

Cross-Sectional Dynamics of REIT Market Efficiency ¹

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Abstract

The efficiency of price discovery in the REIT market is an issue of enduring interest. Unfortunately, existing studies focus on REIT index data, and the general equity efficiency literature that uses individual assets typically excludes this sector. Our first contribution is a comprehensive assessment of the pricing efficiency of the U.S. REIT market that uses every listed REIT trading over the 1993-2011 period. Our variance ratio analysis finds that the typical REIT is efficient throughout our sample period. We show that the distribution of REIT-level variance ratios exhibits excess kurtosis, implying a non-trivial mass of inefficiently-priced REITs. Our second contribution is to document that the relatively inefficiently-priced REITs tend to become relatively more efficient over time, consistent with the actions of arbitrageurs. We explore the importance of informed trading, cash flow variability, and market frictions measures in explaining the cross-sectional dynamics of informational efficiency. Our third contribution is methodological: we show that quantile regression methods help to isolate the impact of arbitrageurs since they are more likely to affect the pricing efficiency of REITs in the extreme quantiles of the efficiency distribution.

JEL Classification: G12, R00

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1. Introduction

The efficiency of price discovery in the equity markets is of enduring interest, and this is no less true in the market for securitized real-estate (REITs). For many investors, particularly institutional investors who do not want to own buildings or land, real estate-related portfolio diversification is often undertaken in the REIT market.

Existing research shows that price discovery in real estate occurs primarily through securitized assets, not in the underlying property markets. As Barkham and Geltner (1995) note, this conduit of price discovery suggests that market-specific factors such as “trading density, liquidity and micro-structure advantages of the securities markets” may be particularly important for real estate price discovery and the information aggregation process, even outweighing the effects of “market breadth and participant sophistication advantages of the un-securitized private markets in commercial real estate.”

Studies examining the efficiency of REIT markets limit their attention to index returns. For example, Stevenson (2002) studies market index returns across multiple countries using index returns. Such a narrow focus may overlook important asset-level dynamics, and fail to leverage cross-sectional variation that may help to identify the drivers of efficiency. In turn, this deeper understanding of efficiency determinants may prove useful for asset allocation, risk management, or policy design.

There is virtually no evidence on REIT market efficiency from the broad equity market efficiency literature that uses individual security data (see Conrad, Wahal, and Xiang (forthcoming) for a recent example). These studies typically exclude REITs and other securities such as ADRs and ETFs.¹ To the best of our knowledge, there is no comprehensive study of REIT market efficiency conducted at the level of individual REITs. This gap is also important because many investors trade the individual REITs and not an aggregate REIT index.

The first contribution of our paper is to provide a comprehensive assessment of REIT market efficiency at the level of the individual REIT. We construct the empirical distribution of market efficiency using REIT-level variance ratios estimated using both annual and quarterly samples of

¹For recent examples of this sample selection, see OHara-Ye (2011) and Conrad, et al. (forthcoming).

intraday midpoint prices (data and computational details are provided later in the paper). We find that the mean of these distributions are centered very close to one, signaling price efficiency. Yet, these distributions also show a high degree of excess kurtosis, indicating that a large number of REITs appear to be inefficiently priced.

We also find dramatic changes in the shape and character of this efficiency distribution over time. It appears that these changes are, in part, associated with changes in market structure and regulation. Prices that were quoted for many decades in 1/8ths shifted to 1/16ths and then to a decimal basis. Research shows these changes had important impact on markets, often leading to lower trading costs.² In addition, the SEC rule, Reg NMS, went into effect later in 2007, and this affected multiple dimensions of market quality and trade execution. While there is a substantial literature studying the impact of these changes on equity market quality, virtually none of this research has been focused on the efficiency of price discovery in the REIT market. We find that the distribution of the REIT-level variance ratio is significantly affected by the end of quotes in 1/8ths, largely unaffected by shifting to decimal quotes, and significantly affected by Reg NMS.

Our second contribution is to document how individual REITs move through the cross section of the measured efficiency distribution over time. Figure 2 presents a time series view of REIT-level efficiency measures, and our analysis find that REITs typically move throughout the cross sectional distribution in a non-random fashion. Basic intuition suggests that inefficiently-priced REITs should draw the attention of arbitrageurs who exploit these inefficiencies. As a result, REITs in the tails of the efficiency distribution would move toward the center. We find that by the end of our 17 year sample, REITs do, in fact, tend to become more efficient, regardless of their level of efficiency at the beginning of the sample.

The third contribution of our paper is to identify REIT-specific factors that account for the cross sectional dynamics within the distribution of measured price efficiency. Although such factors have been identified in research focused on equities generally (see Boehmer and Kelley RFS, 2008), there is, to the best of our knowledge, no comparable investigation in the REIT literature. We find that the principal asset-specific characteristics emphasize in BK (2008), institutional ownership, is

²A careful treatment is Foucault, Pagano, and Röell (2013).

also relevant in the REIT space. Moreover, we find that our measures of REIT option trading also affect the level of measured deviations from efficient pricing. To our knowledge, this is the first demonstration of the importance of REIT option trading in the price discovery process.

The fourth issue we explore in this paper is the connection between REIT efficiency dynamics and the limits to arbitrage in capital markets more broadly. It is well understood that arbitrageurs act to take advantage of departures from efficiency: forecastable returns (or forecastable risk premia) generate attention among investors armed with an understanding of how to take advantage of persistence in under- and overvaluation. High bid-ask spreads, limited depth, and a lack of liquidity play a role in limiting arbitrage in asset markets. In turn, these characteristics of individual REIT markets may help to explain why we might see persistence in the variance ratio, especially when it isn't close to one. At the end of the paper, we provide some preliminary results potentially connecting measured efficiency and arbitrage activity.

Our empirical approach to these issues relies on constructing a longitudinal database for equity REITs from the TAQ data that covers our sample period of 1993-2011. We also fold in daily data from the CRSP tape and quarterly data from Compustat, IBES, and SEC 13-f statements. We describe our data in more detail in Section 3. To our knowledge, no other research papers focused on the REIT sector specifically have covered such an extensive sample period.³ The length of our sample period provides an unparalleled opportunity to study the dynamics of market efficiency in the REIT sector. In addition to the structural changes noted earlier, there are remarkable changes in the REIT sector, too. Over the first eight years of the 19 years covered by our data, there was a significant boom in REIT IPOs as the number of traded equity REITs increases from 74 in 1993 to 141 in 1997. Consolidation in the sector reduced this number to 121 in 2001 and 94 in 2008. The number of traded REITs rose to 107 in 2011. Investor interest as indicated by trading in REIT shares also increased, as the number of annual trades in the REIT sector rises from 390,000 in 1993 to well over a billion per year by the end of our sample.

In the next section, we provide more detail on the existing literature, including papers from both the equity market microstructure and the REIT market research areas. Section 3 explains our

³Chordia, Roll, and Subrahmanyam (2011) look at a similar sample period with a cross-section of equities that is substantially larger. However, it explicitly excludes REITs.

research design in detail, and also discusses our dataset and measurement issues. We present the basic picture of REIT market efficiency in Section 4. Our discussion encompasses the role of market structure and regulation changes on REIT market efficiency dynamics at the REIT level. Section 5 extends this analysis to consider the role of REIT-level and market factors that are associated with REIT-level efficiency dynamics. We summarize our findings in the final section.

2. Previous Literature

As we noted in the introduction, the real estate price discovery and information aggregation process is central to the efficient operation of public real estate markets. A number of papers explored the efficiency of REIT markets in the years after the start of the REIT IPO boom in about 1993. Most studies relied on REIT index returns, and generally reported varying levels of efficiency depending on the time period and specific sample.

From Chordia, Roll, and Subrahmanyam (2011), we know that the price discovery process in U.S. equities is more efficient now than 20 years ago, and market quality (proxied by trading costs and liquidity levels) is also substantially improved on average. As we noted in the introduction, there is surprisingly little direct evidence on the efficiency of price discovery at the level of individual REIT securities since market structure changes began in the late 1990s.⁴ Much of the published research on securitized real estate market efficiency was completed nearly 20 years ago, well before changes in market structure and establishment of the national market system in 2007 (Reg NMS).⁵ The evidence from these early studies on REIT market efficiency is somewhat mixed, but generally points to rising efficiency over time.

For U.S. equity markets broadly defined (but explicitly excluding REITs), Chordia, Roll, and Subrahmanyam (2011) show that changes in U.S. equity market structure are associated with improvements in the efficiency of the price discovery process. In addition to quote rule changes that began to take hold in 1997, market participants have increasingly relied on electronic markets, order platforms, and similar IT capital-intensive operating methods in the past 20 years. While

⁴In a companion paper this is in process, we study changes in REIT trading after 1992.

⁵Indeed, we found only one paper that studies the equity REIT price discovery directly, and it focuses on the relatively special case of index additions involving REITs (Huang, Su, and Chiu, 2009).

there are many studies of these factors in the market microstructure literature, the REIT market is typically excluded at the sample selection stage. In the real estate literature, we have found comparatively little evidence on the implications of these changes for the equity REIT market. One notable exception is Hardin, Liano, Huang, and Nagel (2007). They study REIT price dynamics around ex-dividend days, comparing behavior before and after introduction of decimal price quotes.

Despite its size and analytical sophistication, there is also very little evidence on equity REIT market efficiency and quality from the equity microstructure literature per se. Studies of bid-ask spreads, liquidity, market structure changes, and so forth usually focus on equities and exclude REITs; these papers, typically argue that the exclusion is warranted because REITs may be different than regular equities.⁶ For example, sophisticated analyses at the nexus of equity market efficiency and market quality such as Chordia, Roll, and Subrahmanyam (2011) and OHara and Ye (2011) explicitly exclude REITs from their data samples. An interesting study of market efficiency and market quality in the post-Reg NMS world by Conrad, Wahal, and Xiang (2014) also excludes REITs.

There is a thriving literature focused on REIT market quality analysis that draws on the market microstructure literature. Cannon and Coles (2011) focused on changes in REIT market liquidity over time, concluding that it has improved in recent years. Jain, Sunderman, and Westby-Gibson (2013) compare market quality for REITs and non-REIT equity during and after the 2008 financial crisis. They show that REITs suffered more substantial declines in market quality during the crisis than 'regular' equities, but there was a substantial reversal after the crisis as REITs were relatively more liquid, less costly to trade, and less volatile than non-REIT equities. Glascock and Lu-Andrews (2014) explore the impact of variations in market funding liquidity for REITs, concluding that macroeconomic factors affect funding liquidity and REIT market liquidity is positively related to funding liquidity. None of these papers explores the connection between liquidity and the efficiency of price setting.

Some papers have studied spreads and liquidity in REIT markets; with one exception, an impor-

⁶Somewhat ironically, there is a large literature in the real estate area that explores whether REITs are real estate. Boudry, Coulson, Kallberg, and Liu (2012) show that REITs and real estate share a long run relationship. However, in the short run they can deviate from one another.

tant theme in these studies is the differences between transaction costs and liquidity in securitized (i.e., public) vs. private markets.⁷ The REIT-focused papers don't typically extend their analysis to develop a more fundamental picture of market efficiency. As noted earlier, the efficiency-oriented papers in the finance literature that connect their analysis to market efficiency considerations typically don't include any analysis of the REIT sector (in addition to Chordia, et al. (2011), see OHara-Ye (2011)).

3. Data and Methods

Broadly, our approach in this paper is to develop a comprehensive database of REIT trading from which we can extract appropriate measures of the efficiency of price setting and market quality. With these measures in hand, we will document the evolution of REIT market efficiency at the REIT level. Our work moves past efficiency 'on average,' in favor of exploiting the entire distribution of measured REIT-level efficiency across the 1993-2011 period. With measures in hand, we connect the changes in REIT-level efficiency back to underlying economic theory, and use probability transition matrices to characterize the longer-term dynamics of measured REIT-level efficiency. We also exploit the model proposed in Boehmer and Kelley (2009) to study the role of institutional investors in the temporal development of REIT market efficiency. We augment their model to include additional factors such as option trading and analyst coverage that might affect efficiency of price discovery in the REIT market over time. In this section, we describe our data sources and aspects of our measurements.

3.1. Data Sources

We draw our data from several sources. Initially, we begin with a comprehensive list of equity REITs for each year, 1993-2011.⁸ With this year-by-year list of REITs, we constructed yearly data

⁷See Clayton and MacKinnon (2000) for analysis of relatively high-frequency bid-ask spreads and related liquidity measures. By contrast, Brounen, Eichholtz, and Ling (2009), use low-frequency data across countries to characterize developments in real estate market liquidity over longer periods. Subrahmanyam (2007) extends his influential work on order imbalances and liquidity to the real estate market, but the efficiency implications are not as fully developed in that paper. For example, there are no variance ratio tests for market efficiency, although this analysis plays a substantial role in Chordia, et al. (2011). In his other work, REITs are not part of the data used in the analysis.

⁸Our sample begins in the same year in which the TAQ data first becomes available. Coincidentally, 1993 also marks the start of a REIT IPO wave. We discuss this in more detail later in this section of the paper.

sets drawn from the daily CRSP return file. For every REIT in our sample, the daily CRSP data sets reports daily measures of closing returns, trading volume, shares outstanding, closing bid and ask prices, and additional indicators including the REIT’s primary exchange (where it is listed) and trading status. We also make use of midpoint prices in our calculations.⁹ Particularly in periods where bid-ask spreads are at least 12.5 cents, use of trade prices generates mean reversion in prices that typically results in lower variance ratio estimates. In fact, we documented this downward bias when we made our variance ratio calculations using trade data instead of midpoint prices. None of our results use trade prices. From these data, we calculate a daily turnover measure for each REIT for each trading day. In the early years of the sample, not every REIT traded every day, but in the later years of the sample, zero trading days are relatively rare.

