

Option Price Implied Information and REIT Returns[†]

Jie Cao

The Chinese University of Hong Kong
jiecao@cuhk.edu.hk

Bing Han

University of Toronto
bing.han@rotman.utoronto.ca

Linjia Song

The Chinese University of Hong Kong
slinjia@link.cuhk.edu.hk

Xintong Zhan

The Chinese University of Hong Kong
xintongzhan@cuhk.edu.hk

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Abstract

Option-based measures can predict underlying stock returns, due to differences in price discovery and price pressure effects between options and underlying stocks. We investigate stock return predictability by various option price-based measures using REITs. REITs are more transparent and efficiently priced than general stocks, but REIT options are less liquid. Consistent with the model of Easley, O'Hara, and Srinivas (1998), most of the option price-based measures do not significantly forecast REIT stock returns, but changes in option implied volatilities are robust and significant return predictors. We provide further evidence supporting the informed trading channel instead of the price pressure effects.

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Option Price Implied Information and REIT Returns

Option-based measures can predict underlying stock returns, due to differences in price discovery and price pressure effects between options and underlying stocks. We investigate stock return predictability by various option price-based measures using REITs. REITs are more transparent and efficiently priced than general stocks, but REIT options are less liquid. Consistent with the model of Easley, O'Hara, and Srinivas (1998), most of the option price-based measures do not significantly forecast REIT stock returns, but changes in option implied volatilities are robust and significant return predictors. We provide further evidence supporting the informed trading channel instead of the price pressure effects.

Keywords: informed trading in options; stock return predictability; real estate investment trusts

JEL Classification: G12; G14; R30

1. Introduction

A growing recent literature has documented that various option-implied variables are important determinants of the cross-section of expected stock returns. For example, future stock returns can be predicted by the difference between option-implied volatility and realized volatility (Bali and Hovakimian (2009)), volatility spread (Cremers and Weinbaum (2010)), volatility smirk (Xing, Zhang, and Zhao (2010)), the ratio of option volume to stock volume (Johnson and So (2012)), the changes in option implied volatility (An, Ang, Bali, and Cakici (2014)), and the deviation of option implied stock price from traded stock price (Goncalves-Pinto, Grundy, Hameed, van der Heijden, and Zhu (2020)). However, there are debates about the underlying mechanism for the ability of option-implied variables to predict future stock returns.

One channel is that informed investors prefer to trade in options (e.g., due to the leverage advantage of options) and stock market is not informationally efficient (e.g., due to some frictions) so that options contain informed traders' private signals that are not fully impounded into stock prices. Under this explanation, the options market is informationally superior to the stock market. Another important source of stock return predictability by option-implied variables is temporary price pressure in the stock market that is not reflected in option prices, as supported by the evidence in Goncalves-Pinto et al. (2020). Under this alternative explanation, the option-based predictability of stock returns is driven by stock illiquidity instead of faster price discovery in the options market. We contribute to the debate by studying the return predictability by all these option-implied variables using data from the real estate investment trust (REIT) market.

REIT market is an interesting laboratory to investigate the return predictability by option-based measures and to understand the underlying mechanisms. On one hand, REITs are relatively more liquid. Therefore, the price pressure channel (Goncalves-Pinto et al. (2020)) is unlikely to apply and induce stock return predictability by option-based variables. Any documented predictability would be cleaner evidence of informed trading in options. On the other hand, REITs are known for their informational transparency and pricing efficiency.¹ Therefore, there is less

¹ The intrinsic value of equity REIT is highly linked to the value of its underlying tangible real estate. Compared with less asset-intensive industries, the REIT business franchise plays a less important role in the market value, which makes it easier to value REITs. Moreover, REITs are required to distribute 90% of their income and accumulate less cash through retained earnings. They access the capital market frequently to raise capital, which increases the monitoring and reduces information asymmetry problems. Dolvin and Pyles (2009) show that REIT IPOs are associated with lower levels of underpricing and smaller price revisions than non-REITs and attribute these differences to the lower uncertainty of REIT pricing. Blau, Hill, and Wang (2011) examine the predictability of REIT short sale

incentive to collect private information in REITs, and new information can be expected to get incorporated quickly into the REIT stock price. Moreover, we find that REIT options are relatively illiquid over our sample period. The informed trading model of Easley, O'Hara, and Srinivas (1998) implies less informed trading in REIT options. These arguments lead us to expect weaker stock return predictability by option-based variables compared to the general case of common stocks. If we still find evidence of stock return predictability by option-based variables in REITs, it would lend strong support for the important price discovery role of the options market more generally.

REITs provide diversification benefits and have become an increasingly important part of investment portfolios for both institutions and individuals. The total market capitalization of equity REITs reached 1.24 trillion in 2019.² However, previous studies on stock market anomalies typically exclude REITs from the sample, following a common practice dating back to a period when REITs are under-developed and less important. With the rapid growth of REIT option market in recent years³, it is both important and feasible to study informed trading in REIT options and whether REIT options contain useful information for the underlying stock returns. Moreover, unlike the large variations in stock characteristics within other industries, REIT market is a homogeneous industry and offers the opportunity to study the return predictability with less concern that the predictability is driven by cross-industry or within-industry heterogeneity in firm characteristics. A number of studies have exploited this unique setting to study stock return anomalies (e.g., Chui, Titman, and Wei (2003), Chen, Downs, and Patterson (2012), Ling, Ooi, and Xu (2019)).

To explore whether and how REIT options can be used to predict the cross-section of future stock returns, we investigate the return predictability power by 5 option price-based measures for equity REITs. We form weekly portfolios sorted by each option price-based predictor and document that their abilities to REIT returns differ substantially from those for the general common stocks. In the common stock market, all the option price-based predictors significantly predict future stock returns. However, in the REIT market, most predictors fail to significantly predict the future REIT returns. Out of the 5 option price-based measures, the only robust (across

transactions and document that short sellers are less able to predict the future REIT returns than non-REITs, supporting the higher pricing efficiency of REITs.

² According to National Association of Real Estate Investment Trusts (see <https://www.reit.com/>), around 87 million U.S. residents own REITs through their retirement savings and other investment funds.

³ As shown in Figure 1, both the number and the fraction of equity REITs with options traded have increased dramatically from 1996 to 2017.

different weighting-schemes and asset pricing models) predictor of REIT stock returns is the difference between changes in call implied volatility and changes in put implied volatility ($\Delta CVOL - \Delta PVOL$) as in An et al. (2014).

Our findings support the prediction of the model in Easley, O'Hara, and Srinivas (1998) that there would be more informed trading in equity options when stock liquidity is relatively low and option liquidity is relatively high. Indeed, we document that the market quality of REITs is significantly better than that of common stocks, while the market quality of REIT options is lower than that of the general equity options. It is also possible that the weaker predictability by option price-based predictors is due to the absence of price pressure mechanism. Consistent with this idea, we find that in the REIT market, the deviation of option implied price from traded stock price ($\Delta DOTS$, as in Goncalves-Pinto et al. (2020)) does not predict the future stock returns. This is clear evidence that the price pressure of underlying asset is less likely to drive the return predictability by option-implied variables, in the more liquid REIT market.

We then focus on the difference between call implied volatility changes and put implied volatility changes ($\Delta CVOL - \Delta PVOL$) and conduct further analyses to test the informed trading hypothesis. Tercile portfolios formed according to $\Delta CVOL - \Delta PVOL$ have a high-minus-low spread of 12 basis points per week. We use CAPM, Fama-French 3-factor model, and Fama-French 6-factor model to adjust for common risk factors. We also follow Bond and Xue (2017) and construct an investment-based factor model for REITs. In all specifications, the risk-adjusted return spreads are significant with little changes in magnitude. We further document that the predictability by $\Delta CVOL - \Delta PVOL$ mainly comes from the change in call implied volatility ($\Delta CVOL$). Consistent with the high liquidity and transparency of the REIT market, we find that the return predictability diminishes quickly and is no longer significant after 4 weeks. Our findings are also robust to Fama-MacBeth regressions, which control for option volume-based return predictor (O/S ratio) and a set of REIT stock characteristics and fundamentals, including size, book-to-market ratio, illiquidity, return volatility, reversal, and momentum.

The positive return spreads we document between high and low $\Delta CVOL - \Delta PVOL$ portfolios in REIT market are consistent with the informed trading hypothesis. Under a noisy rational expectations model, An et al. (2014) argue that a high $\Delta CVOL - \Delta PVOL$ captures positive private information about future firm cash flows. Specifically, if informed traders possess private information about future price increases (decreases), they will demand more call (put) options and

push the implied volatilities to increase. Therefore, an increase of call implied volatility signals favorable information about the underlying firm while an increase of put implied volatility signals unfavorable information. The difference between call implied volatility change and put implied volatility change captures the net positive information about future cash flows and hence positively predicts future REIT returns.

We further explore the mechanisms of return predictability by option price implied information ($\Delta CVOL - \Delta PVOL$). First, we investigate whether $\Delta CVOL - \Delta PVOL$ indeed captures fundamental information by studying the cumulative abnormal returns (CARs) around earnings conference calls. We document a positive relation between the difference between call and put implied volatility changes and earnings conference call returns. Such evidence is consistent with the argument that option prices convey information about the future earnings calls and informed trading related to REIT fundamentals indeed occurs first in the option market.

Second, we explore whether information environment and limits to arbitrage affect our documented predictability. Informed trading is more rewarding among firms that are less transparent. We document that the return predictability is more pronounced among younger REITs, REITs with lower analyst coverage, REITs focusing on noncore property types, and REITs headquartered in less transparent MSAs. The return predictability is also stronger among REITs with higher limits to arbitrage, proxied by idiosyncratic risk and the bid-ask spread of REITs.

Last, we examine whether the incentive for information collection of REIT option traders differs across regions. We focus on the land supply elasticity measure from Saiz (2010) and expect our results to be stronger for REITs located in regions with high land supply elasticity. The flexibility of land supply indicates more real estate development opportunities and encourages option traders to actively collect information. Indeed, we document a stronger predictability among REITs exposed more to the regions with higher land supply elasticity. Collectively, our results provide strong support for the information trading channel as the underlying driver of the significant return predictability by the option-implied measure $\Delta CVOL - \Delta PVOL$.⁴

⁴ We also find another evidence supporting the informed trading channel based on the order imbalance from end-users of REIT options. Specifically, we find a positive (negative) option order imbalance on REITs when their changes in option-implied volatilities ranked in the top (bottom) tercile. This is consistent with informed investors with good (bad) news buy calls (puts) more than write calls (puts). The difference in call option order imbalance between high and low $\Delta CVOL$ is significantly positive. This result is available upon request.

Our paper contributes to a large literature on the interactions between derivatives and the underlying assets. In particular, our paper complements previous studies documenting that options are not redundant and contain useful information about the underlying asset.⁵ Among others, Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), and An et al. (2014) document various variables implied from option prices can predict underlying stock return and interpret the evidence as slow diffusion of value-relevant signals inferred from informed trading in options.⁶ Goncalves-Pinto et al. (2020) document stock return predictability by the deviation of option-implied stock price from traded stock price, but argue that the predictability is primarily driven by the temporary stock price pressure rather than informed trading in options. Our paper provides evidence supporting the informed trading channel even in a setting where the information trading in options is expected to be weak. Consistent with An et al. (2014) and the interpretation that $\Delta CVOL$ - $\Delta PVOL$ proxies for private information about future cash flow, we find that $\Delta CVOL$ - $\Delta PVOL$ significantly predicts the returns of REITs especially around earnings conference calls. Different from An et al. (2014), we find more pronounced REIT return predictability by $\Delta CVOL$ (positive information) than $\Delta PVOL$ (negative information), so that the profits of a trading strategy that form long-short portfolios by sorting on $\Delta CVOL$ - $\Delta PVOL$ come from the long side instead of short side. This suggests that informed traders mainly use options to trade on their positive information.

