higher expectations of future stock return potential. Refer to Stambaugh, Yu, and Yuan (2012) for more detailed variable construction. |
| Inst. Own. (%) | Percentage of intuitional holdings, defined as the percentage of outstanding shares held by institutions as of December of each year. The data are obtained from Thomson Financial. |
| Year< = 2006 | For each firm‐week, the dummy variable "Year< = 2006" equals 1 if the observation is before year 2007, and 0 otherwise. |
| Year2007∼2009 | For each firm‐week, the dummy variable "Year2007∼2009" equals 1 if the observation is between year 2007 and year 2009, and 0 otherwise. |
| Year> = 2010 | For each firm‐week, the dummy variable "Year> = 2010" equals 1 if the observation is after year 2009, and 0 otherwise. |
| Short‐sale Constrained | A dummy variable set equal to 1 if both the ratio of short interest to shares outstanding is above the 95 percentile of the distribution of the ratio in the week and the institutional ownership is in the lowest tercile, and 0 otherwise. |
| ΔSISO | Change in the ratio of short interest over shares outstanding, defined as the difference between the ratio of short interest over shares outstanding in the week of the O/S measures and the ratio of short interest over shares outstanding in the prior week. |
| Lag1\_ SISO | Prior week's ratio of short interest over shares outstanding. |

# C Appendix Descriptive Statistics: REITs Compared to Non‐REITs

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **REITs (n = 14,608)** | **Non‐REITS (n = 947,822)** | **Mean Difference t‐Test** |
| O/S | 0.030 | 0.117 | −0.087\*\*\* |
| Δ(O/S) | −0.067 | −0.102 | 0.036\*\*\* |
| AVG(O/S) | 0.025 | 0.087 | −0.062\*\*\* |
| ΔIV | 0.015 | 0.012 | 0.002 |
| RET | 0.000 | 0.000 | 0.000 |
| SIZE ($millions) | 7,635 | 11,211 | −3,576\*\*\* |
| BM | 0.528 | 0.467 | 0.060\*\*\* |
| MOM | 0.073 | 0.111 | −0.038\*\*\* |
| ILLIQ | 0.934 | 12.555 | −11.621\* |
| CM | 4.346 | 5.060 | −0.714\*\*\* |
| Inst Own% | 78.629 | 71.809 | 6.820\*\*\* |
| Short Interest/Shares Outstandinga | 0.071 | 0.082 | −0.011\*\*\* |

Due to the limited data for short interest, the number of observations for Short Interest/Shares Outstanding in REITs is 10,441 and 824,654 in non‐REITs. \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively.

# Footnotes

1. *This possibility takes on enhanced significance in light of the findings of Roll, Schwartz and Subrahmanyam ([72]), who show that the relative option to stock volume ratio is indeed systematically related to observable firm attributes.*
2. *See Blau, Hill and Wang ([11]) for additional discussion on the transparency of REITs and REIT assets. See Blau, Nguyen and Whitby ([12]) and Ametefe, Devaney and Marcato ([2]) for comprehensive reviews of REIT liquidity issues. For an introduction to REIT dealer rules and other prohibited transactions, see Mühlhofer ([66]).*
3. *Potentially mitigating this incentive, Wang, Erickson and Gau ([79]), Bradley, Capozza, and Seguin ([17]) and Feng, Price and Sirmans ([46]) all find many REITs pay well in excess of the regulatory mandated threshold. As such, the degree to which REITs are truly financially constrained remains an open empirical question.*
4. *Consistent with this notion, recent evidence by Lang, Lins and Maffett ([61]) shows enhanced financial transparency increases firm valuations, and reduces capital acquisition costs, by enhancing firm liquidity. Similarly, Firth, Wang and Wong ([47]) suggest that corporate transparency mitigates the potential impact of investor sentiment on equity market valuations, while Bhat, Callen and Segal ([9]) demonstrate that enhanced transparency of a firm's financial disclosures is associated with reductions in spreads on credit default swaps. Conversely, He et al. ([53]) find that enhanced transparency of corporate disclosures does not have to lead to improvements in the liquidity of the underlying security.*
5. *Our assertion that informationally transparent firms may be less likely to have informed traders is based on the potential benefits associated with becoming informed about the company. If the process required to become informed is costly, rational investors would only be willing to bear these costs when the potential expected rewards justify the expense. As informationally transparent firms are less likely to be mispriced, investors may be less likely to choose to bear the costs associated with becoming informed about transparent firms. In turn, the reduction in the number of informed traders within the option markets for these firms could mitigate the return predictability of their O/S‐based option measures.*