Using the same list of REITs, we also constructed data files from the TAQ dataset. The intra-day TAQ data includes both the complete record of trades and the quote history for each day for each REIT.¹⁰ The TAQ data typically requires some processing. With the trades data, we eliminated records where the price or trade size (in shares) is non-positive, or if there were indications that a specific trade was unusual according to a variety of indicators. These filters are commonly used in TAQ data-intensive research, and their aim is to ensure that inferences reflect typical trades. For each transaction on every day in the sample for every REIT, the trade records provide the transaction price, transaction size (in shares), transaction time (to the second) and exchange on which each trade is executed.¹¹ From this data, we construct for each REIT on each trading day the midpoint of the NBBO quotes every 15 minutes.

From the TAQ data, we also compute a set of market quality measures using the algorithm (and SAS code) developed by Holden and Jacobsen (2014). These measures include market depth on the bid and ask side, buy and sell order imbalances, and a variety of spread measures. The depth and imbalance measures are available in both dollar and share amounts. We also generate

⁹We gratefully acknowledge Jennifer Conrad’s insights on the use of trade vs. midpoint prices.

¹⁰Some REITs began or ended trading during a particular year, so there is an ‘incomplete’ trading record relative to REITs that trade throughout the year. Occasionally (and especially in the early years of the sample), there were no trades on a given day, so the TAQ data was ‘missing’ as a result. We don’t delete these records. Instead, we carry the last midpoint price in the record.

¹¹In this paper, we do not exploit the millisecond data available from TAQ in this paper, but our algorithm for making NBBO and trading cost calculations applies the Holden-Jacobsen (2014) approach to spacing out trades stamped to the second, rather than using the (substantially more expensive) millisecond data.

TAQ-based measures of daily buy- and sell-initiated trades, total trades, total quotes, and changes in NBBO quotes. We construct some additional, alternative REIT market quality measures with these data.

3.2. Measuring Market Efficiency

It is well established in the literature that price movements within an efficient market should approximate a random walk. Though myriad approaches to measure efficiency exist, we follow O’Hara-Ye (2011) and Conrad, et al. (forthcoming), by relying on a variance ratio calculation. As developed in Lo and MacKinlay (1988, hereafter referred to as L-M), the variance ratio test exploits the fact that the variance of random walk increments is linear in the sampling interval. For instance, define p_t as the log price process, the one-period return as $r_t = p_t - p_{t-1}$, and the two-period continuously compounded return as $r_t(2) = r_t + r_{t-1}$. The variance ratio is then computed as $VR = \frac{Var[r_t(2)]}{2Var[r_t]}$, which is equal to $1 + \rho(1)$, where $\rho(1)$ is the first order autocorrelation coefficient of returns (r_t). According to L-M, if an asset truly follows a random walk, then $\rho(1) = 0$, suggesting that the VR should be equal to 1. If the VR is less than one, it signals mean reversion in returns. Whereas a VR greater than one signals mean aversion.

A critical choice during construction of the VR is how to set the sampling intervals. Generalizing the notation above, we can write $r_{t-h,t} = p_t - p_{t-h}$, and $VR_h(q) = \frac{Var[r_{t-h,t}(q)]}{qVar[r_{t-h,t}]}$. How do we set the return horizon (h), and the number of periods (q)? Our choices are driven by a desire to capture high frequency dynamics of the price process, but are constrained by the uneven speed of trading over our sample. Notice that Conrad, et al. (forthcoming) define their sampling intervals in 15 seconds, which we could mimic, but only for the years 2006 -2011. Instead, we follow O’Hara-Ye by setting our base case with a return horizon (h) equal to 15 minutes, and the number of periods to 2 (q), implying that the variance ratio in our base case compares 15 minutes to 30 minutes. We believe that this strikes a reasonable balance, and it permits us to track efficiency consistently over our entire sample. For robustness, we extend this base case in several directions. We consider shorter and longer holding period horizons of $h = 5$ minutes and $h = 60$ minutes, and we also

explore several variance ratio periods $q = 4, 8, 26$.¹²

The basic test designed by L-M is a pormanteau type. Customizing for our base case, the test statistic and approximation to the asymptotic distribution is $\sqrt{2T}(VR_{15mt}(2) - 1) \sim N(0, 2)$. The associated null hypothesis is that prices follow a random walk. We follow L-M by refining this basic test in several ways. First, we use unbiased estimators for the asymptotic variances. Second, we use overlapping samples when conducting the sampling so that we can improve the power of our inference. Third, we test the null under the assumption of heteroscedastic increments as well as under iid increments (see L-M for details). In the analysis we present in the following sections, we report results for heteroscedastic increments, noting that there is little substantive difference using estimates calculated made under an iid assumption.

We recognize the vast literature documenting the weaknesses involving inferences based on a standard VR test (see Charles and Darne (2009) for an overview). As such, the reader should use care when interpreting our inference results. Importantly, however, the focus of our paper is not one of inference directed narrowly at whether prices of an individual REIT follow a random walk. This paper’s goal is not to determine whether a particular asset is efficient. Rather, our focus is in documenting the variation and drivers of efficiency over time. As such, the main body of our methodology should mitigate such concerns.

4. REIT Efficiency Over Time

In this section we document the dynamics of informational efficiency in the REIT market over the period 1993-2011. As detailed in section 3.2, we use the variance ratio as our measure of efficiency, and set a sampling interval of 15 minutes to 30 minutes as our base case. For each year and quarter in our sample, we compute the variance ratio for each REIT. Due to the natural birth and death process of REIT’s, we are left with an unbalanced panel of variance ratios. Figure 1 depicts the number of REITs available in each year across our base case and several alternative sampling designs.¹³ Regardless of the interval chosen, the REIT boom beginning in 1993 and continuing

¹²We have a tables with results for these choices, but we don’t discuss them explicitly in this draft.

¹³Since we find a about a dozen and a half extremely large (or small) variance ratios in several of the years, we trim the sample using a three-standard deviation filter in every year: any variance ratio that is more than three standard

through 1998 is obvious in the diagram. The number of REITs increased more than 80% before a consolidation process began that reduced the number of traded REITs in our sample through 2002. There is a small increase between 2002 and 2005 before the number of traded REITs fell to a low point in 2008, and then recovered as REIT IPO's pick up beginning in 2010. We find that there are 31 REITs that are alive for the entire 76 quarter (19 year) long history. We drop any REITs that are in our sample for less than 20 quarters.

In the first subsection below, we document how the empirical distribution of these variance ratios changes over time. In the second subsection, we document how individual REITs move through the support of that cross sectional distribution. We believe that this is the first paper to look explicitly at the cross-sectional dynamics within the REIT efficiency distribution.

4.1. Characterizing the Empirical Distribution

How efficient is the REIT market on average? Do many REITs deviate from a VR of 1? If so, how does efficiency evolve over time? To address these questions, we construct the cross sectional empirical distribution of variance ratios for each REIT trading in a given year, and repeat for each year from 1993-2011. The central tendency of these distributions is depicted in Figure 2. Moreover, the empirical distributions for each year in the sample are depicted in Figure 3. The first thing to note is that the center mass of these distributions is consistently near one, indicating that the typical REIT is indeed efficient.

This visual finding is corroborated by the summary statistics provided in Table 1. The column labeled "Mean" contains the average variance ratio during a given year. The last row displays the grand average across those years, which is .976. The minimum and maximum variance ratios are .947 and 1.017, respectively. In addition, the grand average of the annual standard deviation of the variance ratios is only .044.

Overall, it appears that the central tendency of the VR distribution is centered upon one, suggesting that the typical REIT is indeed efficient. This is precisely what we see in the last column of Table 1, which depicts the percent of REITs in a given year that are efficient. Specifically, this

deviations different than the mean for a given quarter (year) is dropped from the sample of variance ratios for that quarter (year).

is the percent of REITs trading during a given year that fail to reject the L-M null hypothesis of a random walk at a 5% significance level. We see that the grand average is 35.5%, with the minimum and maximum percent efficient in any given year being 13.0% and 61.1%, respectively. This data implies that a fair number of REITs are indeed efficient over our sample, although there is considerable variation year-by-year.¹⁴

Notice, however, that the central tendency of the VR distributions masks important cross sectional variability, witness the changing shape of the distributions depicted in Figure 3. To address this more precisely, we conduct a two-sample Kolomogorov-Smirnov (K-S) test of equal empirical distributions for each pair of adjacent years. For instance, we compare the empirical distribution of 1994 to that of 1993. The p-value K-S test statistic for that comparison is 0.11, suggesting that we fail to reject the null of equal empirical distributions (p-value = 0.53). We repeat this test for each of the 18 pairs of adjacent years, and find that we are able to reject the null at the five per cent level for 12 of the 18 pairwise comparisons (i.e, 1994 vs. 1995, etc.). This test results suggest that the distributions do indeed change over time.¹⁵

Visual inspection of Figure 3 suggests that the source of the changing shape is the peakedness and tails of the distribution vary dramatically over time. This observation is supported by the sample statistics in Table 1. We find that 12 of the 19 years exhibit a kurtosis greater than 3, with the maximum kurtosis being 7.32 in 2010. The empirical quantiles provided in columns 6-11 of Table 1 suggest that the tails of this distribution are time varying. For example, the spread of the 95% to 5% quantiles varies from 0.18 in 2002 to 0.06 in 2010.

To test this notion more formally, we use variance ratios constructed using data for each of the 76 quarters covering our sample period. For each quarter, we extract the 1%, 5%, 25%, 50%, 75%, 95%, and 99% quantiles from the empirical distribution from that quarter. We then test whether each of these time series of VR quantiles is white noise using a simple Q-test across 1-5 autocorrelation lags. We find that the more extreme quantiles (1% and 99%) fail to reject the null hypothesis of random movements. By contrast we find rejections with .000 p-values for the 5%,

¹⁴We remind the reader that these inferences are to be taken with a grain of salt, given the small sample performance of random walk hypothesis tests.

¹⁵K-S tests also reject the null of equal empirical distributions for comparisons of 1993 vs. 2011, 1993 vs. 1998, and 2006 vs. 2011, but not 1999 vs. 2005.

25%, and 95% quantiles. We cannot reject the null hypothesis for the 50% and 75% quantiles.

Together, these findings lead us to conclude that the cross sectional distribution of variance ratios is time varying, and that much of the source of the time variation lies in the tail quantiles, not in the center and center right of the empirical distributions.

In Table 2, we repeat the exercise from Table 1, but restrict our analysis only to the 49 REITs that traded over the entire 19 years of our sample.¹⁶ We present this as a way of isolating at least partially the effects of REIT birth and death processes (IPOs and consolidations) on the annual density of variance ratios.¹⁷ Again, we find that the typical REIT is efficient, but there are many REITs that exhibit mean aversion/reversion.

4.2. Structural Changes in Efficiency

In this section we examine how the evolution of efficiency over our sample period depends upon the prevailing market structure, tick size, and market states.

As discussed earlier, arbitrageurs should be attracted to assets that are inefficiently priced. The ability of arbitrageurs to exploit these inefficiencies for gain may be limited by transaction costs. One such transaction cost is the degree of minimum price variation (tick size) permitted by the SEC. Smaller tick sizes represent lower transaction costs, and thus a smaller barrier to profitable arbitrage activity. There were two major changes in tick size during our sample period. On June 23, 1997, the NYSE changed the tick size from 1/8 of a dollar to 1/16 of a dollar. Then, on Jan. 28, 2001, tick sizes adjusted from 1/16 of a dollar to decimals.

In Panels A and B of Figure 4, we compare the empirical distributions of variance ratios across these three quote regimes. In each regime, we compute the variance ratio of every REIT available for the one year prior to the end of that regime (we exclude ten trading days on each side of the ‘event’ date when constructing our one-year sample periods). Note that since each of the regimes are more than one year apart, we avoid any overlap across the regimes. We then compute the cross

¹⁶There are actually only 19 REITs present in every year, but another 30 REITs are in the sample from 1995 - 2011, so we also include them in this analysis.

¹⁷Arguably, new REITs might have lower analyst coverage and perhaps be less well understood by investors. In turn, this may limit trading and the price discovery process. On the other hand, this is an ideal setting for an arbitrageur to operate, and their (informed) trades would presumably lead to more price discovery.

sectional empirical distribution. In Panel A, we compare the distributions of the 1/8 and 1/16 quote regimes. Despite the fact that a simple visual inspection suggests little change across the regimes, a two-sample t-test of equal means ($t=-2.35$) yields a p-value of 0.019, implying that the typical level of REIT efficiency in the 1/8 regime is actually lower than it is in the 1/16 regime. Likewise, a two-sample K-S test for equal empirical distributions yields a p-value of 0.022, implying that there is a significant difference in the entire cross-sectional distribution of REIT-level efficiency across the regimes.

In Panel B, we compare the 1/16 and Decimalization quote regimes. In contrast to Panel A, the empirical distributions here are not statistically different. The Decimalization regime has a slightly lower mean level of efficiency than the 1/16 regime, and the 1/16 regime looks to be more clustered around a variance ratio value of 1.00. A two-sample t-test of equal means yields a p-value of 0.59. A one tail test with a null of equal means and alternative of the 1/16 regime having a larger mean than the Decimalization regime cannot be rejected at reasonable size levels. Lastly, a two-sample K-S test yields a p-value of 0.56, implying that there is no empirical difference between the empirical variance ratio distributions across these two quote regimes.

Over the July 1, 2007 - Aug. 8, 2007 period, the exchanges implemented the SEC's Regulation NMS (National Market System). Among other things, the order protection (or trade through) provisions in Reg NMS linked exchanges by requiring an exchange to pass an order to the exchange offering the best price. We think that might impact efficiency of price discovery by linking order flow across individual exchanges.¹⁸ In Panel C of Figure 4, we compare the the pre-Reg NMS period to the post reg-NMS period. Visually, these two distributions are virtually identical, except for the large right tail of the post-Reg NMS distribution. A two-sample t-test of equal means ($t=-1.84$) yields a p-value of 0.068, and a two-sample K-S test yields a p-value of 0.343. From the perspective of these two tests, it appears the imposition of Reg-NMS had little impact on the overall distribution of REIT-level efficiency.