We add to the growing literature on the return predictability in the REIT market. Though most assets pricing studies focus on common stock market, the more transparent and homogenous REIT market potentially provides a better platform for understanding the determinants of assets prices. For example, Chui, Titman, and Wei (2003) find a significant momentum effect in REITs in the post-1990 period. Different from the findings in the stock market, however, the momentum effect in REIT market is stronger for larger and more liquid REITs. Ling, Ooi, and Xu (2019) document the “asset growth” anomaly in the REIT market and find the effects of asset growth interact with NAV premium and discount. Consistent with the limited attention argument in the stock market, Chen, Harrison, and Khoshnoud (2020) find that REITs with the best performing

⁵ See Figlewski (1989), Conrad (1989), Figlewski and Green (1999) and subsequent studies for evidence that options are not redundant.

⁶ There is a related but distinct line of studies documenting that ex ante measures of risk-neutral higher moments of stock returns inferred from equity options are strongly related to future stock returns (see, e.g., Conrad, Dittmar, and Ghysels (2013)).

tenants generate higher abnormal returns than those with the worst performing tenants, highlighting the importance of real estate specific characteristics in determining REIT returns. Liu and Lu (2020) document a continuing overreaction in the REIT market, supporting that active mutual funds suffer from behavioral biases. Our paper highlights that the growing derivatives market for REITs may offer more informational advantages and potentially benefit the investors by pointing out arbitrage opportunities in REIT market.

Last, our paper connects to an emerging literature that investigates the role of derivatives market in REIT return predictability. Cashman, Harrison, and Sheng (2018) explore the relation between option trading volume and REIT returns. They find that relative option trading volume (measured by O/S ratio) negatively predicts future REIT returns, echoing the findings in Johnson and So (2012) for stocks in general. Instead, we focus on the option price-based predictors and our results are robust to controlling for the O/S ratio. Whereas O/S ratio captures negative private information mainly for stocks facing short-sales constraints, while our $\Delta CVOL - \Delta PVOL$ captures both positive and negative private information. Chung, Fung, Shilling, and Simmons-Mosley (2016) show that REIT vega-weighted implied volatility change negatively predicts future daily returns. Our paper differs from Chung et al. (2016) in three ways. First, we focus on the difference between changes in call implied volatility and changes in put implied volatility. Second, our documented predictability is driven by the diffusion of fundamental information from option market to the REIT market. Third, we study return predictability at weekly frequency and over longer horizons.

The remainder of the paper is organized as follows. Section 2 describes the data and measures. Section 3 presents our baseline findings and robustness tests. Section 4 further explores the mechanisms of the return predictability. Section 5 concludes the paper.

2. Data and Variables

2.1. Data and measures

Our analyses focus on publicly traded equity REITs.⁷ The REIT type information is from CRSP ZIMAN database. Our sample contains all publicly traded equity REITs that are included in FTSE

⁷ We use the list of equity REITs posted on McKay Price's website <http://www.mckayprice.com/research.html>. Our results are similar if we identify REITs with share code of 18 or 48 from CRSP or using the CRSP ZIMAN REIT database.

NAREIT All REITs Index as identified by NAREIT.⁸ We obtain stock price data from CRSP and accounting data from Compustat. The option information is from OptionMetrics which includes the daily closing bid and ask quotes, trading volume, and open interest of each REIT option. We extract implied volatility information from OptionMetrics Volatility Surface data, which contains implied volatilities for options with fixed times to expiration and deltas constructed using interpolation. The analyst coverage data are from I/B/E/S. We obtain Fama-French risk factors and risk-free rates from Kenneth French's data library.

We construct the following option price-based measures, which have been documented to predict the cross-section of future stock return. The detailed descriptions of each measure are listed in the Appendix.

- $\Delta CVOL - \Delta PVOL$ is the difference of changes between call and put implied volatilities. We construct this measure following An et al. (2014), who document that $\Delta CVOL - \Delta PVOL$ positively predicts future stock returns. We choose standardized options with a delta of 0.5 (at-the-money, ATM hereafter) and expiration of 30 days. $\Delta CVOL$ ($\Delta PVOL$) is the end-of-week implied volatility (IV) minus last week-end implied volatility (IV) of call (put) option.
- $IV - RV$ is the difference between implied volatility (IV) and realized volatility (RV). Bali and Hovakimian (2009) show that $IV - RV$ is positively related to future returns. We define IV as the average of end-of-week ATM call and put implied volatilities in the previous week and define RV as the annualized realized volatility of daily returns over the previous 22 trading days.
- *Volatility Spread* is computed following Cremers and Weibbaum (2010), who find stocks with higher volatility spreads, measured as the weighted-average difference between strike- and maturity-matched call-implied and put-implied volatilities, with weights determined by open interest. We use the end-of-week implied volatility spread.
- *Volatility Smirk* is from Xing, Zhang, and Zhao (2010) who show that volatility smirk negatively predicts future stock returns. The daily implied volatility smirk measure is the difference between the implied volatilities of out-of-the-money (OTM hereafter) puts and ATM calls.

⁸ To mitigate concern that our results are driven by small REITs or REITs with low price, we repeat the analysis using a sample which excludes REITs with stock prices below \$1, \$3, and \$5, respectively. The results are similar.

- *DOTS* is the difference between option implied stock price and the traded stock price. We construct *DOTS* following Goncalves-Pinto et al. (2020), who document that *DOTS* positively predicts stock returns. We take the week-end *DOTS* as our weekly measure.

In our Fama-MacBeth regression analysis, we control for the option volume-based predictor (O/S ratio) and a set of REIT stock-level characteristics and fundamentals.

- *O/S Ratio* is the logarithm of 1 plus option volume times 100 divided by stock volume, where option volume is the sum of option contracts during the week (Cashman, Harrison, and Sheng (2018)).
- *Size* is the natural logarithm of the market value of REIT at the end of last month.
- *Book-to-Market Ratio* is the natural logarithm of book equity for the fiscal year-end in a calendar year divided by market equity at the end of December of that year, as in Fama and French (1992).
- *Illiquidity* is the average ratio of the absolute daily return divided by daily dollar trading volume over the past month, following Amihud (2002).
- *Realized Return Volatility (RetVol)* is the standard deviation of daily returns over the previous 22 trading days.
- *Reversal* is the stock return in percentage of the previous week.
- *Momentum* is the stock cumulative return in percentage over the previous 11 months starting from twelve months ago to two months ago.

2.2. Sample summary

Figure 1 shows the rapid growth of equity REITs with exchange-traded options. Both the number and the fraction of equity REITs with options increase dramatically. From 1996 to 2017, the number of REITs with options has increased from 16 to 151 and the fraction of equity REITs with options increase from 8% (16 out of 211) to 88% (151 out of 171). Regarding market capitalization, the ratio of total market capitalization of optionable equity REITs divided by the total market capitalization of all equity REITs has increased from 11% to 96%.

Our final sample contains 78,329 REIT-week observations from 230 unique equity REITs with non-missing required information from January 1996 to December 2017. Panel A of Table 1

presents the summary statistics for options and the underlying REITs in our sample. We first compute the cross-sectional summary statistics each week and then take the time-series averages. The average market capitalization of REITs in our sample is \$3.90 billion. This number is higher than the size of REITs in previous studies as our sample only contains REITs with listed options and these firms are generally larger.⁹ The magnitude of five option price-based predictors and other control variables are in line with previous related studies.

Panel B of Table 1 reports the time-series averages of the cross-sectional correlations among various variables of interest. The correlations among five option price-based predictors are in general very low except for the one between $\Delta CVOL-\Delta PVOL$ and *Volatility spread* (0.29). The option volume-based predictor *O/S ratio* has close to zero correlations with $\Delta CVOL-\Delta PVOL$, *Volatility Spread*, and *DOTS*, and moderate correlations with *IV-RV* and *Volatility Smirk*. It implies that these 5 option price-based measures capture different information embedded in the REIT option price, which is also distinct from information in the REIT option volume. Moreover, $\Delta CVOL-\Delta PVOL$, *Volatility Spread*, and *DOTS* exhibit very low correlations with REIT stock-level characteristics and fundamentals. These low correlations indicate that our results are less likely to be confounded by other predictors documented in the literature. Nevertheless, we control for all these variables in the regression analysis.

3. Option Price-based Return Predictors and Future REIT Returns

In this section, we examine the performance of each of the option price-based predictors. Then we focus on the predictability by $\Delta CVOL-\Delta PVOL$ and conduct a variety of robustness tests.

3.1. Option price-based return predictability for REITs and common stocks

We start our analysis by comprehensively examining the predictability by option price implied information in the REIT market at weekly frequency. We also replicate the predictability of these measures in common stock market to understand the difference and similarity between REITs and common stocks.

Table 2 reports the portfolio sort results of each option price-based predictor, respectively. At the end of each week, we sort REITs into terciles based on the option price-based predictors and calculate the average return and alpha of each portfolio. Specifically, we report the value-

⁹ For example, the average market capitalization in Liu and Lu (2020) is around \$2 billion.

weighted (equal-weighted) 3-1 spreads of raw return, CAPM alpha, Fama-French 3-factor alpha, and Fama-French 6-factor alpha in Panel A (Panel B). To make a comparison between REITs and common stocks, we do the decile portfolios sorts and report the 10-1 return spread for common stocks sample to avoid potential bias by the difference in portfolio diversification.¹⁰ The left panel presents the return and alpha spreads for REITs and the right panel presents the results for common stocks. The results show that the return predictability of option price implied measures is much stronger in common stock market than that in REIT market. For instance, the value-weighted return spreads of decile portfolios sorted on *IV-RV*, *Volatility Spread*, and $\Delta CVOL-\Delta PVOL$ are all around 30 basis points per week in common stock market and *Volatility Spread* shows the strongest return predictability.¹¹

However, in the REIT sample, most of these return predictors fail to predict future REIT returns in a robust way except for $\Delta CVOL-\Delta PVOL$. For example, the return predictability by *Volatility Spread* is only significant for equal-weighted return, but not for value-weighted return. *Volatility Smirk*, however, only exhibits weak predictability for value-weighted returns. Only $\Delta CVOL-\Delta PVOL$ has a significant REIT return predictability both statistically and economically. A strategy that longs the REITs with highest $\Delta CVOL-\Delta PVOL$ and shorts the REITs with lowest $\Delta CVOL-\Delta PVOL$ produces a value-weighted (equal-weighted) weekly return spread of around 12 (13) basis points, which translates to a return spread of about 6.5% when annualized.

The sharp contrast in return predictability by option price-based predictors in REIT and common stock market highlights the difference between these two markets. Cremers and Weinbaum (2010) argue that stock return predictability is stronger when stock liquidity is relatively low and when option liquidity is relatively high, i.e., option market is informationally superior to the stock market. We thus examine whether the difference in return predictability is related to the difference in market quality between REITs and common stocks, as well as the difference in market quality between REIT options and common stock options.