6. *Purchasing a put is typically less costly than shorting the shares directly, while informed investors can profit from negative information in a cash flow positive manner by selling calls.*
7. *Specifically, they conclude O/S signals are strongest when short‐sale constraints are high and when option leverage is low. Both situations provide a direct incentive for informed investors to be active option market participants.*
8. *Interestingly, the return predictability they observe is eliminated once preannouncement equity returns are fully accounted for, further highlighting the complex nature of equity and option market linkages and relations.*
9. *While Chung et al. ([30]) use vega‐weightings to estimate their implied volatilities, Johnson and So ([59]) indicate that moneyness categories do not affect the relation between volume‐based option measures and stock returns.*
10. *Throughout the empirical specifications which follow, our results are qualitatively robust to the relaxation of this constraint.*
11. *See Crack and Ledoit ([32]) for a discussion of the denominator effect. As option listing requirements mandate a more restrictive $3 per share underlying equity price, this requirement is generally nonbinding and allows for considerable downward drift in security prices for even the lowest priced REIT shares within our sample. For additional insight into REIT option listing requirements, including minimum market capitalization and number of shareholder requirements, see Chung et al. ([30]).*
12. *See, for example, Roll, Schwartz and Subrahmanyam ([72]).*
13. *Due to six months of prior data requirement, sample year 1996 has significantly fewer firm‐week observations and lower annual trading volume than other sample years. Additionally, much of the spike in average O/S ratios observed for calendar year 1998 is attributable to a number of (weekly) extreme value observations surrounding the corporate restricting of Irvine Apartment Communities (ticker symbol = "IRV"; CRSP permno = 80,092). As explained in more detail below, our empirical results that follow are robust to both the exclusion and winsorization of this, and similar, outliers.*
14. *For non‐REIT firms, annual option trading volumes averaged 301,689.83 contracts (or approximately 30.17 million shares) per firm, while annual equity trading volume averaged 356.51 million shares.*
15. *Our empirical results that follow are materially unchanged if we keep weeks w – 1 through w – 6.*
16. *The restriction of skipping Friday‐to‐Monday returns does not materially affect our findings.*
17. *Harvey, Yan and Zhu ([52]) list hundreds of stock characteristics that have previously been shown to significantly predict future stock returns.*
18. *See Stambaugh, Yu and Yuan ([76]), Edelen, Ince and Kadlec ([42]) and Stambaugh and Yuan ([77]) for recent examples of this composite metric's application to the analysis of stock returns.*
19. *Appendix C presents the average values of these characteristics for our REIT sample, as well as comparison values for non‐REITs.*
20. *See, for example, Johnson and So ([59]).*
21. *See, for example, Feng, Ghosh and Sirmans ([45]) and Harrison, Panasian and Seiler ([51]) for broad market comparisons of REIT operating characteristics.*
22. *Due to both alternative reporting dates across firms, and potential short‐sale double‐counting, observed levels of institutional ownership may exceed 100% upon rare occasions.*
23. *Though not reported explicitly in Table 2, the Pearson correlation coefficient between our two implied volatility metrics ΔIV and vega IV equals 0.327, while the correlation coefficient between firm size and idiosyncratic volatility as measured by vega IV (ρ = –0.450) also exceeds the aforementioned 0.4 threshold.*
24. *For additional details on the development of, and predictions from, these alternative factor‐based models, see (1) Fama and French ([43]); (2) Carhart ([23]); (3) Amihud ([3]); (4) Chen, Downs and Patterson ([26]) and (5) Stambaugh and Yuan ([77]).*