¹⁸There is a very substantial literature on Reg NMS. See the discussion in Foucault, Pagano, and Röell (2013) for an introduction to the issues.

4.3. Moving through the Empirical Distribution

The previous subsections documented economically and statistically substantial changes in REIT-level variance ratios over time. In particular, evidence presented in section 4.1 suggests that the dynamics of the variance ratio distribution are not random. If the actions of arbitrageurs are central to these dynamics, then we would expect assets that are less efficient than their peers to become more efficient. In other words, we would expect assets with variance ratios much lower than the mean variance ratio to attract the attention of arbitrageurs whose actions will eliminate the temporal persistence in the price process, and raise the variance ratio relative to its peers. A similar mechanism would occur for assets with relatively high variance ratios.

To examine these potential movements through the cross sectional support of the empirical distribution and eliminate the effects of any sector-wide dynamics, we use the z-statistic as a measure of "relative" efficiency. Specifically, each quarter we compute the mean and standard deviation of the empirical distribution of the variance ratios. For each REIT available during that quarter, we then construct a standard z-statistic. REIT's with z-statistics near zero are efficient relative to their peers. Meanwhile, REIT's with z-statistics that are large in absolute value are relatively inefficient.

We begin by examining whether the degree of relative efficiency is random over time. For each REIT in our sample, we compute the efficiency z-statistic. We then track persistence in that z-statistic with a simple Ljung Box Q-test with 5 lags. In Panel A of Figure 5 we depict the density of the associated test statistics for each of the REIT's that are present for at least 20 quarters in our sample. The solid vertical line represents the critical value of this test. Approximately 40% of the REIT's in our sample are in the rejection region, signaling temporal persistence. In Panel B we repeat this exercise for the subset of assets that are present for the entire 19 years of our sample. Again, a large fraction of the REIT's exhibit a persistent movement in their relative efficiency.

Figure 7 explores more carefully how that movement takes place. For each of the REITs in our sample we compute the change in the z-statistic over that REIT's life. On the vertical axis we plot the z-statistic in the last (terminal) period minus the z-statistic in the first (initial) period. On the horizontal axis we plot the initial period z-statistic. The clear downward slope is suggestive

of the presence of arbitrageurs. REITs that enter our sample with variance ratios relatively below their peers, increase their standing in the cross sectional distribution by the time they leave our sample. Likewise, REITs that start with relatively high variance ratios, tend to drop through the cross sectional distribution over time. Lastly, those who start near the average level of efficiency, tend to stay near the average. Overall, this diagram is consistent with the view that arbitrageurs exploit inefficiencies in the REIT market.

To further explore this claim, we compute a series of Probability Transition matrices. To implement this approach, we assign individual REIT z-statistic values to one of seven bins. Bin 1 has the REITs with the lowest relative efficiency measure (i.e., the most negative z-statistic), while bin 7 has the REITs with the highest relative efficiency measure (i.e., the most positive z-statistic). Bin 4 contains REITs which are efficient in the sense that their variance ratio is indistinguishable from one.¹⁹ As a REIT is closer to Bin 1, it displays mean reversion in prices. As a REIT is closer to Bin 7, the price process displays momentum. In principle, both could be exploited by an arbitrageur.

The intuition behind our transition probability matrix analysis is that arbitrage processes are more likely to operate for firms in the extreme bins. Therefore, we expect that over time, the probabilities should pile up in the center of transition matrix. With very powerful arbitrage processes operating, the entries in Bin 4 should dominate every other column. To the extent that arbitrage processes face considerable friction, we expect the sum of the probabilities in Bins 3 - 5 should dominate the rest of the entries on a given row. That is, regardless of where a REIT starts, the likelihood of moving to the middle of the density (i.e, moving toward price efficiency) should be substantially higher than the probability of becoming less efficient or retaining the current level of inefficiency.

Estimation and interpretation of transition probability matrices in our work is somewhat complicated by two factors. First, the initial ten years of our sample witnessed a doubling of traded REITs. There is some consolidation in the latter part of the sample, too (see Figure 1 for details). This makes it more challenging to generate probability estimates from a large, stable underlying

¹⁹We centered bin 4 on 1.01, and after some experimentation with data from various years of the sample period, we set all the bin sizes at .03.

population. Second, there are several important changes in market regulation (e.g., quote conventions, Reg NMS) that arguably affect the frictions in the arbitrage process. It seems important to account for one-time shifts in the efficiency density and to identify whether these regulatory shocks have differential effects on individual REITs. Specifically, we expect that regulatory change that lowers the cost of arbitrage ought to have differential effects on REITs in Bins 1-2 and 6-7 vs. those in Bins 3-5. We expect that kurtosis should fall in the event that a regulatory change spurs greater arbitrage, since it is likely to affect the tails of the efficiency distribution.

There are two limitations of this analysis. The first is that we assume the time periods for adjustment are sufficient to reveal the underlying processes. The second is that the number of REITs involved is matched appropriately to the number of bins we are using to measure relative performance. A smaller number of bins ensure we have representation in each bin, but it may obscure performance differences. A larger number of bins highlights performance differences but we are more likely to have zeros in the bins.

With these limitations in mind, we turn now to our estimates of three sets of transition probability matrices. The first looks at long-horizon movements in relative efficiency, relying on data from 1995 and 2011.²⁰ The aim is to provide an assessment of the impact of arbitrage processes over a long period. Table 3 presents our empirical estimates. Without regard for the initial bin, the overwhelming majority of the probability (93.4%) is attached to ending up in bins 3-4-5. Unconditionally, very little of the probability piles up in bins 1-2 or 6-7. For REITs that begin in bins 1, 2, or 6, the probability of ending up in bins 3, 4, or 5 is 100%. There is only minimal probability associated with ending up in the tails. From this analysis, we conclude that there is very strong evidence that REITs move to the center of the distribution from the tails. Inefficiency does not tend to persist, precisely what we would expect in the presence of an effective arbitrage process.

The second part of our transition probability matrix analysis looks at shorter-horizon efficiency transitions within stable market structure arrangements. Specifically, we look at 1993-1997, 1998-2000, 2001-2006, and 2009-2011.²¹ This identifies the transition probabilities over three- and five-

²⁰We use 1995 instead of 1993 because there are only 30 REITs that are in the sample for the entire period. If we start with 1995 instead, the count is 49.

²¹These periods are chosen to ensure stable market quoting conventions and trading rules within each period.

year adjustment periods, and isolates (although perhaps somewhat noisily) the effects of different market structure arrangements. We present our estimates for these four periods in Table 4.

Our estimates show that the unconditional probability of ending up in bins 3, 4, or 5 are about 65% for the first two periods, rising to 70% for the 2001-2006 period and just over 91% for the 2009-2011 period. We also note that the unconditional probability of ending up in the tail bins (1, 2, 6, or 7) fall substantially as we move to later calendar periods. Both findings strongly imply that the processes that yield efficient trading over time were probably more powerful in later years versus the earlier periods. This is broadly consistent with the implications of higher trading rates, lower trading costs, and cheaper information transmission in the latter years of our sample, all of which contribute to the effectiveness of arbitrage capital.

Finally, we study the transition probability matrix associated with each market regulatory structure change. The aim of this analysis is to isolate as cleanly as possible the effects of these changes on relative efficiency. The first regulatory change is the shift from quotes in 1/8ths to quotes in 1/16ths, which took place on June 23, 1997. We calculate variance ratios for all traded REITs in the one-year period before this date and the one-year period after this date, and create z-statistics in the usual manner.²² We use the same methods with two other events, the advent of decimal quotes on January 28, 2001 and the transition to Reg NMS beginning on July 1, 2007 and culminating on August 8, 2007. Our estimates are reported in Table 5.

The impact of the first regulatory change appears to be fairly substantial in terms of the probabilities of REITs moving from the tails to the center of the distribution. Unconditionally, about two-thirds of the probability is associated with ending in bins 3, 4, or 5. For the shift to decimal quotes, that probability is just over 50% with roughly equal probability (just under 25%) of REITs ending up in the tails. For the onset of Reg NMS, the probability of ending in the middle is even small at just under 43%. Put another way, these estimates strongly imply that the end of quotes in 1/8ths may have played a part in the relative efficiency dynamics documented in Table 3. However, the other two regulatory changes appear to have contributed very little to the transition probabilities documented in Table 3.

²²We delete two weeks of trading on either side of June 23, 1997, and adjust start and ending dates so that there is a full year of trading in the before and after samples.

5. Determinants of Efficiency Dynamics

In this section we explore the factors that drive the cross sectional dynamics within the distribution of measured price efficiency. We begin by discussing the model and estimation in the first subsection, followed by presentation of cross-section results in the second subsection, and discussion of some preliminary results on dynamic adjustment in a third subsection.

5.1. Model and Estimation

Our model design is predicated upon the work of BK. As is standard in this literature, BK use the VR as a proxy for the degree of informational efficiency²³. The particular focus of BK is the linkage between informational efficiency and institutional investor behavior. They find that stocks with greater institutional ownership are priced more efficiently, even when controlling for size, variation in liquidity, share price, and volatility.

We expand the scope of BK’s model by introducing additional factors affecting relative efficiency. We group them roughly into three broad areas, each of which may be proxied by one or more regressors. Briefly, these three factors are informed trading (X_1), market frictions (X_2), and cash flow variability (X_3). These areas may not be mutually exclusively, and certainly are not exhaustive, but do provide a broad framework for understanding our approach to modeling efficiency dynamics.

In our context, informed trading refers to the trader’s ability to acquire and accurately assimilate information regarding the asset. *Ceteris paribus*, we expect that stocks with a higher proportion of informed trading should have more information correctly impounded into their share prices, thereby generating higher informational efficiency, and a VR closer to 1. The focus on institutional ownership (IO) in the BK model is based upon the informational advantage of institutional traders. This advantage may come from access to privileged information (e.g. ”insider” information) and/or from the professional investor’s enhanced ability to process information. Regardless of the source, the fact that there are more institutional investors suggests the possibility more efficient trading.

To measure institutional ownership, we follow the methodology proposed by Yan and Zhang

²³To be more complete, BK explore four dependent variables: a pricing error from a Hasbrouck (1993) model, return autocorrelations, and two measures of variance ratios

(2009), and calculate three institutional ownership variables; we rely on the underlying ownership data from Thomson Financials 13(f) database. Total institutional ownership (TIO) is the level of ownership by all institutions, while short term institutional ownership (SIO) is the percentage ownership of the REIT held by funds in the top tertile of portfolio turnover. Long term institutional ownership (LIO) is the percentage ownership of the REIT held by funds in the bottom tertile of portfolio turnover. Details on these calculations are in the original paper.

The three panels of Figure 8 show how the average level of these three measures changes over time for each of the property types for our REITs. Note that each measure is quite low at the beginning of our sample period, and while all three measures rise, the bulk of the relatively high institutional ownership of REITs is in the middle turnover tertile.

We also augment the BK empirical model with several additional controls that bear on the level of informed trading. REITs that have just issued equity (common or preferred) or debt are likely to have provided substantial information to the markets in the process of selling new securities. From NAREIT, we gather a complete record of REIT-specific debt and equity issues during the 1993-2011 period. We use this to construct a dummy variable that indicates for every REIT whether securities were issued in that quarter. This is a rough proxy for whether the information environment has changed.

From IBES, we extract the record of analyst coverage for each REIT in our sample. Boudry, Kallberg, and Liu (2011) show that average analyst coverage is quite low in REITs during the late 1990's - early 2000's period. We use this data to control for other potential channels through which normal information flow might improve market efficiency, apart from changes in ownership (as in B-K (2009) or REIT market microstructure.

We also collected data on trading in options on REIT shares from Optionmetrics. Coverage begins in 1996, and we find seven REITs that have traded options. We aggregate the volume of trading in call and put options each day, and calculate an average over each quarter. We do the same with option open interest, aggregating across put and call options. Our aim is to proxy for the impact of price discovery in option markets on the efficiency of trading in the underlying REIT markets. To our knowledge, this is the first use of REIT options trading data.

The second set of influences that we use to explain efficiency dynamics centers on market frictions. The premise is that informed trading is not a sufficient condition to ensure efficient pricing. Frictions within the trading process may hinder the market’s ability to successfully impound information into prices. As in BK, we capture these frictions with several liquidity proxies including market value and quoted spreads.

While we principally follow the lead in BK, we also include controls for changes over time in trading behavior that may affect the efficiency of price setting. Dramatically lower trading costs in the second half of our sample period have sparked additional trading. As markets have changed, some traders have adopted trading strategies in which bid/ask quote proliferation serves as a trading technique. In a market with a rapid rate of information arrival, we would naturally expect a large number of quotes and a large number of changes in the NBBO quotes. Our measure scales the average number of daily quotes by the average number of daily changes in NBBO quotes. As this measure is higher, we are more likely to have traders focused on trading strategies that may have little relationship to the efficiency of the price setting process. We also control for the number of quotes per trade as an additional measure that controls for these newer trading strategies.

The last factor we seek to proxy is cash flow variability. It is difficult to find a REIT-level measure of cash flow variability that is defined within a quarter. To control for this potential factor, we create a set of dummy variables that capture the property type of a specific REIT. These variables are also likely to capture other property type-related variation in pricing efficiency that is not captured by our other variables.

With these three regressor categories in mind, we specify a cross-sectional model that is similar in structure to the approach taken in BK:

$$|1 - VR_{i,t}| = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + u_{i,t} \quad (1)$$

where $VR_{i,t}$ is the variance ratio of asset (i) at time (t), X_1 contains information-related variables, X_2 contains trading friction-related variables, and X_3 contains our property type dummy variables. As in BK, the premise is that deviations from efficiency (i.e., $VR \neq 1$) depend on factors falling into these three groups. We have an unbalanced panel (i.e., not every REIT trades in every quarter),

and we estimate a simple cross sectional regression using OLS using data for each REIT for each quarter.