Indeed, we document that the REIT market is of higher quality compared with common stocks in general while the market quality of REIT options is lower than that of the options on common stocks. As reported in Panel A of Table 3, the REIT market, compared with the common

¹⁰ The results hold if we instead form tercile or quintile portfolios for both REITs and common stocks.

¹¹ Our results on weekly return predictability for common stocks are consistent with Bali and Murray (2020) who replicate the monthly return predictability among common stocks by a similar set of option-based predictors.

stock market, has a lower arbitrage risk proxied by idiosyncratic volatility (Pontiff (2006)). Moreover, REIT market is more liquid and less costly to trade with a lower bid-ask spread and a lower Amihud illiquidity measure. The weaker return predictability we have documented is consistent with the better liquidity of REIT market, which may also imply the absence of price pressure mechanism. *DOTS*, a measure of the deviation of option implied price from traded stock price in Goncalves-Pinto et al. (2020), has no predictability power in REIT market. Such evidence is consistent with the absence of price pressure mechanism in REIT market.

Another important condition for the option price-based measures containing useful information is the market quality of options. Informed traders would be more likely to use options when option market is more liquid, more actively traded, and more efficiently priced. In Panel B of Table 3, we compare the market quality measures of REIT options with common stock options. Specifically, we examine the Hasbrouck measure¹², the bid-ask spread, and *O/S* ratio. The empirical findings further shed light on the weaker return predictability in REIT market. Compared with options of common stocks, options of REITs are less efficiently priced (a higher Hasbrouck measure indicating a higher pricing error), less liquid (a higher bid-ask spread), and less traded (a lower *O/S* ratio) by averaging options with different moneyness and maturities. These differences are also statistically significant.

We further look at a subset of ATM options with maturities between 30 and 60 days which correspond to the implied volatility surface information we use to construct $\Delta CVOL - \Delta PVOL$. These short-term ATM options are most actively traded, have a relatively smaller bid-ask spread, and provide more reliable pricing information. For this subsample, we again find that REIT options have a lower market quality than options of common stocks. Such evidence suggests that collecting and trading private information using REIT option is not as rewarding as using options of common stocks. The lower return predictability power of option price implied information in the REIT market is consistent with the possibility of less informed trading in REIT options.

¹² To construct the Hasbrouck (1993)'s measure in equity option market, we obtain intra-day transaction records (execution price, associated quotes, and trading volumes for each transaction) of options from The Options Price Reporting Authority (OPRA) over a sample period of 2004 to 2015. We apply standard filters to transaction records. We apply Lee and Ready (1991) algorithm to sign the transactions. We only include options with the number of transactions greater than 50 in the VAR estimation. Then for each stock, we compute the overall measure of option market quality by taking the average of the natural logarithm of the pricing errors of all the options associated with it. A higher Hasbrouck measure indicates higher pricing error, therefore lower market quality.

In summary, we show that the weaker return predictability of the REIT options is due to the combination of a relatively lower market quality of REIT options and a higher market quality of REITs. However, we still find the evidence of informed trading in the REIT option market by documenting the strong predictability by $\Delta CVOL-\Delta PVOL$, indicating the value of derivatives. We then further investigate the robustness of the return predictability by $\Delta CVOL-\Delta PVOL$ and mechanisms.

3.2. Portfolio sorts by $\Delta CVOL-\Delta PVOL$

3.2.1. The return predictability by $\Delta CVOL-\Delta PVOL$

For each week from January 1996 to December 2017, we sort REITs according to their differences between the changes in call and put implied volatilities ($\Delta CVOL-\Delta PVOL$) at the previous week end and form tercile portfolios.¹³ We require that there are at least 10 stocks in each portfolio.¹⁴ Tercile 1 consists of REITs with the lowest $\Delta CVOL-\Delta PVOL$ and tercile 3 consists of REITs with the highest $\Delta CVOL-\Delta PVOL$. We hold the portfolio for one week and rebalance weekly.

Table 4 reports the value-weighted portfolio return results and the consistent equal-weighted results are reported in Appendix Table A1. To avoid serial correlation, we report Newey-West t-statistics in parenthesis. We also report risk-adjusted returns using CAPM model, Fama-French three-factor model (FF-3 hereafter), and Fama-French six-factor model (FF-6 hereafter) in addition to raw returns. Besides the stock market factors, the REIT literature has also introduced REIT market factors. For example, Bond and Xue (2017) construct an investment-based factor model for REITs which consists of a market factor, an investment factor, and a profitability factor. We construct the weekly investment-based factors for REITs and demonstrate the robustness of the predictability by option implied volatility changes.

We first report the returns and return spreads of portfolios sorted on $\Delta CVOL-\Delta PVOL$ in Panel A of Table 4. The value-weighted average raw return increases from 0.16% (tercile 1) to 0.28% (tercile 3). Such pattern is consistent with the argument that $\Delta CVOL-\Delta PVOL$ captures positive fundamental news and positively predicts future REIT returns. The economic magnitude is also sizeable as the difference in average raw return between tercile 3 and tercile 1 is 0.12% per

¹³ To mitigate nonsynchronous trading effect, we also tried skipping a day between portfolio formation and holding. Specifically, we employ the implied volatility information one day before the week end when forming portfolios and calculate the weekly return for the next week. The results are slightly weaker but still significant.

¹⁴ The results are similar if we remove this requirement.

week (t-statistic=3.04), leading to an annualized portfolio return of 6.43%. The risk-adjusted portfolio spreads according to CAPM, Fama-French 3-factor model, and Fama-French 6-factor are with similar magnitudes of around 0.12% per week and are all significant at 1% level. We obtain similar results using the risk model proposed in Bond and Xue (2017).

3.2.2. *Informed trading and $\Delta CVOL$ versus $\Delta PVOL$*

The positive return spreads we document between high and low $\Delta CVOL$ - $\Delta PVOL$ portfolios in REIT market are consistent with the informed trading argument. If informed traders have favorable information on the performance of underlying REIT, they may exploit this information and buy a call option which provides high leverage and therefore high profitability. The high demand for call options increases the call implied volatility. When the information is gradually reflected in the underlying REIT market, the REITs with higher $\Delta CVOL$ will have higher future returns. The same logics would apply to the changes in put option implied volatility, $\Delta PVOL$. When informed traders have unfavorable information about the underlying, they firstly trade in the option market and buy put options, therefore increasing the implied volatility of put options.

In this subsection, we then investigate the relative contribution of $\Delta CVOL$ and $\Delta PVOL$ to the return predictability by $\Delta CVOL$ - $\Delta PVOL$ in REIT market. The average correlation between $\Delta CVOL$ and $\Delta PVOL$ in our REIT option sample is 0.34, indicating that they may capture different fundamental news of underlying REITs.¹⁵ Specifically, we further sort REITs according to $\Delta CVOL$ and $\Delta PVOL$, respectively.

In Panel B of Table 4, we form weekly value-weighted tercile portfolios according to $\Delta CVOL$. Consistent with the positive news reflected in the change of call implied volatility, we document a significant and positive return spread (0.11%) between portfolios with high $\Delta CVOL$ and portfolios with low $\Delta CVOL$. Risk adjustment using several factor models does not change the predictability by $\Delta CVOL$ qualitatively.

Panel C of Table 4 reports the portfolio spreads sorted on $\Delta PVOL$. While the overall return pattern is consistent with the argument that an increase in put option implied volatility indicates negative fundamental news and therefore negative return predictability, the portfolio spread between high and low $\Delta PVOL$ portfolios has a smaller magnitude (-0.04% for raw return) and are not statistically significant (t-statistics -0.88), compared with that sorted according to $\Delta CVOL$. An

¹⁵ The correlation between implied volatility levels of call and put options is 0.70, consistent with put-call parity.

et al. (2014) find significant return predictability by both $\Delta CVOL$ and $\Delta PVOL$ among the full stock sample, although the effect is also stronger for $\Delta CVOL$ than $\Delta PVOL$, and strongest for $\Delta CVOL - \Delta PVOL$.¹⁶ Different from An et al. (2014), there is no significant weekly return predictability by $\Delta PVOL$ in our study which suggests a larger asymmetric effect between $\Delta CVOL$ and $\Delta PVOL$ in predicting REIT returns. The information embedded in the call options price is relatively more important in predicting the next week REIT return.

One possible explanation is the asymmetric use of call and put options of REITs by informed traders because put option is usually more expensive and put price may also reflect the degree of short-sale constraints.¹⁷ The information embedded in put options of REITs could be more difficult to analyze than the information embedded in call options. As a result, the speed of information diffusion from REIT option market to REIT market could be slower for the negative news than the positive news which we further investigate in the next subsection.¹⁸

3.2.3. Predictability over different horizons

In this subsection, we examine how long the REIT return predictability by $\Delta CVOL - \Delta PVOL$ lasts for. Each week we sort REITs into tercile portfolios according to (the difference in) implied volatility changes and hold the portfolios for the next 2 to 6 weeks. In week t , this strategy holds portfolios that are constructed in the current week as well as in previous $K-1$ weeks ($K = 1$ to 6). Following Jegadeesh and Titman (1993), we calculate portfolio returns with overlapping holding periods.

Table 5 reports the return spreads of value-weighted portfolios sorted on $\Delta CVOL - \Delta PVOL$, $\Delta CVOL$, and $\Delta PVOL$, respectively for different holding periods. The results in Table 5 show that the return predictability by implied volatility changes diminishes quickly over next four weeks. When we sort on $\Delta CVOL - \Delta PVOL$ and hold the portfolios for one week, the return spread between high and low terciles is 12 basis points. The return spread declines to 10 basis points if we expand the holding period to two weeks and further to 4 basis points if we hold the portfolios for three

¹⁶ An et al. (2014) argue that the large common volatility component related to put-call parity is perhaps responsible for the weaker predictability of $\Delta PVOL$ compared to the $\Delta CVOL$ portfolio sorts.

¹⁷ See Chen, Downs and Patterson (2012) and Cashman, Harrison, and Sheng (2018) for the discussions of short-sale constraints of REITs.

¹⁸ Another possibility might be that REITs have a substantial part of income from rents and interests and thus have more stable income stream than industrial firms. Therefore, investors react differently to positive and negative news as the stable nature of income mitigates the effect of unfavorable news.

weeks. After 4 weeks, the return predictability completely disappears. Such results are consistent with the notion that REIT market is very transparent and return predictability by option price implied information is exploited and arbitrated away very quickly.

We also report the return spreads of the long-short portfolios sorted on $\Delta CVOL$ and $\Delta PVOL$, respectively. The return predictability by $\Delta CVOL$ lasts for two weeks. Sorted on $\Delta CVOL$, the average holding return decreases from 11 bps to 10 bps and further to insignificant 3 bps as the holding period increases from 1 week to 2 weeks and then to 3 weeks. Interestingly, sorted on $\Delta PVOL$, the average holding return spread changes from an insignificant -4 bps to significant -5 bps as the holding period increases from 1 week to 2 weeks, and decreases to insignificant -1 bps as the holding period extended to 5 weeks. It is consistent with the possibility that the negative information embedded in REIT options travels to REIT market slower than the positive information. However, once the information becomes available, it will be quickly incorporated into the REIT price and the return predictability disappear quickly.