25. *While the economic magnitude of these potential returns seems quite robust, we readily acknowledge that high transaction costs and other trading frictions associated with weekly portfolio rebalancing may materially impact the ability to profitably operationalize a trading rule based exclusively upon these results, particularly for individual retail investors.*
26. *Chen, Downs, and Patterson ([26]) is the Fama–French four‐factor risk‐adjusted return model augmented to include a REIT factor. We observe qualitatively similar results to those presented in Table 4 using our other risk‐adjustment models.*
27. *The 0.16% economic magnitude is found by multiplying the standard deviation of the O/S ratio (1.3078) by the model 2 coefficient estimate (–0.1190) on this sample variable. Recall that the O/S standard deviation reported in Table 1 (0.125) is for the raw O/S ratio, while the 1.3078 is the standard deviation of the logged O/S ratio that is employed in the model.*
28. *Replacing the traditional ΔIV metrics with vega‐weighted measures as employed by Chung et al. ([30]) yields coefficient estimates that are slightly stronger, but remain statistically insignificant. Regardless, the key point remains that the inclusion of ΔIV (or vega IV) does not appear to materially influence the nature of our focal relations between REIT options measures and future REIT return predictability.*
29. *In untabulated tests where the double‐sorting procedure is based upon either the historical average O/S ratio (AVG(O/S)) or changes in relative option trading volume (Δ(O/S)), we again observe qualitatively similar results. Additionally, exploring this same question using (unreported) panel regressions across REIT characteristic terciles yields qualitatively similar results across all three relative option volume metrics.*
30. *To provide some additional context to these findings, we list those sample observations that were relatively small, illiquid and informationally opaque, but which also possessed a high O/S ration in 2014. These firms include: Boston Properties, Inc. (BXP), CoreCivic Inc. (CXW), Digital Realty Trust, Inc. (DLR), Equity Commonwealth (EQC), Front Yard Residential Corporation (RESI), GEO Group Inc. (GEO), Government Properties Income Trust (GOV), Macerich Company (MAC), Mack‐Cali Realty Corporation (CLI), Mid‐America Apartment Communities, Inc. (MAA), Omega Healthcare Investors, Inc. (OHI), Rayonier, Inc. (RYN), Realty Income Corporation (O), Senior Housing Properties Trust (SNH), SL Green Realty Corp. (SLG), VEREIT, Inc. (VER) and W P Carey, Inc. (WPC).*
31. *See, among numerous examples, Diamond and Verrecchia ([38]), Senchack and Starks ([73]), Desai et al. ([35]), Boehmer, Jones and Zhang ([13]) and Boehmer and Wu ([14]).*
32. *Interestingly, the marginally significant (positive) coefficient estimates on the short‐sale constrained indicator variables in models 5 and 6 are consistent with the notion that such constraints prevent the market from receiving key information signals regarding future firm prospects. Similarly, while statistically insignificant, the negative coefficient estimates on the interaction terms in models 7 and 8 would also be consistent with an enhanced importance for the information content contained within our relative option volume metrics. Given the high degree of noise and statistical insignificance with respect to these parameters, we simply note the observations and refrain from drawing definitive conclusions along this dimension.*
33. *Ten REITs included in both the short‐sale moratorium and our final estimation sample are: Apartment Investment and Management Company (AIV), AMB Property Company (AMB), Strategic Hotels & Resorts (BEE), Developers Diversified Realty Corporation (DDR), General Growth Properties, Inc. (GGP), Hersha Hospitality Trust (HT), Lexington Realty Trust (LXP), ProLogis Trust (PLD), SL Green Realty Corp. (SLG) and United Dominion Realty Trust, Inc. (UDR). We note that ticker symbol NRP does not generate any matches in our options data set, and that Arbor Property Trust (ABR), Winthrop Realty Trust (FUR) and Kite Realty Group Trust (KRG) do not satisfy our data screens.*
34. *While Devaney ([36]) fails to identify significant valuation effects, he does report significant increases in event‐induced volatility. Ironically, the stated purpose of the ban was to mitigate volatility concerns.*