Importantly, we extend the the BK analysis by using quantile regression methods. Quantile regression changes the norm upon which the objective function is minimized, thereby allowing us to explore the power of regressors for different quantiles of the dependent variable. This stands in contrast to a simple OLS estimation, which focuses on the explanatory power within the means of the (in)dependent variables. In section 3, we showed that much of the dynamics in the empirical VR distribution was attributable to the tails (extreme quantiles). Moreover, our earlier discussion connected REITs in the tails of the VR distribution to the activity of arbitrageurs. Therefore, we want to examine whether the effects of the factors described earlier at extreme quantiles, where the arbitrageurs should be most active, are different from those in the rest of the distribution.

Quantile regression is especially well-suited for this purpose. As we noted above, the focus of OLS regression is the conditional mean. Specifically, if we write the conditional mean of our response variable of interest Y given some linear combination of covariates X as $E[Y|X = x] = x'\beta$, then the OLS estimator can be found by minimizing

$$Q(\beta) = \sum_{i=1}^N (y_i - x_i\beta)^2$$

In our application here, our interest lies not in the conditional mean of Y , but rather in the conditional upper/lower tail quantiles, where arbitrageurs are thought to be most active. Following Koenker and Bassett (1978), the τ^{th} quantile regression estimator can be found by minimizing

$$Q(\beta_\tau) = \sum_{i:y_i \geq x_i'\beta} \tau |y_i - x_i'\beta_\tau| + \sum_{i:y_i < x_i'\beta} (1 - \tau) |y_i - x_i'\beta_\tau|$$

5.2. Principal Results

In Table 6, we report OLS estimates of the BK model from our sample of REITs (for comparison, see Table 3 in their paper). Standard errors reported in the table are robust estimates, clustered by REIT. We also present quantile-based estimates in Table 6. The idea here is that while OLS estimates are based on mean responses, there might be important variations in estimated coefficients

depending on the value of the dependent variable. In our setting, the left tail of the dependent variable distribution (e.g., the five or 10 percent quantile) consists of very small deviations from market efficiency while the right tail of this distribution is defined by large deviations from efficiency. Clearly, the gain from arbitrageurs is likely to be much larger from exploiting deviations from efficiency in the right vs. the left tail.

In broad terms, the estimates in Table 6 largely mirror the findings in BK. Total institutional ownership exerts a statistically significant impact on measured pricing inefficiency, but including these regime dummy variables leads to a nearly 35% decline in the size of this effect. This causal interpretation is premised on the assumption that the findings in BK on causality (i.e., ownership causes inefficiency, but inefficiency doesn't draw institutional ownership) are appropriate for the REIT market.

The quantile estimates show that these effects are large and statistically significant only for the 50th and higher quantiles. That is, TIO doesn't have much connection to pricing inefficiencies at lower levels of inefficiency. To the extent that there is more money to be made by addressing departures from efficient pricing, this finding is what we might expect if the causation runs from inefficiency to ownership.

Our multi-dimensional market liquidity measure, the ratio of quoted spread to market depth, is not a statistically significant determinant of the level of pricing inefficiency. It also has the wrong sign. Interestingly, the quantile estimates show that for lower levels of pricing inefficiency, liquidity is negatively related to inefficiency, exactly the result from BK. However, at high levels of inefficiency, we find the opposite: a positive, statistically significant estimate for the very largest levels of inefficiency. Overall, it seems apparent that liquidity is not a first-order influence on the level of measured inefficiency in the REIT market, conditional on other factors related to pricing inefficiency.

We find that pricing inefficiency is increasing in the natural log of REIT market value: it is more likely to be seen in firms with higher value, *ceteris paribus*. In contrast, we find that as REIT share prices are higher, measured pricing inefficiency is lower, *ceteris paribus*. Note that these effects are statistically significant at each of the quantiles in the table, but the estimated coefficients grow

larger with the quantile. From the 10th to the 90th quantile, the coefficient on market value is over five times larger and for price, it is nearly six times larger.

The addition of dummy variables for the quote regimes and the onset of Reg NMS add substantially to the model ($F > 43.0$, $p < .001$), and each is individually statistically significant at the 1% level. The estimates for the quote regime variables are positive, implying that the average measured pricing inefficiency is actually higher relative to the quotes in 1/8ths period, *ceteris paribus*. This reflects, no doubt, the spikes in inefficiency that are apparent in Figure 2. That said, the quantile estimates show how remarkably different these estimates are for higher levels of measured inefficiency. Finally, we note that the Reg NMS dummy variable has a negative sign, indicating an average reduction in measured pricing inefficiency after Reg NMS took hold in 2007. We note also that the impact of Reg NMS on pricing inefficiency rises dramatically as we move across the quantiles of measured pricing inefficiency. The differences between the 10th and the 90th quantile differ by nearly an order of magnitude.

Our OLS estimates show there is persistence in measured inefficiency, although in terms of time-series models, it isn't particularly substantial. Our quantile estimates show there is a substantially higher persistence for quantiles at and above the median, after accounting for other factors related to the level of measured inefficiency. The interpretation is somewhat ambiguous. The coefficient on the lagged level of measured inefficiency may reflect persistence in inefficiency or it may quantify the impact of omitted variables (since the R^2 is so low, this possibility cannot be dismissed out of hand). In the latter case, the pattern of estimates that increase across the quantiles is consistent with what we find for other covariates.²⁴

The fit of these models is increasingly good as we move from lower to higher quantiles. For the smallest quantiles, the R^2 is less than one percent, but it is nearly eight percent for the highest quantile we consider here. This is broadly consistent with the idea that systematic forces are more likely to have significant effects at higher levels of measured inefficiency.

As we argued earlier, there are additional factors that may affect the level of measured pricing

²⁴At first glance, these estimates may appear to be inconsistent with our earlier findings from the analysis of the transition probabilities. However, that analysis is long-term in its orientation, while the persistence estimates in Table 6 capture quarterly dynamics. Clearly, there are interesting opportunities for further work in connecting the short-term and long-term dynamics of measured efficiency.

efficiency. We begin to address these issues by adding a set of additional regressors to the BK model. Specifically, we add analyst coverage, the volume of option trading (both calls and puts), the level of option open interest (summed across calls and puts), the ratio of total quotes to changes in the NBBO quotes, and the ratio of quotes to trades. All of these are measured at the level of the individual REIT, and are entered into the model in lagged form following the approach in BK.

The premise behind including our analyst coverage measure is that REIT shares are more likely to be efficiently priced when valuation-relevant information is provided to market participants. Our measure, the average number of analyst forecasts during a specific quarter, is designed to control for differences across REITs in the production of public information.

The finance literature has long considered whether price discovery in the options markets affects the pricing efficiency in the underlying equity market.²⁵ With this in mind, we include both the aggregate of put and call trading volume and the aggregate of put and call open interest (measured in thousands of shares) as controls for the importance of price discovery in REIT option markets. Note that there is no options trading for many smaller REITs, and this data from OptionMetrics begins in 1996.

Table 7 reports estimates from our expanded model. The first two columns on the left marked OLS differ in respect of the addition of property type dummy variables to soak up differences in measured efficiency related to the types of properties owned by an individual REIT, holding other effects constant.²⁶ When we test an exclusion restriction on these property dummies, we readily reject the null hypothesis of no effect ($F=3.94$, $p=.000$), so we include these dummies in all subsequent applications. When we test an exclusion restriction on the other variables that we add to the original BK model, we also reject the null hypothesis of no effect ($F=4.77$, $p=.004$). Collectively, our additional regressors improve the model fit.

As with the simpler BK model, we find that the average impact of institutional ownership is negative: higher levels of institutional ownership correspond to relatively smaller deviations from efficient pricing. We also note that lagged deviations continue to be statistically significant

²⁵See Conrad (1989), Sorescu (2000) and Danielsen and Sorescu (2001) for analysis of these issues.

²⁶In specific, we have dummy variables for the following property types: shopping centers, industrial, office, multifamily, diversified, other retail, regional mall, self-storage, health care, mobile home, and hotels.

in the regression model. Turning to the additional regressors, we find that while analyst coverage provides little additional explanatory power, option volume and open interest both exert statistically significant impacts on the level of deviations from efficient pricing. Interestingly, higher option trading is associated with larger deviations from efficient pricing, but higher levels of option open interest are associated with smaller deviations. The two quote-based measures contribute virtually no independent impact on deviations from efficient pricing.

The quantile estimates in Table 7 (all of which include property type dummy variables) confirm some of the outcomes that we saw with the simpler model in Table 6. Specifically, the impact of institutional ownership on deviations from efficient pricing grows virtually monotonically from the lowest to the highest quantile (even though estimates in some quantiles are not sharp enough to be statistically significant). Our estimates also show that quarterly persistence of pricing deviations rises across the quantiles, much as we saw in the simpler BK model. The option volume effects are somewhat higher at higher quantiles, and option open interest effects are somewhat larger, too. Analyst coverage has no marginal effect, and our quote-based measures don't generally have statistically significant marginal effects on measured pricing efficiency. Finally, as in the earlier estimates, we note that the model fit improves substantially as we move from the low to the high quantiles.

To this point, we have used the aggregate institutional ownership measure generated using the methods described in Yan and Zhang (2009). We also explore the marginal impact of two different subsets of the institutional owners. We include a short term institutional ownership (SIO) measure, which is the percentage ownership of the REIT held by funds in the top tertile of portfolio turnover. Separately, we include a long term institutional ownership (LIO) measure, given by the percentage ownership of the REIT held by funds in the bottom tertile of portfolio turnover. Table 8 provides estimates related to the marginal impact of SIO, and Table 9 reports comparable estimates using the LIO data.

The estimates in Table 8 show clearly that there is no marginal impact associated with ownership by institutions in the top tertile of portfolio turnover. Based on the OLS model, the frequent traders don't have a statistically significant marginal impact on deviations from efficient pricing. This is

true for the quantile estimates, too, although we also find the *positive* sign of the SIO effects shifts by the 50th percentile to becoming negative. The negative TIO effects remain as before: the OLS and quantile estimates are statistically significant, and the quantile estimates generally rise in value from low to high quantiles. The broad picture of other estimates is similar to what we found in Table 7, including the increase in R^2 as the quantiles increase.

By contrast, the estimates in Table 9 show quite clearly that there are significant marginal effects associated with increased ownership by institutions in the bottom tertile of turnover. That is, the institutional owners who trade relatively little have a robust, negative on pricing deviations: higher ownership by institutional investors who trade less actually reduce deviations from efficient pricing.²⁷ We note that the (OLS) estimated marginal effect of low-trade institutional ownership is nearly five times as large as the baseline institutional ownership effects.

As before, the quantile estimates show generally increasing marginal effects of low-trading institutional ownership on pricing deviations as we move from low to high quantiles. While the same is true for our broad institutional ownership measure, the effects are generally substantially smaller, and only half are statistically significant. Option-related measures continue to have robust effects across quantiles. We also find the model fits better as we move from low to high quantiles.

5.3. Preliminary Evidence on Impact of Arbitrage

We have established that institutional ownership and other dimensions of the REIT market are related to pricing efficiency. Before closing, we offer some additional evidence on the dynamics of REIT efficiency that highlights potential arbitrage-related forces that may act to eliminate mispricing. First, we apply a Dickey-Fuller test to the REIT-specific time-series of quarterly variance ratios. Our aim is to establish whether these series are unit roots or instead that they are generated by a stationary process.

We find that for the 125 REITs with at least 30 quarters of estimated variance ratios, only 10 fail to reject the null hypothesis of a unit root at the five percent level. Only one REIT among those with at least 50 observations fails to reject the null hypothesis; the other nine have between 30 and

²⁷As noted earlier, this interpretation rests on the evidence in BK that ownership causes inefficiency to be smaller, rather than inefficiency drawing institutional shareholders.

36 observation. Among those REITs in the sample continuously from 1993/1995, each rejects the null hypothesis. We interpret these findings as compelling evidence that the typical variance ratio series is well-described as a stationary process.

Second, having established that these are stationary processes, we propose and estimate a simple model that links the level of the variance ratio in a given period to past measured pricing inefficiency. The underlying hypothesis is that the level of the variance ratio reflects past values of the series (i.e., what we might expect with a stationary series) and observed pricing inefficiency in earlier trading. If there are no arbitrage forces operating, we expect that lagged pricing inefficiency will have no systematic connection to the current level of the variance ratio. On the other hand, if these arbitrage forces operate to any economically significant degree, we expect to find that past inefficiencies are systematically related to the current variance ratio in a manner suggesting reversion toward a variance ratio of one.

The model that we use to investigate this is given by

$$VR_{i,t} = \lambda_0 + \lambda_1 VR_{i,t-1} + \lambda_2 |1 - VR|_{i,t-1} + \lambda_3 X_t + \epsilon_{i,t} \quad (2)$$

where $VR_{i,t}$ is the variance ratio for REIT i for quarter t , $|1 - VR|_{i,t-1}$ is the measured pricing inefficiency for quarter $t-1$, X_t are control variables for microstructure regimes over the 1993-2011 period, $\epsilon_{i,t}$ is a random error term, and the λ_i are coefficients to be estimated.

In Table 10, we report OLS and quantile estimates for our simple model. The X_t vector has dummy variables for the period when quotes were in 1/16 (Regime 2), quotes are in decimals (Regime 3), and for the period when Reg NMS is in place (Reg NMS). The simple model (leftmost column in Table 10) shows that there is very little autocorrelation in variance ratios once we account for the lagged pricing inefficiency measure. Our estimates imply that pricing inefficiencies are connected to the current level in an economically appropriate way. When the pricing inefficiency is negative (i.e., the variance ratios is less than one), the coefficient estimate has a positive sign indicating the variance ratio tends to be higher. When the pricing inefficiency measure is positive (i.e., the variance ratio is above one), the coefficient estimate is negative implying that the variance ratio tends to be smaller. Finally, we note that there is a smaller impact on the current variance

ratio of a positive pricing efficiency last period (i.e., $|1-VR| < 1$). That is, there is a more sizeable effect on the current variance ratio of a negative pricing inefficiency last period (.697) vs. a positive pricing inefficiency (-.429).