3.3. Robustness checks

3.3.1 Fama-MacBeth regressions

In this subsection we examine the predictability by $\Delta CVOL$ - $\Delta PVOL$ using Fama-MacBeth (1973) regressions. We run the following regression at weekly frequency and control for an option volume-based predictor (O/S ratio) and a set of REIT stock-level characteristics and fundamentals. We require that there are at least 30 REIT observations in each week for the Fama-MacBeth regression analysis.

$$R_{i,t+1} = \beta_0 + \beta_1 \Delta CVOL - \Delta PVOL_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

$R_{i,t+1}$ is the one-week-ahead return. $\Delta CVOL - \Delta PVOL_{i,t}$ is the difference of changes in call and put implied volatility. $Controls_{i,t}$ contains O/S ratio and a set of REIT stock-level variables including, size, book-to-market (BM), illiquidity, realized return volatility, reversal, and momentum.

We present the Fama-MacBeth regression results in Table 6 with Newey-West adjusted t-statistics in parenthesis. Column (1) shows the effect of $\Delta CVOL$ - $\Delta PVOL$ on future REIT returns without any controls. Consistent with the positive return pattern we have documented in the portfolio sorting, the coefficient on $\Delta CVOL$ - $\Delta PVOL$ is positive and significant at 1% level (t-

statistic 3.19). Column (2) shows that controlling for the Cashman, Harrison, and Sheng (2018) variable, *O/S* ratio, in the regressions does not affect our main result. We find that the coefficient on *O/S* ratio is negative and statistically significant, consistent with Cashman, Harrison, and Sheng (2018), but the coefficients of $\Delta CVOL - \Delta PVOL$ are similar to that reported in Column (1) and are highly statistically significant. In Column (3), we further control for a set of REIT stock-level characteristics and fundamentals and examine the robustness of our results. The coefficient on $\Delta CVOL - \Delta PVOL$ is still positive and significant at 1% level, indicating that the return predictability of option price-based measure ($\Delta CVOL - \Delta PVOL$) is different from other known predictors in the REIT market. The coefficients of control variables are largely consistent with previous literature. For example, size and reversal negatively predict the future REIT returns. Taken together, using Fama-MacBeth regressions, we confirm the positive predictability of $\Delta CVOL - \Delta PVOL$ on the cross-section of REIT returns.

3.3.2 *Alternative moneyness and maturities*

In our main analysis, we use standardized options (ATM options with short maturity) with delta of 0.5 and maturities of 30 days. To examine whether our results are sensitive to how our implied volatility measures are calculated, we use options from the volatility surface with alternative moneyness and maturities for robustness checks. Specifically, we first repeat the portfolio analysis using the standardized ATM options with maturities of 60, 91, and 365 days, respectively. Panel A, B, and C of Table A2 report the value-weighted portfolio returns and the long-short spreads sorted on implied volatility change difference ($\Delta CVOL - \Delta PVOL$) of these options. The spreads of average returns and alphas are significant economically and statistically. The magnitude of the REIT return spreads generated using information from options with longer maturities, however, is smaller. Different from Clements, Kalesnik, and Linnainma (2017), who find that the prices of long-dated options contain more relevant information for predicting stock returns, our results show that the return spreads sorted on implied volatility changes of 30-day standardized options are larger than those sorted on long-dated options. One possibility is that the ATM options with shorter maturities are traded more actively in the illiquid REIT option market, therefore contain more useful information about the REIT returns.

Instead of using ATM options, we repeat our analysis using OTM options. We focus on calls with delta of 0.25 and puts with delta of -0.25 to calculate the difference of implied volatility

changes. Panel D of Table A2 reports the corresponding value-weighted portfolio returns and the long-short portfolio spreads. Overall, the return predictability we document is not sensitive to the way we calculate the implied volatility change measure. The equal-weighted portfolio return results in Panel E-H are also consistent.

4. Informed Trading and Stock Return Predictability by Implied Volatility Change

Easley, O'Hara, and Srinivas (1998) suggest that informed traders may trade in the option market first because of the higher leverage that option provides. An et al. (2014) also provide a model of rational informed trading that contemporaneously moves both option and stock markets. Our documented predictability shows that although REIT market is relatively more transparent while the market quality of REIT options is inferior to that of common stock options, there is still evidence of informed trading. In this section, we further investigate the information and mechanisms behind the predictability by $\Delta CVOL - \Delta PVOL$.

4.1. Abnormal returns around earnings conference calls

One channel that option price implied information predicts future underlying returns is that informed traders successfully predict the nature of future corporate events and the related market reactions. For example, Chan, Ge, and Lin (2015) show that implied volatility spreads predict abnormal returns around merger and acquisition announcements. Gharghori, Maberly, and Nguyen (2017) demonstrate that option implied volatility contains information about stock splits. Johnson and So (2012) find that *O/S* ratio predicts earnings surprise and cumulative abnormal returns (CARs) around the earnings announcements. Atilgan (2014) documents that stocks with higher implied volatility spreads (CVOL-PVOL) before earnings announcements earn significantly positive abnormal returns over a two-day announcement window.

We explore whether the option price implied variable ($\Delta CVOL - \Delta PVOL$) can predict the abnormal returns of REITs around the conference calls. Earnings conference calls are important information resources for REITs (Doran, Peterson, and Price (2012)). We collect quarterly earnings calls data for REITs from Capital IQ. The dependent variable CAR (0, 1) is the two-day cumulative abnormal return around the earnings conference call. We use the market-adjusted return (the difference between the firm return and the market return) and Fama-French three factor adjusted returns to measure the daily abnormal return. Then CAR (0,1) is calculated by cumulating

the abnormal return from the conference call day to the day after. We run the following pooled regression of CAR (0,1) on the lagged $\Delta CVOL - \Delta PVOL$, controlling for the same set of variables as in Table 6:

$$CAR_{i,t+1} = \beta_0 + \beta_1 \Delta CVOL - \Delta PVOL_{i,t} + Controls_{i,t} + \varepsilon_{i,t+1} \quad (2)$$

Table 7 presents the regression results. Column (1) reports the effect of $\Delta CVOL - \Delta PVOL$ on the market-adjusted abnormal return around the conference calls and Column (2) reports the effect on the Fama-French three factor adjusted returns. The positive and significant coefficients of $\Delta CVOL - \Delta PVOL$ suggest informed traders have collected fundamental information related to the future earnings conference calls and started to trade on the option market first before earnings conference calls. Consequently, the option price contains information regarding the nature of the earnings calls and the difference of implied volatility changes between call and put options ($\Delta CVOL - \Delta PVOL$) can predict CAR around earnings conference calls.

4.2. REIT stock characteristics and return predictability

In this subsection, we examine how the predictability by $\Delta CVOL - \Delta PVOL$ varies with the characteristics of underlying REITs. Informed trading is expected to be more rewarding for REITs with higher information asymmetry. We rely on four proxies to measure the transparency of underlying REITs including age, number of unique analysts following, a core REIT indicator, and an indicator whether the headquarter of underlying REIT is in a transparent MSA. We expect more matured REITs, REITs with more financial analyst following, REITs that focus on core property types, and REITs with headquarters in transparent MSAs to be more transparent. Core REITs are REITs focusing on relatively more mature and transparent property types. Specifically, we define core REITs as REITs focusing on apartments, industrial, office and retail properties. The REIT property focus type information is from CRSP Ziman database. Previous literature such as Chen, Downs, and Patterson (2012) and Feng, Pattanapanchai, Price, and Sirmans (2021) find that core REITs are more transparent and less subject to information asymmetry. According to Ling, Marcato, and Zheng (2020), a MSA as transparent if it belongs to 12 highly transparent MSAs as measured by the JLL Real Estate Transparent Index, that is Los Angeles, San Francisco, New York, D.C., Boston, Seattle, Miami, Chicago, Dallas, Houston, Atlanta, and Philadelphia. As the reward

for informed trading reduces when information asymmetry decreases, we expect our documented return predictability by option information to be weaker for more transparent REITs.

To test whether $\Delta CVOL-\Delta PVOL$ has stronger return predictability for less transparent REITs, we interact aforementioned proxies with implied volatility changes difference ($\Delta CVOL-\Delta PVOL$) in the Fama-MacBeth regressions and report the results in Table 8. In line with our expectations, the coefficients on the interaction terms of $\Delta CVOL-\Delta PVOL$ with transparency proxies are all significantly negative. In other words, information transparency of REITs weakens the predictability by option price implied information.

4.3. Limits-to-arbitrage and return predictability

We further explore the impact of limits to arbitrage on the return predictability by $\Delta CVOL-\Delta PVOL$. Arbitrage opportunities diminish very quickly in efficient market without limits to arbitrage. In reality, however, arbitrageurs consider the risk related to the trading strategies and the limits to arbitrage prevent price from reverting to its fundamental value. Therefore, we expect our documented return predictability to be more significant in REITs with higher limits to arbitrage.

We use stock return idiosyncratic volatility and stock bid-ask spread as proxies for limits to arbitrage.¹⁹ We interact $\Delta CVOL-\Delta PVOL$ with limits-to-arbitrage measures in Fama-MacBeth regressions and report the results in Table 9. Consistent with our expectations, the coefficients on the interaction terms are positive and statistically significant in both specifications. In Column (1), we measure limits to arbitrage using IVOL and document that the coefficient on the interaction between $\Delta CVOL-\Delta PVOL$ and IVOL is 0.476 with a t-statistic of 2.19. In Column (2) we use the bid-ask spread of REITs as a proxy for arbitrage cost and the interaction term also has a significantly positive coefficient. These findings are in line with the argument that $\Delta CVOL-\Delta PVOL$ exhibits stronger return predictability among REITs with higher limits to arbitrage. These arbitrage costs create frictions which prevent investors from exploiting information from the REIT option market.

¹⁹ Following Ang, Hodrick, Xing, and Zhang (2006), we estimate IVOL as the standard deviation of daily return residuals from the Fama-French 3-factor model for each firm, each month as per the following regression, with a minimum of 17 daily observations each month although the results are robust to using a minimum of 15 daily observations. The bid-ask spread for each REIT is the weekly average of daily bid-ask spread, which is the difference between ask and bid prices divided by the midpoint of ask and bid prices.

4.4. Regional differences and return predictability

The geographical distributions of REITs vary dramatically, and it is important to investigate whether regional differences affect the incentives for information collection of informed traders and thus affect return predictability by option price implied information. One particular dimension that we explore in this paper is the land supply elasticity which is fundamental to real estate activities. We hypothesize that higher land supply elasticity indicates more flexible real estate development opportunities and encourage option traders to actively search for information. In other words, for informed traders, the reward for information acquisition is potentially higher for REITs in areas with higher land supply elasticity. We measure REIT locations using both headquarter information and property-level information.

We first obtain the land supply elasticity measure from Saiz (2010)²⁰ which varies from 0 to 4 and a higher value indicates higher land supply elasticity. This measure is constructed by processing satellite-generated data on terrain elevation and presence of water bodies and is available at the MSA level. The headquarter data of REITs is obtained from corporate 10-K files. The property holding data is from S&P Global including property sizes, locations, and holding periods. To measure REIT-level land supply elasticity, we either assign the headquarter MSA land supply elasticity to the REIT, or follow the equation below to construct property holding-weighted land supply elasticity.

$$Elasticity_{i,t} = \sum_s \frac{SIZE_{i,s,t}}{\sum_s SIZE_{i,s,t}} Elasticity_s \quad (3)$$

where $SIZE_{i,s,t}$ is the size of REIT i 's property holdings in state s at time t , $\frac{SIZE_{i,s,t}}{\sum_s SIZE_{i,s,t}}$ measures its exposure to state s and is calculated as dividing the size of its property holdings at each state by the sum across states, $Elasticity_s$ is the state-level elasticity.