35. *Theoretically, Back ([7]) argues options contracts further away from their designated strike prices may also be uniquely informative. Untabulated results suggest this may indeed be true, but also exhibit considerably more noise than the simple moneyness classifications reported herein. Similarly, put versus call option volume may also provide differential information signals, and thus be expected to inform prices and returns in a separate fashion. Unfortunately, our data do not allow us to differentiate option contracts originated by buyers versus writers, and hence, we are unable to "sign" the expected information content. As such, and following the previous literature (e.g., Johnson and So [59]), we group both put and call option contracts together for estimation purposes.*
36. *In untabulated analyses, we examine whether our RavenPack News sentiment indicator directly influences O/S return predictability. While we find no evidence that the relation between O/S and subsequent returns is affected by changes in this sentiment index, we encourage future researchers to further explore this possibility using alternative methodologies and/or sentiment indices (e.g., Loughran and McDonald [63], Kim, Kim and Seo [60]).*
37. *Delta is unavailable for approximately 35% of our observations (34.2% of puts and 37.5% of calls). Comparing identification results across both methods for those options where delta is available reveals a nearly 90% correspondence between the two metrics.*
38. *For simplicity and ease of presentation, only results using our five‐factor risk‐adjusted returns are presented. Results from using raw returns and alternative risk‐adjusted pricings models provide qualitatively similar results, and are available from the authors directly upon request. Similarly, all models continue to include our full set of previously employed REIT characteristics and risk factors, though they are suppressed to provide a more parsimonious presentation of the results.*
39. *In general, the first stage of our analysis is: Option Metrici,t = f(Firm Characteristicsi,t–1), while the second stage is: Returni,t+1 = f(Predicted Option Metrici,t, Residual Option Metrici,t, Firm Characteristicsi,t). The difference in the timing of when the firm characteristics are measured prevents multicollinearity issues. Both stages also include property‐type, time and firm fixed effects. We also note qualitatively similar results are observed when we exclude firm characteristics from the second stage of the analysis and include only the predicted and residual option volume metrics.*
40. *In untabulated tests using the historical average O/S ratio (AVG(O/S)), and/or changes in relative option trading volume (Δ(O/S)), we observe qualitatively similar results.*
41. *We thank an astute, anonymous referee for bringing this point to our attention.*
42. *See, for example, Loughran ([62]), Huang and Stoll ([57]), Bessembinder and Kaufman ([8]) and Chan and Lakonishok ([25]) among others for traditional finance studies showing differences in costs or market outcomes across alternative trading venues. With respect to real estate markets, Danielsen and Harrison ([34]), Marcato and Ward ([65]) and Cannon and Cole ([21]) all document liquidity differences across the NYSE and NASDAQ for publicly traded REITs. In related work, both Aguilar, Boudry and Connolly ([1]) and Pavlov, Steiner, and Wachter ([70]) document that Index membership enhances REIT pricing efficiency.*
43. *Consider an investor with negative expectations regarding a company's future stock price. They have multiple alternatives available to them when attempting to capitalize on this information. For example, they could short the stock, buy a put option or write a call option. In writing the call, the investor may even earn positive returns if the underlying equity increases in value, provided it does not increase as much as the purchaser of the option anticipated. Hence, enhanced call option volume does not have to be driven by positive expectations of future market performance.*
44. *These findings should not be particularly surprising given the heavy concentration of options with relatively short maturities.*
45. *Cumulative abnormal returns continue to exhibit marginal significance through week six, though the economic magnitude of those returns is entirely attributable to the significance of the return differentials in weeks one through four.*

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