We find that adding dummy variables improves the fit marginally, and a standard F-test rejects the null that this vector of microstructure regime dummy variables should be omitted. Note that the slope coefficients differ only marginally when we enter these intercept shift variables. As we shall see shortly, the real impact of these microstructure regimes lies in affecting the slope estimates in an interactive specification.

Several aspects of the quantile estimates are worth noting. First, the response to pricing inefficiencies rises substantially from the lowest to the highest quantiles. However, the response to positive pricing inefficiencies is actually falling from the lowest to the highest quantiles, -.508 at the 5th quantile vs. -.333 at the 95th quantile. The economics of this decline aren't immediately obvious. Along the same lines, the autocorrelation in the variance ratio is also falling as the quantile increases. Again, the economics behind this regularity aren't immediately clear. We note in passing that the impact of the microstructure regime dummy variables clearly varies across quantiles.

We also expanded this model to permit the slope coefficients to vary across the various microstructure regimes. Table 11 reports estimates of the slope coefficient on the variance ratio autocorrelation coefficients plus the two coefficients giving the responses to positive and negative pricing inefficiencies. The estimates in the table are net effects calculated from the coefficients of the more complex interaction model. Interestingly, after accounting for adjustments to pricing inefficiencies, there is virtually no autocorrelation left in the Reg NMS period. The level of the variance ratio responds to lagged pricing inefficiencies, but not to the lagged level of the variance ratio.

The response to negative pricing inefficiencies (i.e., $VR > 1$) clearly varies across the four periods. By contrast, there is very limited variation in the estimated response to positive pricing inefficiencies (i.e., $VR < 1$) across the four periods. As in Table 10, we find that there is a larger response to negative vs. positive pricing inefficiencies. It is unclear at this stage what economic influences account for this pronounced asymmetry. It suggests that there may be important difference in how

traders, investors, and arbitrageurs respond to measured pricing inefficiencies.

6. Conclusion

Using individual REIT pricing data, we estimate the time-varying distribution of REIT-level variance ratios covering the 1993-2011 period. Our estimates show that the average individual REIT is efficiently priced, but there are many REITs which are clearly not efficiently priced. We find examples of both mean aversion and mean reversion in the prices of individual REITs. These conclusions are robust to use of variance ratios calculated over different horizons, and are clear in both annual and quarterly data.

We also show that the REIT-level variance ratio estimates do not move randomly through time. For example, we find that the density of variance ratios responds to changes in market regulation. Our analysis shows specifically that REITs in the extremes of the empirical distribution are very likely to move toward the center of the distribution over time, while those in the center are very unlikely to move to the extremes. We interpret this as evidence that arbitrageurs act over time to improve the efficiency of pricing. We don't provide explicit evidence on how this process works, and this remains an interesting issue for further research.

Finally, we adopt the Boehmer-Kelley (2009) approach to modeling cross-sectional variation in pricing errors. We confirm their finding that institutional ownership tends to reduce the measured deviations from pricing efficiency, and long-term institutional owners (i.e., those that trade relatively infrequently) are particularly important in this respect. The precise mechanism through which these investors affect efficiency isn't clear from our work, and this, too, remains an interesting issue for further research.

We show that pricing efficiency deviations for individual REITs are also affected by trading in options on those REITs. To our knowledge, this is the first use of REIT option data, and our findings suggest that there may be other interesting questions that REIT option data may help to address. Our estimates also show that there are statistically significant differences in measured REIT efficiency deviations depending on property type, holding constant other REIT-level effects. The source of these differences isn't immediately obvious from our work here. Finally, we find a

relatively limited role for trading friction influences in our cross-sectional work, but there are clearly other trading-related measures that we hope to study in further work.

Our quantile regression methods confirm some important intuition: the effects of independent variables on measured REIT pricing efficiency deviations are much stronger as deviations from efficiency are larger. The 'action' is in the tails of the distribution, and our quantile model estimates highlight this regularity. This appears to be an innovation in the analysis of pricing efficiency that could be applied in other settings, too.

Finally, our estimates show that the level of the variance ratio adjusts to lagged measures of pricing inefficiency in a manner consistent with an arbitrage process. That is, variance ratios above one tend to adjust down to one, while variance ratios below one tend to adjust up toward one. Interestingly, this adjustment process is not symmetric: there is a larger adjustment for variance ratios above one vs. below one. In addition, our estimates imply that after Reg NMS takes hold, there is no autocorrelation in variance ratios: all the dynamics in levels are accounted for by adjustments to variance ratios above or below one.

The interesting issue raised by our analysis is the role of arbitrageurs, investors, and traders in generating the time series of measured pricing efficiency. This appears to be a potentially interesting area for further work, and we hope to contribute to this work.

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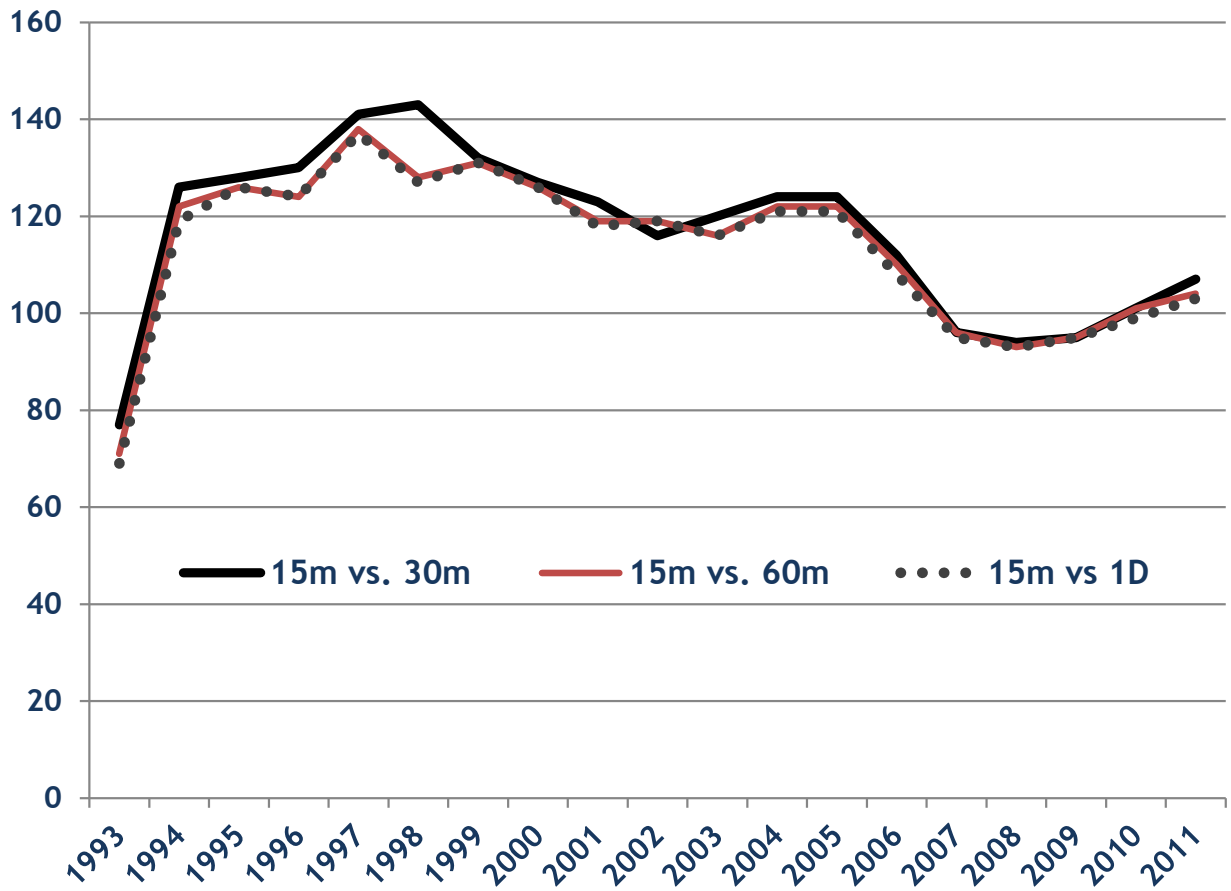


Figure 1: Size of Trimmed REIT Sample By Year.