To understand the effect of land supply elasticity on our documented predictability, we include the interaction of REIT-level land supply elasticity measure and $\Delta CVOL$ - $\Delta PVOL$ in the Fama-MacBeth regressions. In column (1) we use the land supply elasticity of the MSA in which the REIT is headquartered. In column (2) we use a high land supply elasticity dummy which equals

²⁰ The Saiz (2010) measure is widely used in the literature as a measure for land supply elasticity. See, for example, Chaney, Sraer, and Thesma (2012), Favara and Imbs (2015), and so on.

one if the property holding-weighted land supply elasticity measure defined as in equation (3) is higher than the cross-sectional median. Table 10 reports the regression coefficients and the coefficients on the interaction between $\Delta CVOL$ - $\Delta PVOL$ and land supply elasticity measure are positive and statistically significant. This finding suggests that the return predictability of option price implied information is more pronounced if the underlying REIT is operating in regions with higher land supply elasticity. It is in line with our hypothesis that option investors are more likely to gather information if the REIT operates in markets with higher flexibility and more opportunities.

5. Conclusion

Option-based measures can predict underlying stock returns, due to differences in price discovery and price pressure effects between options and underlying stocks. We contribute to the debate by investigating whether option price implied information predicts REIT returns. REITs are characterized by tangible assets and mandatory regulations, and thus are shown to be more informationally transparent and liquid by previous studies. In such case, price pressure in REITs is less likely to be the dominating channel. Any predictability, therefore, is cleaner evidence of informed trading in REIT options.

We compare the predictive power of option price-based variables for REITs and common stocks. Return predictability is weaker in the REIT market, possibly because of the relatively low market quality of REIT options (consistent with the model of Easley, O'Hara, and Srinivas (1998)) or the absence of price pressure effect. Nevertheless, we still find that the difference between changes in call-implied volatility and changes in put-implied volatility ($\Delta CVOL$ - $\Delta PVOL$) significantly predicts future REIT returns, with a weekly spread of 0.12%. This cross-sectional predictability is robust to various controls in the REIT market and lasts for less than 4 weeks.

We demonstrate that $\Delta CVOL$ - $\Delta PVOL$ predicts cumulative abnormal returns during earnings conference calls. This is consistent with the informed trading argument that option trading conveys private information related to future cash flows of the underlying firm. We also conduct cross-sectional tests to examine whether the return predictability differs across different REITs. The results show that implied volatility changes have stronger predictability for younger REITs, REITs with lower analyst coverage, REITs focusing on noncore property types, and REITs headquartered in less transparent regions. The return predictability is also stronger among REITs

with higher limits to arbitrage and in regions where the incentives for collecting real estate information are higher. Overall, our results provide consistent evidence of information transmission from option market to the underlying stock market. We also contribute to the limited research that examines the link between REIT and its options although the REIT option market has grown dramatically.

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Figure 1. Number and Ratio of Equity REITs with Options

This figure reports the average number of equity REITs each year, the number of equity REITs each year, the ratio of equity REITs with options divided by all equity REITs and the ratio of total market capitalization of equity REITs with options divided by total market capitalization of all equity REITs.

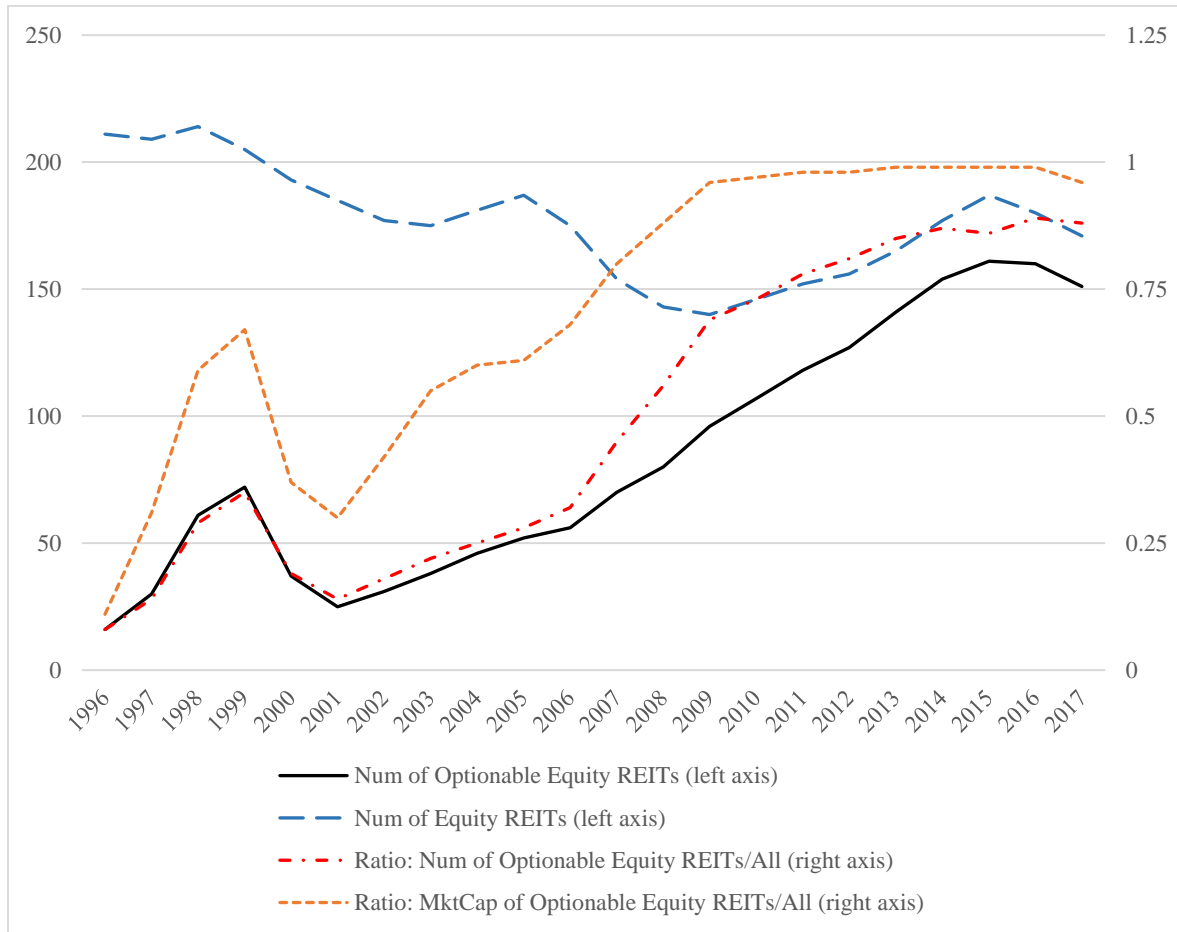


Table 1. Descriptive Statistics

This table presents the summary statistics. Panel A reports the time-series average of cross-sectional statistics of option price-based predictors and characteristics of underlying REITs. $\Delta CVOL-\Delta PVOL$ is the difference between changes in call implied volatility and changes in put implied volatility. $IV-RV$ is the difference between implied volatility (IV) and realized volatility (RV) following Bali and Hovakimian (2009). *Volatility Spread* is the difference between call and put implied volatilities from Cremers and Weinbaum (2010). *Volatility Smirk* is the difference between the implied volatilities of OTM puts and ATM calls from Xing, Zhang, and Zhao (2010). *DOTS* is the difference between option implied stock price and the traded stock price following Goncalves-Pinto, Grundy, Hameed, van der Heijden, and Zhu (2020). *O/S Ratio* is the logarithm of 1 plus option trading volume times 100 divided by stock trading volume following Cashman, Harrison, and Sheng (2018)). We times O/S ratio with 100 in this table. *Size* is the REIT market capitalization, reported in \$ billion. *BM* is the book-to-market ratio. *Illiquidity* is the Amihud (2002) illiquidity measure. *RetVol* is the standard deviation of the daily REIT return in the month. *Reversal* is the REIT return in percentage on the previous week. *Momentum* is the cumulative REIT return in percentage over the previous 11 months of [-12, -2]. Panel B reports the time-series average of cross-sectional Pearson correlations. The sample period is from January 1996 to December 2017.

Panel A: Summary Statistics

Variables	N	Mean	Standard deviation	25 th percentile	Median	75 th percentile
$\Delta CVOL-\Delta PVOL$	78,329	0.00	0.14	-0.04	0.00	0.04
$IV-RV$	78,329	0.04	0.14	-0.02	0.02	0.08
Volatility Spread	65,793	-0.01	0.06	-0.04	-0.01	0.01
Volatility Smirk	57,254	0.12	0.08	0.06	0.10	0.17
DOTS %	50,896	0.00	1.73	-0.42	-0.03	0.31
O/S Ratio	78,329	0.88	2.28	0.03	0.16	0.67
Size	78,329	3.90	4.72	1.16	2.30	4.56
BM	78,329	0.57	0.51	0.39	0.55	0.75
Illiquidity	78,329	3.12	5.90	0.58	1.23	3.01
RetVol %	78,329	1.74	0.82	1.24	1.59	2.04
Reversal %	78,329	0.26	3.02	-1.29	0.22	1.76
Momentum %	78,329	10.92	18.94	-0.15	10.12	20.89

Panel B: Time-Series Average of Cross-sectional Correlations

Variables	$\Delta\text{CVOL}-\Delta\text{PVOL}$	IV-RV	Volatility Spread	Volatility Smirk	DOTS	O/S Ratio	Size	BM	Illiquidity	RetVol	Reversal	Momentum
$\Delta\text{CVOL}-\Delta\text{PVOL}$	1.00											
IV-RV	0.00	1.00										
Volatility Spread	0.29	-0.04	1.00									
Volatility Smirk	-0.04	0.09	-0.13	1.00								
DOTS	-0.03	-0.01	0.05	-0.05	1.00							
O/S Ratio	0.00	-0.20	0.01	-0.32	-0.03	1.00						
Size	0.00	-0.21	0.00	-0.35	0.01	0.39	1.00					
BM	-0.00	0.12	-0.02	0.27	0.01	-0.26	-0.34	1.00				
Illiquidity	-0.00	0.15	-0.02	0.32	-0.01	-0.38	-0.88	0.30	1.00			
RetVol	0.00	-0.20	-0.01	0.00	0.00	0.00	-0.13	0.07	0.31	1.00		
Reversal	-0.09	-0.06	-0.14	0.03	-0.06	0.03	0.03	0.00	-0.01	0.00	1.00	
Momentum	0.00	-0.02	0.00	-0.06	0.01	0.03	0.15	-0.08	-0.13	-0.07	0.02	1.00

Table 2. Performance of Option Price-Based Predictors

This table presents the results of the return predictability of option price-based predictors. At the end of each week, we sort REITs and common stocks into groups based on the predictor and calculate the value-weighted return and alpha in each portfolio. The column “return” presents the return spread of value-weighted tercile portfolios sorted on the option price-based predictor. The columns “Return”, “CAPM Alpha”, “FF-3 Alpha” and “FF-6 Alpha” present the spread of excess return, CAPM alpha, FF-3 alpha and FF-6 alpha of portfolios sorted on the option price-based predictor. Tercile portfolios are formed for REITs and decile portfolios are formed for common stocks. Panel A reports value-weighted results and panel B reports equal-weighted results. The left panel reports results for REITs and the right panel reports results for common stocks. We value-weight stocks in each tercile portfolio and rebalance weekly. Newey-West *t*-statistics are given in parentheses. The sample period is from January 1996 to December 2017.