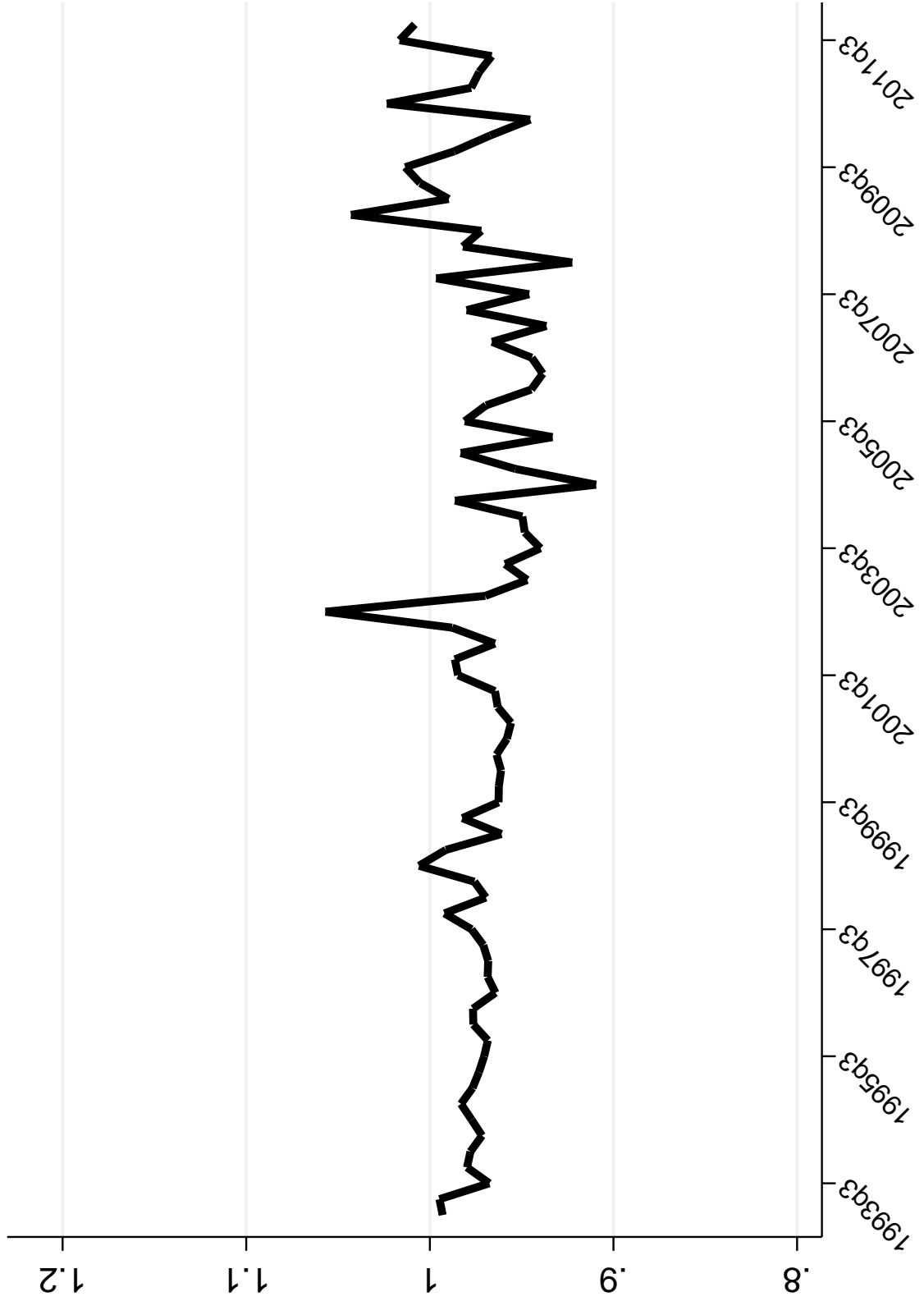


Figure 2: Variation in Quarterly REIT Variance Ratio Means, 1993-2011

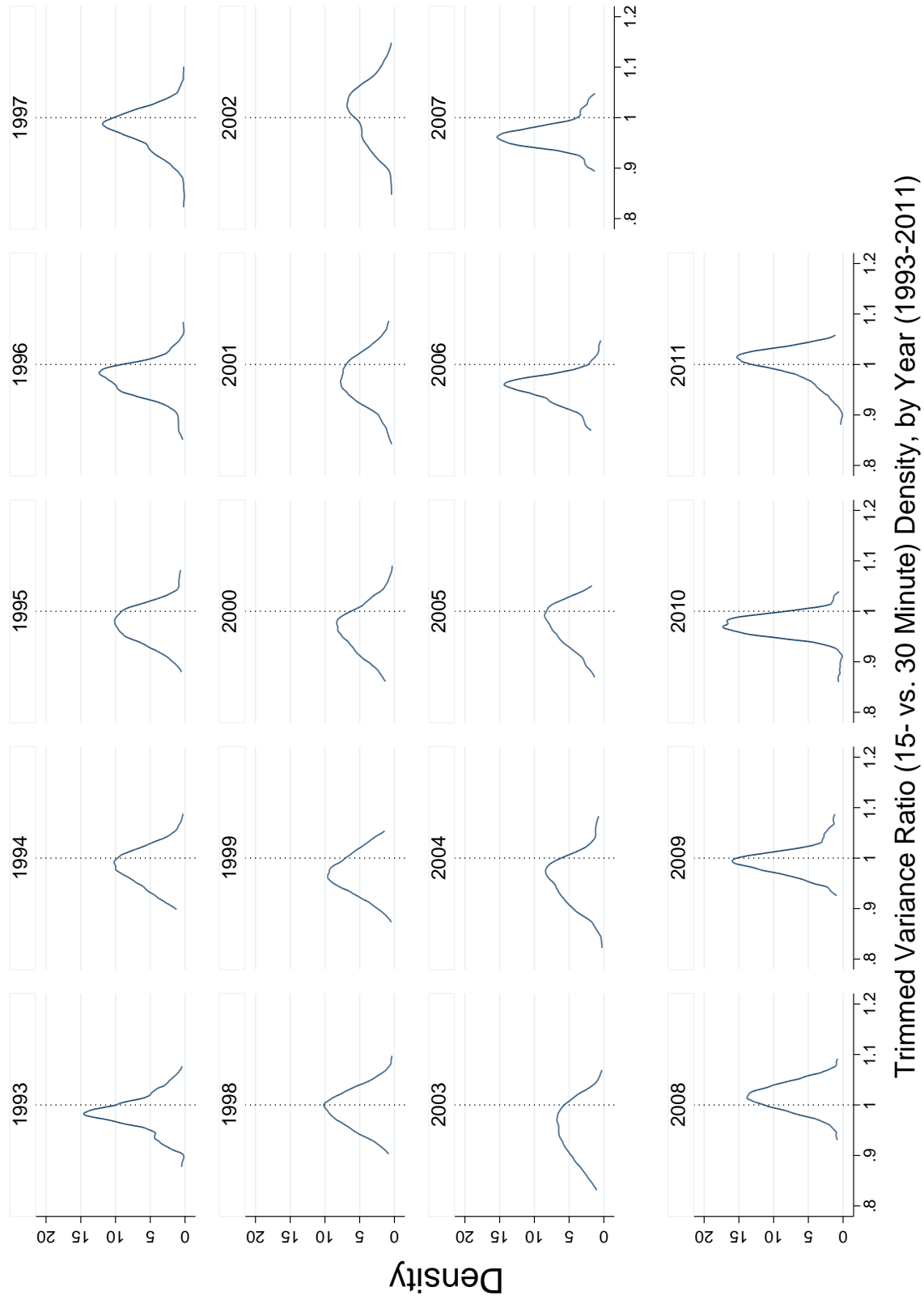
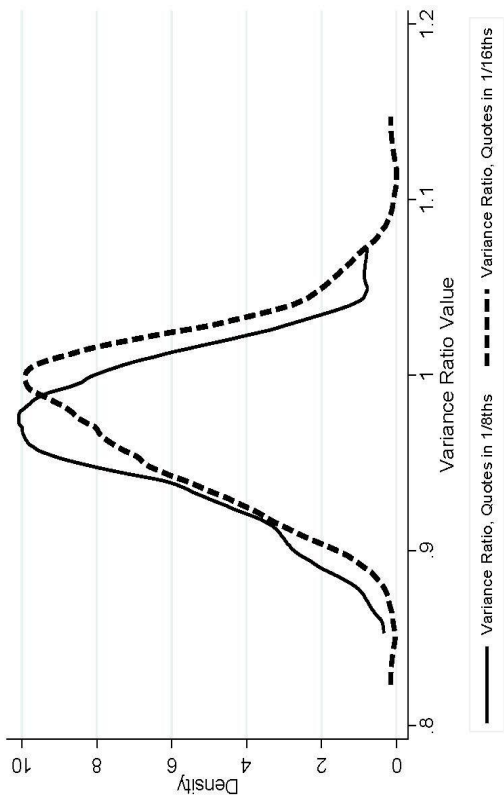
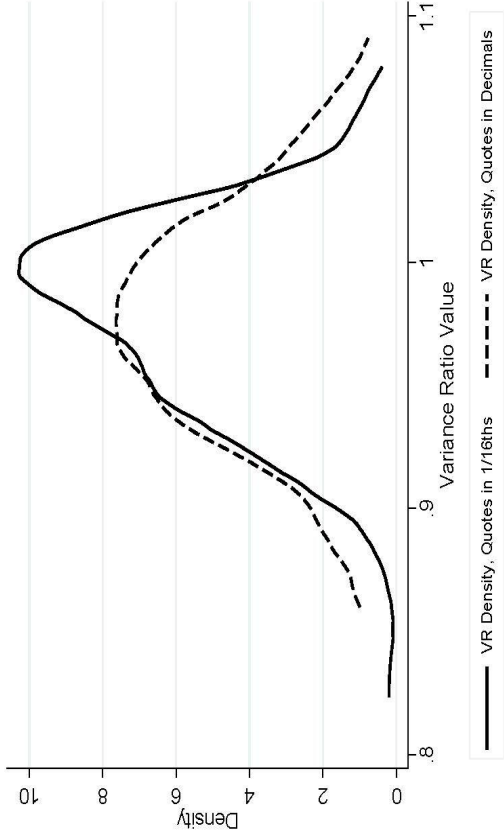


Figure 3: Annual REIT Variance Ratio Densities, by Year (1993-2011).
Trimmed Variance Ratio (15- vs. 30 Minute)

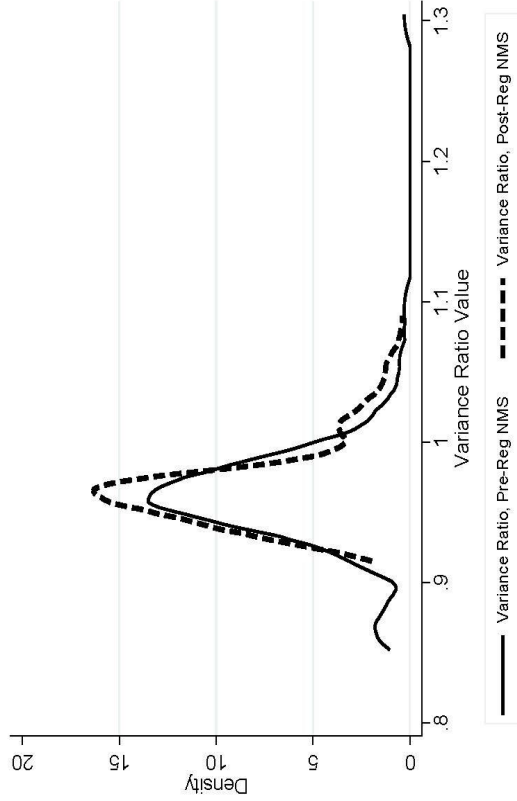
Figure 3: Annual REIT Variance Ratio Densities, 1993-2011.



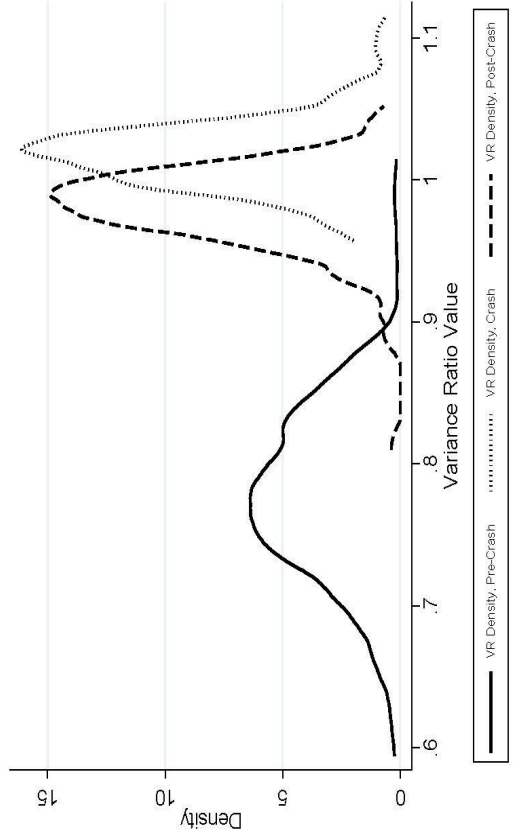
Panel A: Variance Ratio Densities Before vs. After End of Quotes in 1/8ths (Event 1).



Panel B: Variance Ratio Densities Before vs. After Change to Decimal Quotes (Event 2).

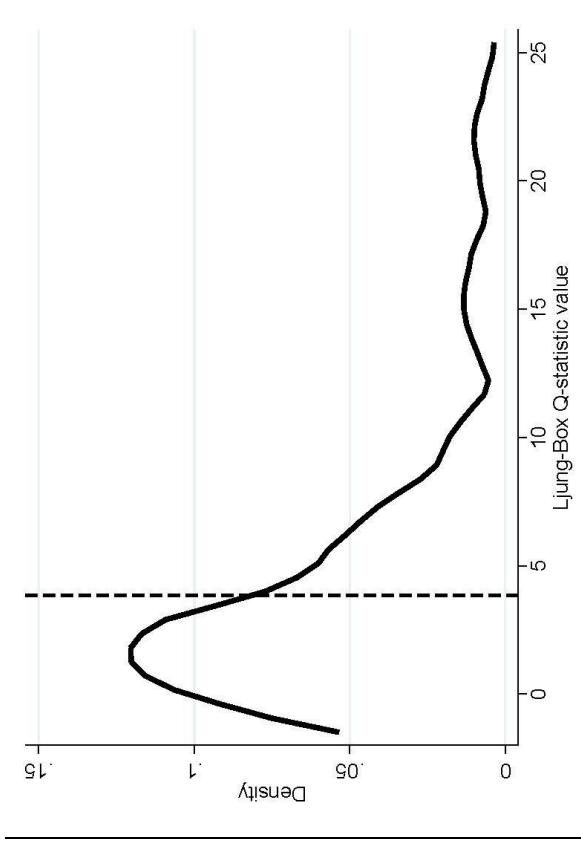


Panel C: Variance Ratio Densities Before vs. After Start of Reg NMS.

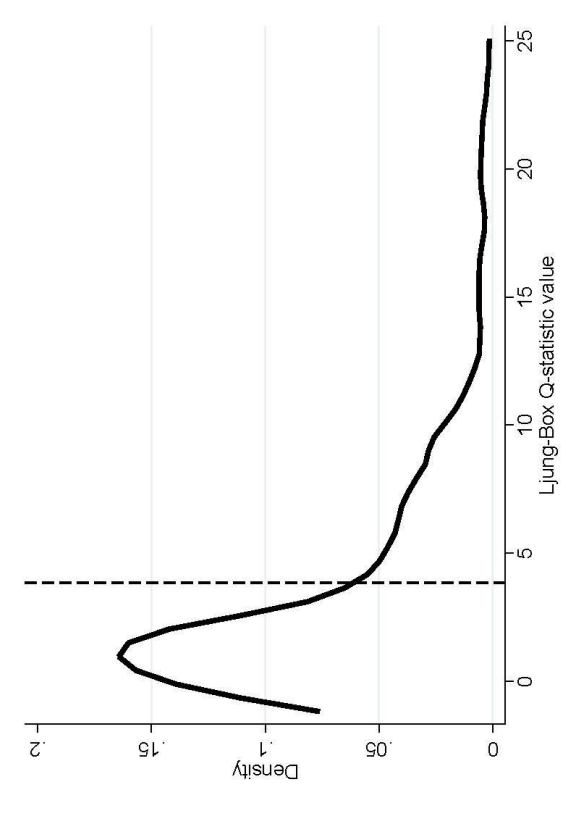


Panel D: Variance Ratio Densities Before, During, and After 2008 Market Crash.

Figure 4: Event-Related REIT Variance Ratio Densities.

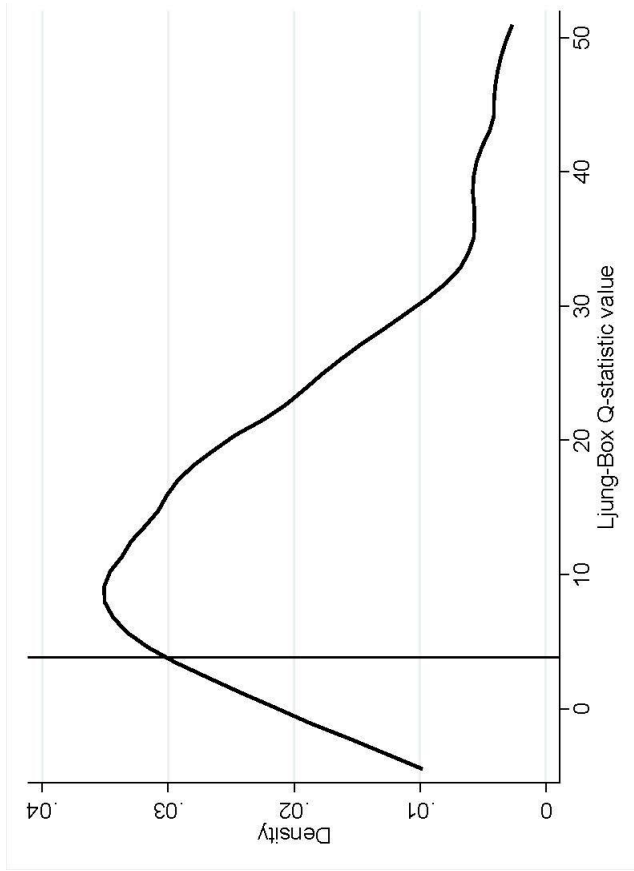


Panel A: Ljung-Box test statistic density for all REITs with 20 quarters of data.