Panel A. Value-Weighted Return Spreads

Predictors	REITs (3-1)				Common Stocks (10-1)			
	Raw Return	CAPM Alpha	FF-3 alpha	FF-6 Alpha	Return	CAPM Alpha	FF-3 Alpha	FF-6 Alpha
$\Delta\text{CVOL}-\Delta\text{PVOL}$	0.12*** (3.04)	0.12*** (2.94)	0.12*** (3.04)	0.13*** (3.16)	0.36*** (5.66)	0.36*** (5.66)	0.36*** (5.67)	0.37*** (5.67)
IV-RV	0.01 (0.12)	0.01 (0.24)	0.02 (0.34)	0.01 (0.27)	0.28*** (3.17)	0.28*** (3.15)	0.28*** (3.27)	0.28*** (3.26)
Volatility Spread	0.06 (1.54)	0.06 (1.45)	0.06 (1.46)	0.06 (1.46)	0.45*** (6.17)	0.44*** (5.96)	0.44*** (6.00)	0.45*** (5.91)
Volatility Smirk	-0.09* (-1.84)	-0.09* (-1.81)	-0.08* (-1.68)	-0.08* (-1.67)	-0.23*** (-3.54)	-0.20*** (-2.88)	-0.17*** (-3.11)	-0.18*** (-3.56)
DOTS	-0.05 (-0.98)	-0.06 (-1.14)	-0.05 (-1.08)	-0.05 (-1.07)	0.13** (2.14)	0.13** (2.13)	0.13** (2.14)	0.13** (2.24)

Panel B. Equal-Weighted Return Spreads

Predictors	REITs (3-1)				Common Stocks (10-1)			
	Raw Return	CAPM Alpha	FF-3 Alpha	FF-6 Alpha	Return	CAPM Alpha	FF-3 Alpha	FF-6 Alpha
$\Delta\text{CVOL}-\Delta\text{PVOL}$	0.13*** (3.60)	0.14*** (3.62)	0.13*** (3.57)	0.13*** (3.46)	0.36*** (9.04)	0.36*** (9.01)	0.36*** (9.02)	0.36*** (8.97)
IV-RV	0.01 (0.26)	0.03 (0.54)	0.03 (0.53)	0.02 (0.41)	0.12** (2.13)	0.15*** (2.71)	0.15*** (2.66)	0.14*** (2.59)
Volatility Spread	0.18*** (4.38)	0.17*** (4.19)	0.17*** (4.19)	0.17*** (4.22)	0.59*** (10.47)	0.58*** (10.45)	0.58*** (10.50)	0.58*** (10.18)
Volatility Smirk	-0.07 (-1.41)	-0.06 (-1.29)	-0.05 (-1.12)	-0.05 (-1.13)	-0.23*** (-4.21)	-0.18*** (-3.27)	-0.16*** (-3.91)	-0.18*** (-5.04)
DOTS	0.05 (1.07)	0.04 (0.87)	0.04 (0.92)	0.04 (0.92)	0.18*** (4.68)	0.18*** (4.64)	0.18*** (4.57)	0.18*** (4.62)

Table 3. Market Quality of Stocks and Options: REITs versus Common Stocks

This table presents the summary statistics of market quality measures of stocks and options for both REITs and common stock samples from January 1996 to December 2017. Panel A reports the summary statistics of idiosyncratic volatility, bid-ask spread, and Amihud illiquidity measure of REITs and common stocks. Panel B reports the pricing error Hasbrouck measure (available from 2005), bid-ask spreads, and O/S ratios of corresponding equity options. We times O/S ratio with 100 as in table 1. For the full sample of options, we calculate the mean bid-ask spread and Hasbrouck measure of all options on the same stock each day and then report the pooled average. For at-the-money (ATM) options with maturity days between 30 and 60, we calculate the mean bid-ask spread and Hasbrouck measure of options in this subgroup on the stock each day and then report the pooled average. We define options with delta between 0.4 and 0.6 as ATM options. The quoted bid-ask spread of each stock or option is the difference between bid and ask quotes divided by the midpoint of bid and ask quotes.

Panel A. Stock Market Measures											
	REITs					Common Stocks					Diff in Mean
	Mean	Standard deviation	25 th percentile	Median	75 th percentile	Mean	Standard deviation	25 th percentile	Median	75 th percentile	
IVOL	0.062	0.046	0.040	0.050	0.067	0.106	0.089	0.053	0.083	0.130	-0.044***
Bid-ask Spread (%)	0.265	0.728	0.039	0.068	0.129	0.398	0.827	0.054	0.118	0.329	-0.133***
Illiquidity	3.122	5.899	0.583	1.227	3.012	17.112	49.627	0.533	2.183	9.375	-13.99***
Panel B. Option Market Measures											
	REITs					Common Stocks					Diff in Mean
	Mean	Standard deviation	25 th percentile	Median	75 th percentile	Mean	Standard deviation	25 th percentile	Median	75 th percentile	
Hasbrouck (Full Sample)	0.121	0.072	0.073	0.105	0.152	0.105	0.058	0.066	0.090	0.125	0.016***
Hasbrouck (ATM, 30-60 Days)	0.115	0.074	0.065	0.096	0.143	0.103	0.065	0.058	0.087	0.129	0.012***
Bid-ask Spread (Full Sample)	0.376	0.219	0.233	0.314	0.449	0.302	0.209	0.168	0.256	0.366	0.074***
Bid-ask Spread (ATM, 30-60 Days)	0.372	0.347	0.142	0.241	0.464	0.224	0.265	0.076	0.135	0.248	0.149***
O/S Ratio	0.884	2.284	0.029	0.156	0.670	3.721	7.332	0.142	1.044	4.127	-2.837***

Table 4. Weekly Tercile Portfolios of REITs Sorted by Changes in Implied Volatilities

At the end of each week, we sort REITs into terciles. In Panel A, tercile 1 is the portfolio with the lowest difference of call and put implied volatility changes ($\Delta CVOL - \Delta PVOL$) and tercile 3 is the portfolio with the highest difference of call and put implied volatility changes. Panel B sorts REITs into terciles according to the change in call implied volatility ($\Delta CVOL$). Panel C sorts REITs into terciles according to the change in put implied volatility ($\Delta PVOL$). The portfolios are held for one week and rebalanced weekly. Portfolios are value-weighted using the prior week's REIT market capitalization as weights. We report the average returns of the terciles as well as portfolio alphas. Alphas are calculated using models including the CAPM model, the three-factor Fama-French (FF-3) factor model, six-factor Fama-French (FF-6) factor model and Bond and Xue factor model. We also report raw return and alphas for the H_L spread, and the annualized profits. All returns and alphas are expressed in percent. Newey-West adjusted t -statistics are reported in parenthesis below returns/alphas. The sample period is from January 1996 to December 2017.

	1 (Low)	2	3 (High)	H_L	Annualized H_L
Panel A. Portfolios Sorted on $\Delta CVOL$ - $\Delta PVOL$					
Return	0.16 (1.40)	0.24 (2.22)	0.28 (2.38)	0.12*** (3.04)	6.43
CAPM Alpha	-0.08 (-0.93)	0.01 (0.15)	0.04 (0.45)	0.12*** (2.94)	6.43
FF-3 Alpha	-0.05 (-0.65)	0.04 (0.53)	0.07 (0.90)	0.12*** (3.04)	6.43
FF-6 Alpha	-0.05 (-0.75)	0.03 (0.45)	0.07 (0.92)	0.13*** (3.16)	6.99
Bond-Xue Alpha	-0.06 (-2.66)	0.01 (0.72)	0.06 (2.29)	0.12*** (3.00)	6.43
Panel B. Portfolios Sorted on $\Delta CVOL$					
Return	0.17 (1.46)	0.23 (2.22)	0.28 (2.38)	0.11** (2.55)	5.88
CAPM Alpha	-0.06 (-0.73)	0.01 (0.14)	0.03 (0.32)	0.09** (2.19)	4.79
FF-3 Alpha	-0.04 (-0.45)	0.04 (0.51)	0.06 (0.75)	0.09** (2.24)	4.79
FF-6 Alpha	-0.04 (-0.59)	0.03 (0.41)	0.06 (0.78)	0.10** (2.50)	5.33
Bond-Xue Alpha	-0.05 (-1.99)	0.01 (0.50)	0.04 (1.53)	0.08** (2.07)	4.25
Panel C. Portfolios Sorted on $\Delta PVOL$					
Return	0.24 (2.02)	0.25 (2.33)	0.20 (1.79)	-0.04 (-0.88)	2.10
CAPM Alpha	0.01 (0.07)	0.03 (0.31)	-0.04 (-0.53)	-0.05 (-1.21)	2.63
FF-3 Alpha	0.04 (0.44)	0.05 (0.69)	-0.02 (-0.21)	-0.05 (-1.24)	2.63
FF-6 Alpha	0.03 (0.41)	0.04 (0.57)	-0.02 (-0.23)	-0.05 (-1.15)	2.63
Bond-Xue Alpha	0.02 (0.67)	0.03 (1.25)	-0.03 (-1.12)	-0.05 (-1.08)	2.63

Table 5. Return Predictability over Different Horizons

This table presents the average weekly return spreads of overlapping portfolios sorted according to the difference of call and put implied volatility changes ($\Delta CVOL - \Delta PVOL$), changes in call implied volatility ($\Delta CVOL$), and changes in put implied volatility ($\Delta PVOL$). The return spreads of overlapping portfolios are calculated following Jegadeesh and Titman (1993). The portfolios are held over the next two to six weeks and returns spreads on overlapping portfolios are calculated. Newey-West adjusted t -statistics are reported in parenthesis below returns. The sample period is from January 1996 to December 2017.

Sorting Variables	Holding Periods					
	1 week	2 weeks	3 weeks	4 weeks	5 weeks	6 weeks
$\Delta CVOL - \Delta PVOL$	0.12*** (3.04)	0.10*** (4.01)	0.04** (2.39)	0.03** (2.40)	0.02 (1.33)	0.01 (1.17)
$\Delta CVOL$	0.11** (2.55)	0.10*** (4.02)	0.03 (1.30)	0.02 (1.55)	0.01 (0.41)	0.01 (0.49)
$\Delta PVOL$	-0.04 (-0.88)	-0.05** (-2.05)	-0.04** (-2.12)	-0.03* (-1.84)	-0.01 (-1.03)	-0.00 (-0.35)

Table 6. Fama-MacBeth Regressions for the Cross-section of REIT Returns

This table presents time-series averages of the weekly Fama-MacBeth regression coefficients and their corresponding Newey-West adjusted t -statistics. The one-week-ahead returns of individual stocks are regressed on difference between the changes in call and put implied volatilities. The control variables include O/S ratio, size, book-to-market ratio, illiquidity, realized return volatility, reversal, and momentum. All variables are winsorized each week at the 0.5% level. The sample period is from January 1996 to December 2017.

	(1)	(2)	(3)
$\Delta\text{CVOL}-\Delta\text{PVOL}$	0.776*** (3.19)	0.832*** (3.37)	0.675*** (3.13)
O/S Ratio		-6.799** (-2.23)	-4.155 (-1.47)
Size			-0.047* (-1.71)
BM			-0.010 (-0.31)
Illiquidity			-5.915 (-0.51)
RetVol			0.097 (0.03)
Reversal			-4.150*** (-4.81)
Momentum			0.206 (1.02)
Adjusted R^2	0.009	0.014	0.142
Obs.	78,329	78,329	78,329

Table 7. Evidence from Stock Market Reaction to Earnings Conference Call

This table presents panel regression coefficients of CAR (0, 1) on implied volatility changes and control variables. The control variables include size, book-to-market ratio, illiquidity, realized return volatility, reversal and momentum. We also control for firm and year fixed effects in the regressions. Robust t-statistics with firm clustering are reported in the parentheses. In Column (1), stock market reaction around earnings call is estimated using cumulative abnormal return from market-adjusted model. In Column (2), cumulative abnormal return is estimated using Fama-French 3-factor model. All variables are winsorized each week at the 0.5% level. The sample period is from January 1996 to December 2017.

	(1)	(2)
	CAR (0,1) based on CAPM model	CAR (0,1) based on Fama-French 3-factor model
$\Delta\text{CVOL}-\Delta\text{PVOL}$	0.458** (2.50)	0.322* (1.87)
O/S Ratio	-0.905 (-0.81)	-1.110 (-1.06)
Size	-0.566*** (-4.14)	-0.519*** (-4.06)
BM	0.008 (0.06)	-0.055 (-0.44)
Illiquidity	-36.744** (-2.48)	-16.144 (-1.16)
RetVol	3.299 (0.98)	-6.130* (-1.95)
Reversal	0.855 (0.95)	-0.153 (-0.18)
Momentum	-0.177 (-1.05)	-0.464*** (-2.95)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adjusted R^2	0.038	0.045
Obs.	4,722	4,722

Table 8. Return Predictability and Information Transparency

This table examines the effect of information transparency on weekly REIT return predictability by option implied volatility changes. We present time-series averages of the weekly Fama-MacBeth regression coefficients and their corresponding Newey-West adjusted *t*-statistics. The one-week-ahead returns of individual stocks are regressed on the difference between the changes in call and put implied volatilities. We examine four proxies for REITs information asymmetry: 1) logarithm of firm age, 2) the number of unique analysts following, 3) a core dummy that equals 1 if the REIT holds core property types including residential, industrial, office and retail, 4) a HQ transparency dummy that equals 1 if the headquarter of the REIT is in one of the 12 highly transparent MSA according to the JLL Real Estate Transparent Index. We interact the information asymmetry measures with the difference between the changes in call and put implied volatilities. The control variables include O/S ratio, size, book-to-market ratio, illiquidity, realized return volatility, reversal, and momentum. All variables are winsorized each week at the 0.5% level. The sample period is from January 1996 to December 2017.

	(1)	(2)	(3)	(4)
	Firm age	Analyst coverage	Core dummy	HQ transparency dummy
$\Delta\text{CVOL}-\Delta\text{PVOL}$	3.560** (2.32)	1.745*** (2.69)	1.296*** (2.96)	1.156*** (3.23)
$(\Delta\text{CVOL}-\Delta\text{PVOL}) \times \text{Transparency}$	-1.060* (-1.70)	-0.101* (-1.68)	-0.889* (-1.87)	-0.931* (-1.95)
Transparency	0.023 (0.80)	0.010* (1.66)	0.004 (0.10)	-0.023 (-0.78)
O/S Ratio	-4.670* (-1.70)	-3.173 (-1.21)	-4.684 (-1.59)	-4.577 (-1.58)
Size	-0.045 (-1.55)	-0.082** (-2.31)	-0.046* (-1.70)	-0.041 (-1.43)
BM	-0.014 (-0.42)	-0.007 (-0.18)	-0.003 (-0.11)	-0.006 (-0.19)
Illiquidity	-21.687* (-1.87)	-7.066 (-0.60)	-8.510 (-0.75)	-2.343 (-0.21)
RetVol	1.033 (0.30)	0.346 (0.11)	0.689 (0.22)	2.075 (0.68)
Reversal	-3.939*** (-4.49)	-4.610*** (-5.27)	-3.961*** (-4.52)	-4.229*** (-4.58)
Momentum	0.159 (0.81)	0.278 (1.35)	0.177 (0.89)	0.158 (0.75)
Adjusted R^2	0.154	0.152	0.157	0.143
Obs.	70,531	70,531	70,531	70,106

Table 9. Return Predictability and Limits to Arbitrage

This table presents time-series averages of the weekly Fama-MacBeth regression coefficients and their corresponding Newey-West adjusted t -statistics. The one-week-ahead returns of individual stocks are regressed on difference between the changes in call and put implied volatilities and its interaction with limits to arbitrage measures. The control variables include O/S ratio, size, book-to-market ratio, illiquidity, realized return volatility and momentum. In column (1) we use idiosyncratic volatility to proxy for limits to arbitrage and in column (2) we use bid-ask spread to proxy limits to arbitrage. All variables are winsorized each week at the 0.5% level. The sample period is from January 1996 to December 2017.

	(1) Idiosyncratic Volatility	(2) Bid-Ask Spread
$\Delta\text{CVOL}-\Delta\text{PVOL}$	-1.458 (-1.39)	-0.719 (-1.31)
$(\Delta\text{CVOL}-\Delta\text{PVOL}) \times \text{Limits to Arbitrage}$	0.476** (2.19)	5.550* (1.92)
O/S Ratio	-2.724 (-1.06)	-3.563 (-1.13)
Size	-0.058** (-2.11)	-0.033 (-1.21)
BM	-0.011 (-0.32)	-0.022 (-0.62)
Illiquidity	-5.242 (-0.45)	-6.364 (-0.54)
RetVol	-0.741 (-0.25)	-1.120 (-0.35)
Reversal	-4.205*** (-4.84)	-3.778*** (-4.28)
Momentum	0.169 (0.81)	0.188 (0.95)
Limits to Arbitrage	-0.007 (-0.69)	-0.037 (-0.11)
Adjusted R^2	0.164	0.150
Obs.	78,329	78,329

Table 10. Land Supply Elasticity and Return Predictability

This table presents time-series averages of the weekly Fama-MacBeth regression coefficients and their corresponding Newey-West adjusted t -statistics. The one-week-ahead returns of individual stocks are regressed on difference between the changes in call and put implied volatilities. The control variables include O/S ratio, size, book-to-market ratio, illiquidity, realized return volatility, and momentum. We interact implied volatility spread changes with land supply elasticity (Saiz (2010)). In column (1) we use the elasticity of REIT headquarter as REIT-level land supply elasticity. In column (2) we introduce a dummy indicating whether the REIT's property holding-weighted land supply elasticity is above cross-sectional median. All variables are winsorized each week at the 0.5% level. The sample period is from January 1996 to December 2017.

	(1)	(2)
	HQ elasticity	High elasticity dummy
$\Delta\text{CVOL}-\Delta\text{PVOL}$	-1.044 (-1.15)	-0.994 (-1.63)
$(\Delta\text{CVOL}-\Delta\text{PVOL}) \times \text{Elasticity}$	0.879* (1.81)	1.827** (2.36)
O/S Ratio	-6.618*** (-2.62)	-16.695 (-1.54)
Size	-0.053* (-1.77)	-0.074** (-2.06)
BM	-0.023 (-0.57)	0.001 (0.03)
Illiquidity	-14.544 (-1.13)	-2.315 (-0.09)
RetVol	1.431 (0.39)	-13.503 (-1.08)
Reversal	-4.636*** (-4.87)	-5.528*** (-3.83)
Momentum	0.114 (0.52)	0.318 (1.45)
Elasticity_Saiz	-0.003 (-0.16)	0.088 (1.32)
Adjusted R^2	0.141	0.164
Obs.	61,545	52,008

Supplementary Appendix for Option Price Implied Information and REIT Returns

Variable Definitions

<i>Option Price-Based Predictors</i>	
$\Delta\text{CVOL}-\Delta\text{PVOL}$	$\Delta\text{CVOL}-\Delta\text{PVOL}$ is calculated following An, Ang, Bali, and Cakici (2014). It is the difference between the changes in call and put implied volatilities. We choose standardized options with a delta of 0.5 and expiration of 30 days. ΔCVOL (ΔPVOL) is the end-of-week IV minus last week-end IV of at-the-money call (put) option.
IV-RV	IV-RV is the difference between implied volatility and realized volatility. Its calculation follows Bali and Hovakimian (2009). IV is the average of end-of-week ATM call and put implied volatilities in the previous week and RV is the annualized realized volatility of daily returns over the previous 22 trading days. Bali and Hovakimian (2009) show that the difference between option implied volatility and historical realized volatility is positively related to future returns.
Volatility Spread	Volatility spread is computed following Cremers and Weibbaum (2010). For each stock i and each day t , we take all combinations of expiration date and strike prices for which a pair of call and put is available and calculate the difference between call and put implied volatilities. Then we calculate the weighted average of these differences using the sum of call and put open interests as weights. We take the end-of-week volatility spread as our weekly volatility spread measure.
Volatility Smirk	Volatility smirk is from Xing, Zhang, and Zhao (2010). The daily implied volatility smirk measure is the difference between the implied volatilities of OTM puts and ATM calls. We first choose options that have expiration days between 10 and 60 days. Then we select ATM call options which have strike price to stock price ratio (strike price/stock price) between 0.95 and 1.05 and OTM put options with strike price to stock price ratio (strike price/stock price) between 0.8 and 0.95. When there are multiple available OTM puts and ATM calls, we choose OTM options with strike price to stock price ratio closest to 0.95 and ATM options with strike price to stock price ratio closest to 1. We compute the weekly volatility smirk by averaging the daily volatility smirk over a week.
DOTS	DOTS is the difference between option implied stock value and the traded stock price. The calculation of DOTS follows Goncalves-Pinto, Grundy, Hameed, van der Heijden, and Zhu (2020). We first form option pairs which consist of a call and put with same strike prices and maturities and calculate the upper bound and lower bound implied by each pair. We require that the option pairs have expiration days between one week and one month. We also require that the ask price is strictly higher than the bid prices and the open interests are positive. For each option pair j of a stock i on date t , DOTS_{ijt} is the difference between the midpoint of the upper and lower price bounds and the underlying stock price. Then for each stock i on date t , DOTS_{it} is the weighted-average of all the DOTS_{ijt} with weights given by the inverse of the sum of the bid-ask spreads for each option pair. We take the week-end DOTS as our weekly measure.