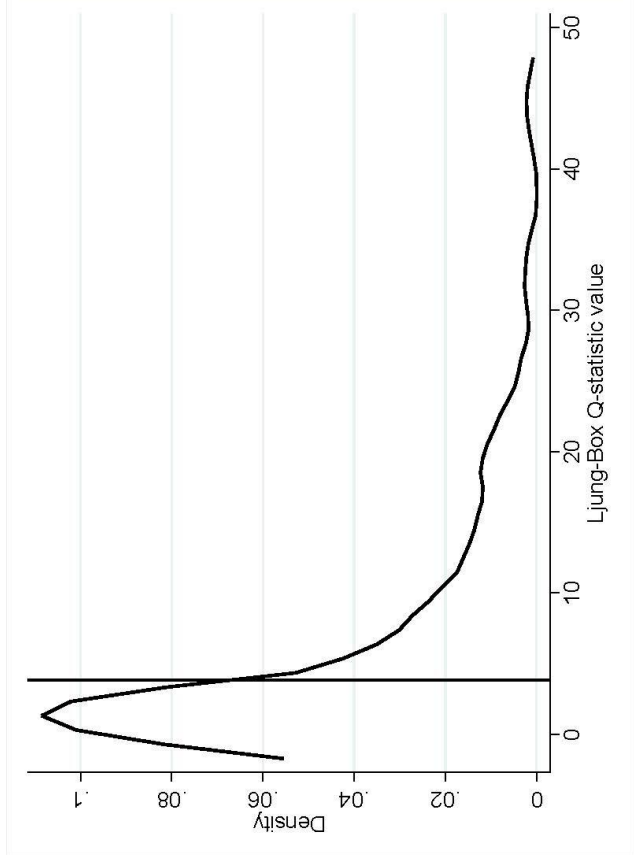


Panel B: Ljung-Box test statistic density for REITs trading in every year.

Figure 5: Density of Ljung-Box tests on variance ratios for entire sample (left) and Base REIT sample (right).



Panel B: Ljung-Box test statistic density for z-statistics for REITs trading in every year.



Panel A: Ljung-Box test statistic density for z-statistics for all REITs with 20 quarters of data.

Figure 6: Density of Ljung-Box tests on variance ratios converted to z-statistics for entire sample (left) and Base REIT sample (right).

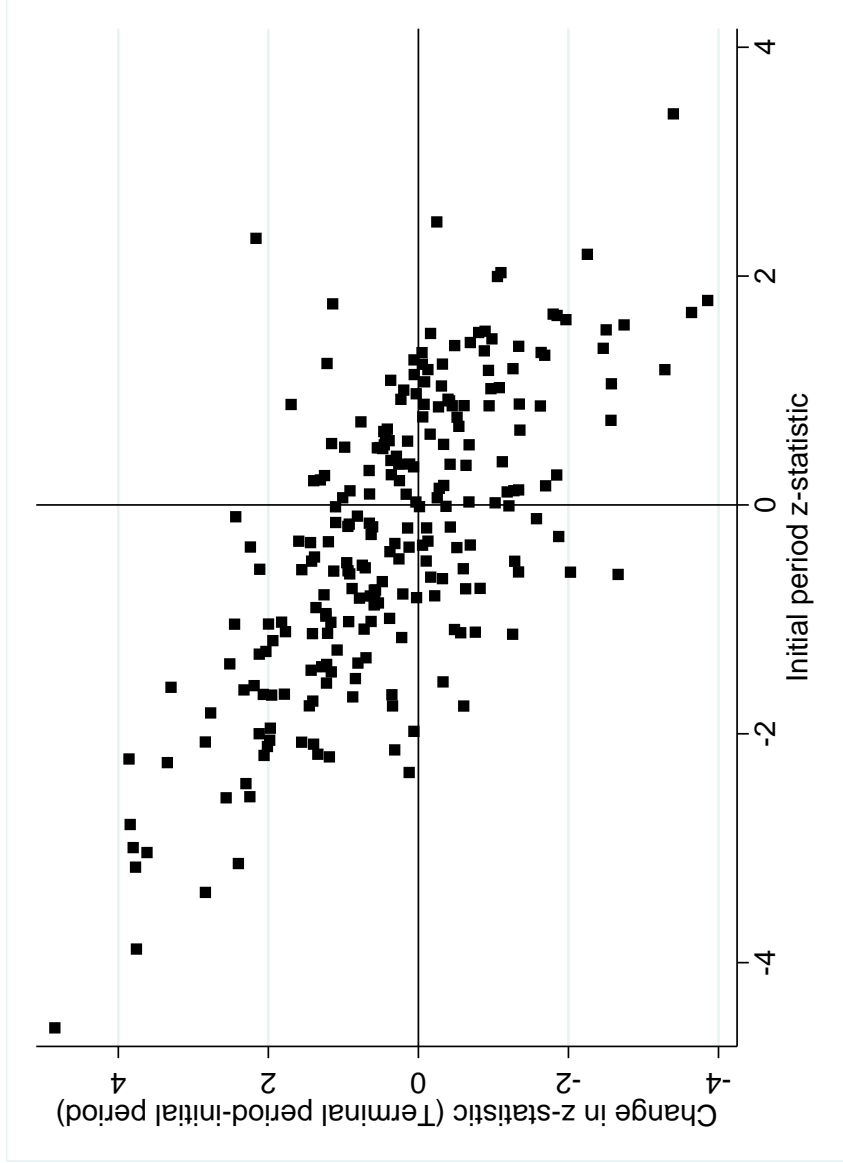


Figure 7: Change in z-statistics vs. initial z-statistic level for entire REIT sample.

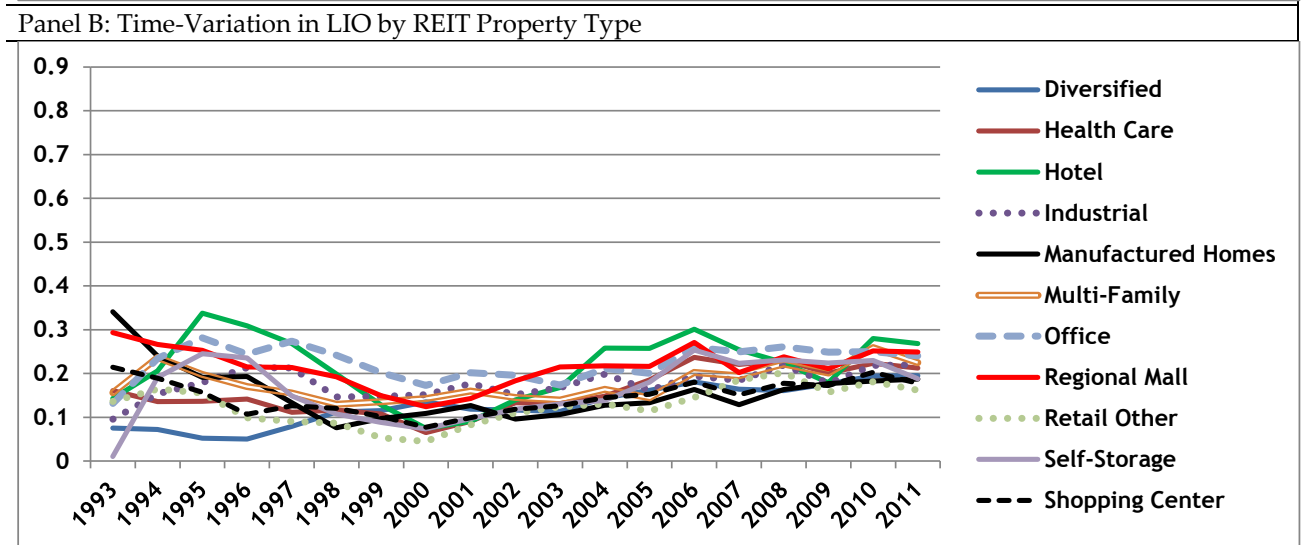
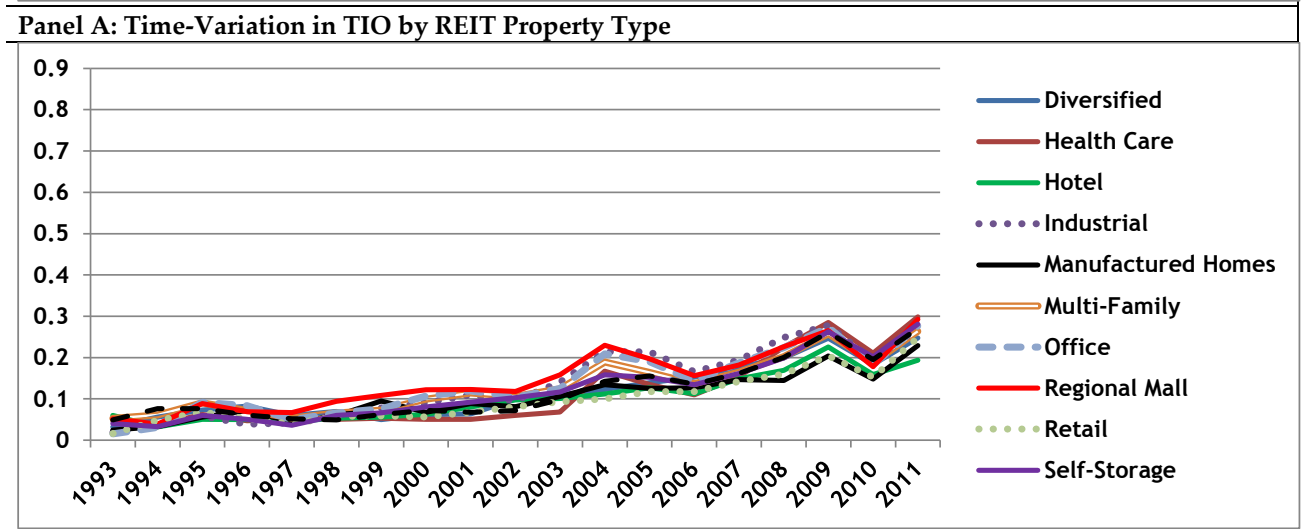
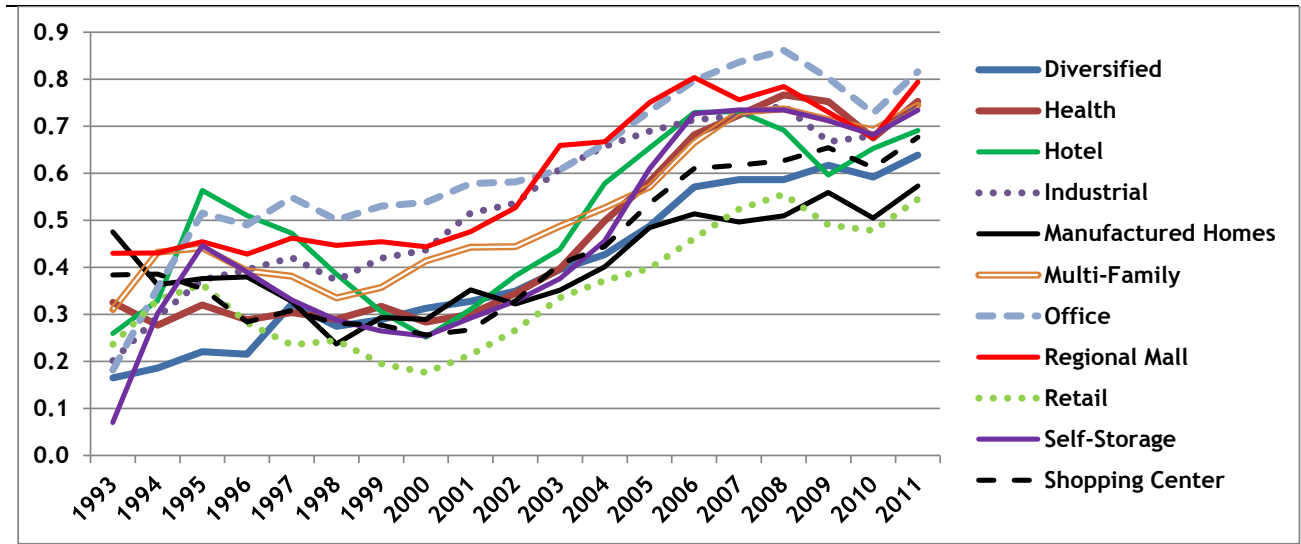


Figure 8: Time Variation in Institutional REIT Stock Ownership.

Table 1: Variance Ratio Densities: 15 minutes vs. 30 minutes

Year	Mean	Std. Dev.	Skew	Kurt	1%	5%	25%	75%	95%	99%	% Efficient
1993	0.981	0.036	-0.11	3.41	0.88	0.92	0.96	1.00	1.04	1.08	19.0%
1994	0.982	0.040	0.08	4.01	0.90	0.92	0.96	1.01	1.04	1.09	31.2%
1995	0.975	0.037	0.17	3.29	0.89	0.91	0.95	1.00	1.04	1.08	43.4%
1996	0.971	0.038	0.02	5.05	0.87	0.91	0.95	0.99	1.03	1.08	39.2%
1997	0.978	0.039	-0.47	4.57	0.87	0.91	0.95	1.00	1.03	1.07	23.9%
1998	0.992	0.037	0.02	2.79	0.91	0.93	0.97	1.02	1.05	1.08	27.6%
1999	0.971	0.038	-0.02	2.49	0.89	0.91	0.94	1.00	1.04	1.05	47.0%
2000	0.961	0.046	0.05	2.87	0.86	0.88	0.93	0.99	1.04	1.08	45.3%
2001	0.972	0.048	-0.08	2.90	0.86	0.89	0.94	1.00	1.06	1.09	34.1%
2002	1.007	0.056	-0.41	2.92	0.86	0.91	0.97	1.04	1.10	1.12	35.3%
2003	0.947	0.051	-0.25	2.37	0.83	0.86	0.91	0.99	1.02	1.04	52.5%
2004	0.958	0.048	0.04	3.20	0.84	0.88	0.92	0.99	1.05	1.08	46.4%
2005	0.970	0.044	-0.41	2.45	0.87	0.89	0.94	1.00	1.04	1.05	37.6%
2006	0.949	0.033	-0.13	3.44	0.87	0.88	0.93	0.97	1.00	1.03	61.1%
2007	0.967	0.034	0.73	4.29	0.89	0.91	0.95	0.98	1.03	1.09	38.9%
2008	1.017	0.031	0.14	4.00	0.93	0.97	1.00	1.03	1.06	1.12	14.0%
2009	0.997	0.033	0.81	4.02	0.93	0.94	0.98	1.01	1.07	1.10	22.3%
2010	0.971	0.026	-1.16	7.32	0.87	0.94	0.96	0.99	1.00	1.03	28.8%
2011	1.000	0.031	-1.03	4.29	0.92	0.94	0.99	1.02	1.04	1.05	13.0%
1993-2011	0.976	0.044	-0.14	3.42	0.87	0.90	0.95	1.00	1.05	1.09	35.5%

Note: We report sample statistics by year for the variance ratio estimates for each REIT in the sample in a given year. We construct these using 15- and 30-minute intervals. We also report the values of the empirical distribution of these variance ratios each year at the 1%, 5%, 25%, 50%, 75%, 95%, and 99% quantiles. The row marked 1993-2011 summarizes the annual variance ratio distribution across the entire 1993-2011 sample period. The last column indicates the percentage of variance ratios in a given year that are efficient using a standard variance ratio significance test.