<i>Other Variables</i>	
O/S Ratio	O/S Ratio is the logarithm of 1 plus option volume times 100 divided by stock volume, option volume refers to the sum of option contracts during the week (Cashman, Harrison, and Sheng (2018)).
Size	The natural logarithm of the market value of the firm's equity.
BM	Following Fama and French (1992), for each month from July of year t to June of year t+1, book-to-market ratio is calculated as the ratio of book value of common equity for the fiscal year ending in year t-1 divided by market value at the end of December in year t-1.
Illiquidity	The average ratio of the absolute daily return divided by daily dollar trading volume over the past month, following Amihud (2002).
RetVol	The standard deviation of daily returns over the previous month.
Reversal	The return on the stock of the previous week.
Momentum	The cumulative return on the stock over the previous 11 months starting from twelve months ago to two months ago.
REIT Bid-ask Spread	The REIT stock bid-ask spread is the weekly average of daily bid-ask spread, which is the difference between ask and bid prices divided by the midpoint of bid and ask prices.
IVOL	IVOL is the standard deviation of daily return residuals from regressions of daily returns on the Fama-French 3-factor model over the previous month.
Firm Age	Firm age is the number of years since the first reported fiscal year in Compustat.
Analyst Coverage	The number of analysts following the firm in the previous year.
Core Dummy	Core dummy is a dummy variable which equals one if the REIT focuses on apartments, industrial, office and retail properties. We obtain REIT property type information from CRSP Ziman database.
HQ Transparent	HQ Transparent is a dummy variable which equals one if the REIT headquarter is in one of the 12 transparent MSAs: Los Angeles, San Francisco, New York, D.C., Boston, Seattle, Miami, Chicago, Dallas, Houston, Atlanta, and Philadelphia.
Option Bid-ask Spread	Option bid-ask spread is the average quoted bid-ask spread of all options on the REIT. Quoted bid-ask spread is the difference between bid and ask quotes divided by the midpoint of bid and ask quotes.
Option Hasbrouck	Option Hasbrouck is the average Hasbrouck (1993) measure of all options on the REIT and proxies for option market quality. We first calculate the Hasbrouck measure for each option by using intra-day transaction records (execution price, associated quotes, and trading volumes for each transaction) of options from The Options Price Reporting Authority (OPRA) over a sample period of 2004 to 2015. We apply standard filters and Lee and Ready (1991) algorithm to sign the transactions. We only include options with the number of transactions greater than 50 in the VAR estimation. Then for each stock, we compute the overall measure of option market quality by taking the average of the natural logarithm of the pricing errors of all the options associated with it. A higher Hasbrouck measure indicates higher pricing error, therefore lower market quality.

**Table A1. Equal-Weighted Weekly Tercile Portfolios of REITs Sorted by ΔCVOL - ΔPVOL ,
 ΔCVOL and ΔPVOL**

In Panel A, Portfolio 1 (Low ΔCVOL - ΔPVOL) contains stocks with the lowest weekly changes in difference between call and put implied volatilities in the previous week and Portfolio 3 (High ΔCVOL - ΔPVOL) includes stocks with the highest weekly changes in difference between call implied volatilities in the previous week. We equal-weight stocks in each tercile portfolio and rebalance weekly. For each tercile of ΔCVOL - ΔPVOL , the columns report the average raw returns, the CAPM alpha, the three-factor Fama-French (FF-3) alphas, six-factor Fama-French (FF-6) alphas and Bond and Xue factor model alphas. The column H-L reports the difference in average raw and risk-adjusted returns between the High ΔCVOL - ΔPVOL and Low ΔCVOL - ΔPVOL terciles. Newey-West t -statistics are given in parentheses. Panel B reports the corresponding results from the tercile portfolios sorted on ΔCVOL . Panel C presents the corresponding results from the tercile portfolios sorted on ΔPVOL .

	1 (Low)	2	3 (High)	H_L	Annualized H_L
Panel A. Portfolios Sorted on $\Delta CVOL - \Delta PVOL$					
Return	0.19 (1.54)	0.24 (2.12)	0.32 (2.65)	0.13*** (3.60)	6.99
CAPM Alpha	-0.07 (-0.77)	0.00 (0.03)	0.07 (0.74)	0.14*** (3.62)	7.55
FF-3 Alpha	-0.03 (-0.43)	0.03 (0.44)	0.10 (1.29)	0.13*** (3.57)	6.99
FF-6 Alpha	-0.03 (-0.44)	0.03 (0.41)	0.10 (1.37)	0.13*** (3.46)	6.99
Bond-Xue Alpha	-0.03 (-1.30)	0.02 (0.96)	0.10 (3.20)	0.13*** (3.46)	6.99
Panel B. Portfolios Sorted on $\Delta CVOL$					
Return	0.20 (1.56)	0.23 (2.05)	0.32 (2.71)	0.13*** (2.90)	6.99
CAPM Alpha	-0.05 (-0.58)	-0.00 (-0.04)	0.06 (0.68)	0.11** (2.58)	5.88
FF-3 Alpha	-0.02 (-0.23)	0.03 (0.36)	0.09 (1.23)	0.11** (2.53)	5.88
FF-6 Alpha	-0.02 (-0.25)	0.02 (0.33)	0.09 (1.29)	0.11** (2.50)	5.88
Bond-Xue Alpha	-0.02 (-0.70)	0.02 (0.82)	0.09 (3.42)	0.12*** (2.71)	6.43
Panel C. Portfolios Sorted on $\Delta PVOL$					
Return	0.28 (2.17)	0.26 (2.35)	0.21 (1.79)	-0.07 (-1.49)	3.71
CAPM Alpha	0.03 (0.26)	0.03 (0.37)	-0.05 (-0.62)	-0.08* (-1.77)	4.25
FF-3 Alpha	0.06 (0.70)	0.06 (0.82)	-0.02 (-0.25)	-0.08* (-1.81)	4.25
FF-6 Alpha	0.06 (0.77)	0.05 (0.76)	-0.01 (-0.21)	-0.08* (-1.78)	4.25
Bond-Xue Alpha	0.05 (1.47)	0.05 (2.22)	-0.01 (-0.54)	-0.07 (-1.52)	3.71

**Table A2. Weekly Tercile Portfolios of REITs Sorted by ΔCVOL - ΔPVOL , Using Options
with Different Maturities and Moneyness**

This table presents tercile portfolio returns sorted on ΔCVOL - ΔPVOL using options with different maturities and deltas. The sorting procedure is the same as Table 4. Panel A-D report the value-weighted portfolio return and Panel E-H report equal-weighted portfolio returns, respectively. In Panel A (E), we use ATM options with 60 days to maturity when calculating implied volatility changes. In Panel B (F), we use ATM options with 91 days to maturity when calculating implied volatility changes. In Panel C (G), we use ATM options with 365 days to maturity when calculating implied volatility changes. In Panel D (H), we use OTM options with 30 days to maturity and delta of 0.25 when calculating implied volatility changes.

Value-weighted return	1 (Low)	2	3 (High)	H_L	Annual_Ret
Panel A. ATM Options with 60 Days to Maturity					
Return	0.18 (1.56)	0.22 (2.04)	0.28 (2.38)	0.09** (2.19)	4.79
CAPM Alpha	-0.06 (-0.75)	-0.00 (-0.02)	0.04 (0.41)	0.10** (2.29)	5.33
FF-3 Alpha	-0.03 (-0.44)	0.02 (0.32)	0.07 (0.84)	0.10** (2.31)	5.33
FF-6 Alpha	-0.04 (-0.52)	0.02 (0.24)	0.07 (0.87)	0.10** (2.45)	5.33
Panel B. ATM Options with 91 Days to Maturity					
Return	0.19 (1.58)	0.24 (2.22)	0.26 (2.21)	0.07* (1.87)	3.71
CAPM Alpha	-0.06 (-0.72)	0.01 (0.16)	0.02 (0.21)	0.08** (2.03)	4.25
FF-3 Alpha	-0.03 (-0.41)	0.04 (0.51)	0.05 (0.64)	0.08** (2.08)	4.25
FF-6 Alpha	-0.04 (-0.49)	0.03 (0.42)	0.05 (0.68)	0.09** (2.30)	4.25
Panel C. ATM Options with 365 Days to Maturity					
Return	0.18 (1.52)	0.25 (2.40)	0.26 (2.13)	0.08** (2.01)	4.25
CAPM Alpha	-0.07 (-0.77)	0.03 (0.37)	0.01 (0.13)	0.08* (1.94)	4.25
FF-3 Alpha	-0.04 (-0.48)	0.06 (0.75)	0.04 (0.52)	0.08* (1.95)	4.25
FF-6 Alpha	-0.04 (-0.57)	0.05 (0.70)	0.04 (0.50)	0.08** (2.08)	4.25
Panel D. OTM Options with 30 Days to Maturity					
Return	0.16 (1.38)	0.25 (2.34)	0.27 (2.38)	0.11*** (2.90)	5.88
CAPM Alpha	-0.08 (-0.89)	0.02 (0.24)	0.04 (0.39)	0.11*** (2.93)	5.88
FF-3 Alpha	-0.05 (-0.63)	0.05 (0.61)	0.07 (0.85)	0.12*** (3.01)	6.43
FF-6 Alpha	-0.05 (-0.69)	0.04 (0.53)	0.06 (0.80)	0.11*** (2.90)	5.88

Equal-weighted return	1 (Low)	2	3 (High)	H_L	Annual_Ret
Panel E. ATM Options with 60 Days to Maturity					
Return	0.20 (1.59)	0.25 (2.23)	0.30 (2.49)	0.11*** (2.65)	5.88
CAPM Alpha	-0.06 (-0.70)	0.01 (0.16)	0.05 (0.55)	0.11*** (2.78)	5.88
FF-3 Alpha	-0.03 (-0.35)	0.04 (0.61)	0.08 (1.04)	0.11*** (2.73)	5.88
FF-6 Alpha	-0.03 (-0.35)	0.04 (0.57)	0.08 (1.11)	0.11*** (2.64)	5.88
Panel F. ATM Options with 91 Days to Maturity					
Return	0.20 (1.65)	0.25 (2.27)	0.30 (2.41)	0.09*** (2.61)	4.79
CAPM Alpha	-0.06 (-0.63)	0.02 (0.20)	0.04 (0.46)	0.10*** (2.73)	5.33
FF-3 Alpha	-0.02 (-0.28)	0.05 (0.62)	0.08 (0.98)	0.10*** (2.74)	5.33
FF-6 Alpha	-0.02 (-0.27)	0.04 (0.56)	0.08 (1.06)	0.10*** (2.71)	5.33
Panel G. ATM Options with 365 Days to Maturity					
Return	0.21 (1.67)	0.24 (2.26)	0.30 (2.38)	0.09** (2.17)	4.79
CAPM Alpha	-0.05 (-0.54)	0.01 (0.11)	0.04 (0.44)	0.09** (2.27)	4.79
FF-3 Alpha	-0.01 (-0.17)	0.04 (0.53)	0.08 (0.93)	0.09** (2.22)	4.79
FF-6 Alpha	-0.01 (-0.17)	0.03 (0.49)	0.08 (1.01)	0.09** (2.25)	4.79
Panel H. OTM Options with 30 Days to Maturity					
Return	0.20 (1.61)	0.25 (2.17)	0.30 (2.56)	0.10*** (2.71)	5.33
CAPM Alpha	-0.05 (-0.57)	0.01 (0.08)	0.05 (0.52)	0.10*** (2.59)	5.33
FF-3 Alpha	-0.02 (-0.23)	0.04 (0.50)	0.08 (1.06)	0.10*** (2.68)	5.33
FF-6 Alpha	-0.02 (-0.24)	0.04 (0.49)	0.08 (1.11)	0.10*** (2.61)	5.33