Table 2: Variance Ratio Densities: 15 minutes vs. 30 minutes, Base REITs Only

Year	Mean	Std. Dev.	Skew	Kurt	1%	5%	25%	75%	95%	99%	% Efficient
1993	0.985	0.057	-2.63	12.97	0.75	0.94	0.98	1.01	1.05	1.08	16.7%
1994	0.979	0.044	0.37	3.17	0.90	0.91	0.95	1.00	1.06	1.09	43.3%
1995	0.968	0.040	-0.21	2.47	0.88	0.90	0.94	0.99	1.04	1.05	46.7%
1996	0.972	0.031	-0.43	3.81	0.88	0.93	0.95	1.00	1.03	1.04	26.7%
1997	0.976	0.030	-0.66	2.78	0.91	0.91	0.96	1.00	1.02	1.02	23.3%
1998	0.979	0.029	0.35	3.03	0.93	0.93	0.96	0.99	1.02	1.05	33.3%
1999	0.950	0.043	0.69	3.04	0.87	0.90	0.92	0.97	1.04	1.05	73.3%
2000	0.940	0.040	-0.09	2.31	0.86	0.87	0.92	0.97	1.01	1.01	63.3%
2001	0.966	0.050	0.25	3.22	0.86	0.88	0.94	0.99	1.06	1.09	40.0%
2002	1.014	0.062	-0.21	3.03	0.86	0.93	0.97	1.06	1.12	1.14	40.0%
2003	0.956	0.052	-0.12	2.96	0.83	0.87	0.93	0.99	1.04	1.07	46.7%
2004	0.977	0.045	0.36	3.49	0.89	0.90	0.95	0.99	1.08	1.08	33.3%
2005	0.983	0.041	-0.48	3.42	0.87	0.92	0.95	1.01	1.05	1.05	26.7%
2006	0.954	0.026	-0.58	2.99	0.89	0.91	0.94	0.97	1.00	1.00	53.3%
2007	0.962	0.023	0.38	4.95	0.91	0.92	0.95	0.97	0.99	1.03	43.3%
2008	1.025	0.029	0.96	4.87	0.98	0.98	1.01	1.04	1.06	1.12	13.3%
2009	0.992	0.019	0.35	3.37	0.96	0.96	0.98	1.00	1.01	1.04	16.7%
2010	0.973	0.016	-0.09	1.91	0.94	0.95	0.96	0.99	1.00	1.00	26.7%
2011	1.006	0.033	-2.21	8.71	0.88	0.94	1.00	1.02	1.04	1.04	10.0%
1993-2011	0.977	0.044	-0.17	4.79	0.87	0.90	0.95	1.00	1.05	1.09	35.6%

Note: We report sample statistics by year for the variance ratio estimates for the REITs which are in the sample from 1993/1995 through 2011. Nineteen are in the sample in every year, and another 31 are in the sample for every year from 1995 - 2011. We construct these using 15- and 30-minute intervals. We also report the values of the empirical distribution of these variance ratios each year at the 1%, 5%, 25%, 50%, 75%, 95%, and 99% quantiles. The row marked 1993-2011 summarizes the annual variance ratio distribution across the entire 1993-2011 sample period. The last column indicates the percentage of variance ratios in a given year that are efficient using a standard variance ratio significance test.

Table 3: Transition Probability Matrix Estimates, 1995-2011

		Terminal VR Bin						
		1	2	3	4	5	6	7
Initial VR Bin	1	0.0%	0.0%	0.0%	42.9%	57.1%	0.0%	0.0%
	2	0.0%	0.0%	9.1%	54.5%	36.4%	0.0%	0.0%
	3	14.3%	0.0%	14.3%	0.0%	71.4%	0.0%	0.0%
	4	0.0%	0.0%	11.1%	38.9%	44.4%	5.6%	0.0%
	5	0.0%	20.0%	0.0%	40.0%	40.0%	0.0%	0.0%
	6	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%
	7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Prob. of Ending in		Unconditionally	Probability if Starting in Bin					
Bins 1/2:		5.7%	1	2	6	7		
Bins 3/4/5:		93.4%	100.0%	100.0%	100.0%	0.0%		
Bins 3/4:		35.1%	42.9%	63.6%	0.0%	0.0%		
Bins 6/7:		0.9%	0.0%	0.0%	0.0%	0.0%		

Note: The top portion of the table reports our estimates of the probability transition matrix using the entire sample of data from 1993 - 2011. The bottom part of the table reports estimates of the probability of beginning in specific bins and ending in other specific bins, based on the probability transition matrix at the top of the table. To make these calculations, we assign every individual REIT z-statistic value to one of seven bins. Bin 1 has the REITs with the lowest relative efficiency measure (i.e., the most negative z-statistic), while bin 7 has the REITs with the highest relative efficiency measure (i.e., the most positive z-statistic). We center Bin 4 on 1.01, so it contains REITs which are efficient in the sense that their variance ratio is statistically indistinguishable from one. We set all the bin sizes at 0.03.

Table 4: Transition Probability Matrix Estimates, Between Regulatory Changes

Period: 1993-1997	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	20.7%	25.0%	27.3%	50.0%	100.0%
Bins 3/4/5:	65.0%	75.0%	72.7%	50.0%	0.0%
Bins 3/4:	54.7%	50.0%	45.5%	50.0%	0.0%
Bins 6/7:	0.0%	0.0%	0.0%	0.0%	0.0%
Period: 1998-2000	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	32.1%	0.0%	66.7%	30.0%	0.0%
Bins 3/4/5:	64.4%	100.0%	33.3%	60.0%	100.0%
Bins 3/4:	52.3%	50.0%	26.7%	50.0%	100.0%
Bins 6/7:	3.5%	0.0%	0.0%	10.0%	0.0%
Period: 2001-2006	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	29.1%	0.0%	42.1%	66.7%	0.0%
Bins 3/4/5:	70.0%	100.0%	57.9%	33.3%	100.0%
Bins 3/4:	67.8%	90.0%	52.6%	33.3%	100.0%
Bins 6/7:	0.9%	0.0%	0.0%	0.0%	0.0%
Period: 2009-2011	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	6.0%	0.0%	20.0%	0.0%	0.0%
Bins 3/4/5:	91.2%	0.0%	80.0%	100.0%	100.0%
Bins 3/4:	57.7%	0.0%	60.0%	66.7%	80.0%
Bins 6/7:	2.8%	0.0%	0.0%	0.0%	0.0%

Note: Each of the four parts of the table reports our estimates of the probability of beginning in specific bins and ending in other specific bins holding constant market microstructure and regulation. All these entries are based on estimated probability transition matrices specific to the indicated period. To make these calculations, we assign every individual REIT z-statistic value to one of seven bins. Bin 1 has the REITs with the lowest relative efficiency measure (i.e., the most negative z-statistic), while bin 7 has the REITs with the highest relative efficiency measure (i.e., the most positive z-statistic). We center Bin 4 on 1.01, so it contains REITs which are efficient in the sense that their variance ratio is statistically indistinguishable from one. We set all the bin sizes at 0.03.

Table 5: Transition Probability Matrix Estimates, Regulatory Changes

Quotes in 1/8ths vs. 1/16ths	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	17.4%	58.8%	30.4%	0.0%	50.0%
Bins 3/4/5:	65.8%	41.2%	69.6%	50.0%	50.0%
Bins 3/4:	41.3%	35.3%	60.9%	0.0%	0.0%
Bins 6/7:	9.7%	0.0%	0.0%	50.0%	0.0%

Quotes in 1/16ths vs. Decimals	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	24.4%	37.5%	27.8%	0.0%	0.0%
Bins 3/4/5:	52.3%	62.5%	55.6%	66.7%	0.0%
Bins 3/4:	43.1%	37.5%	50.0%	66.7%	0.0%
Bins 6/7:	23.4%	0.0%	16.7%	33.3%	100.0%

Reg NMS	Unconditional	Probability if Starting in Bin			
Probability of Ending in	Estimate	1	2	6	7
Bins 1/2:	37.1%	55.6%	22.7%	100.0%	0.0%
Bins 3/4/5:	42.9%	44.4%	68.2%	0.0%	0.0%
Bins 3/4:	36.9%	44.4%	63.6%	0.0%	0.0%
Bins 6/7:	20.0%	0.0%	9.1%	0.0%	100.0%

Note: Each of the three parts of the table reports our estimates of the probability of beginning in specific bins and ending in other specific bins around changes in market microstructure and regulation. All these entries are based on estimated probability transition matrices specific to the indicated period. These transition probability matrices use z-statistics created in the usual manner from variance ratios for all traded REITs in the one-year period before the indicated date and the one-year period after this date. We delete two weeks of trading on either side of the indicated date, and adjust start and ending dates so that there is a full year of trading in the before and after samples.

Table 6: Boehmer-Kelley Model Estimates

RHS Variables	Quantile (Bootstrap SE)									
	OLS	0.05	0.1	0.2	0.5	0.8	0.9	0.95		
TIO _{<i>i,t-1</i>}	-0.0143*** [0.003]	-0.0003 [0.001]	-0.0011 [0.001]	-0.003 [0.002]	-0.0096*** [0.002]	-0.0121*** [0.005]	-0.0144** [0.006]	0.95 [0.008]		
1-VR _{<i>i,t-1</i>}	0.1779*** [0.018]	0.0063 [0.005]	0.0290*** [0.007]	0.0471*** [0.009]	0.1550*** [0.017]	0.2321*** [0.026]	0.2620*** [0.027]	0.2917*** [0.047]		
QSpread/Depth _{<i>i,t-1</i>}	0.0269 [0.052]	-0.1651 [0.116]	-0.4311 [0.309]	-0.2602 [0.437]	-0.0685 [0.380]	0.0526 [0.604]	0.0151 [1.117]	2.1350* [1.269]		
ln(MV) _{<i>i,t-1</i>}	0.0051*** [0.001]	0.0006*** [0.000]	0.0014*** [0.000]	0.0022*** [0.000]	0.0055*** [0.001]	0.0084*** [0.001]	0.0079*** [0.001]	0.0078*** [0.002]		
ln(Price) _{<i>i,t-1</i>}	-0.0072*** [0.001]	-0.0009*** [0.000]	-0.0026*** [0.001]	-0.0039*** [0.001]	-0.0078*** [0.001]	-0.0147*** [0.002]	-0.0156*** [0.003]	-0.0181*** [0.003]		
Regime 2 _{<i>i,t</i>}	0.0029** [0.001]	0.0010** [0.000]	0.0005 [0.001]	0.0008 [0.001]	0.0036*** [0.001]	0.0046** [0.002]	0.0068*** [0.002]	0.0068 [0.004]		
Regime 3 _{<i>i,t</i>}	0.0116*** [0.002]	0.0011** [0.000]	0.0015** [0.001]	0.0038*** [0.001]	0.0114*** [0.002]	0.0196*** [0.002]	0.0244*** [0.003]	0.0287*** [0.005]		
Reg NMS _{<i>i,t</i>}	-0.0176*** [0.002]	-0.0016*** [0.001]	-0.0035*** [0.001]	-0.0060*** [0.001]	-0.0169*** [0.002]	-0.0275*** [0.002]	-0.0334*** [0.004]	-0.0368*** [0.004]		
Constant	0.0027 [0.007]	-0.0023 [0.002]	-0.0048 [0.004]	-0.0039 [0.004]	-0.0141** [0.006]	0.0026 [0.010]	0.0320** [0.015]	0.0551*** [0.020]		
R ² / Pseudo-R ²	0.048	0.068	0.008	0.011	0.037	0.065	0.076	0.077		

Note: Dependent variable is |1 - Variance Ratio|. For OLS, we report clustered, robust standard errors in brackets with statistical significance as follows, *** p<0.01, ** p<0.05, * p<0.1. We generate standard errors for the quantile estimates using bootstrap methods with 250 replications. Sample size is 8,104. The values of the dependent variable at each quantile are as follows: 5%: 0.003, 10%: 0.007, 20%: 0.014, 50%: 0.040, 80%: 0.083, 90%: 0.109, and 95%: 0.134.

Table 7: OLS and Quantile Estimates of Modified Boehmer-Kelley Model

RHS Variables	Quantile (Bootstrap SE)									
	OLS	0.05	0.1	0.2	0.5	0.8	0.9	0.95		
TIO _{<i>i,t-1</i>}	-0.0093*** [0.004]	-0.0011 [0.001]	-0.0023 [0.002]	-0.0038* [0.002]	-0.0102*** [0.003]	-0.0150*** [0.005]	-0.0158** [0.007]	-0.0135 [0.009]		
1-VR _{<i>i,t-1</i>}	0.1451*** [0.018]	0.0079* [0.004]	0.0255*** [0.008]	0.0441*** [0.009]	0.1413*** [0.020]	0.2100*** [0.026]	0.2413*** [0.033]	0.2731*** [0.046]		
QSpread/Depth _{<i>i,t-1</i>}	0.0610 [0.047]	-0.1602 [0.173]	-0.3075 [0.345]	-0.2224 [0.518]	-0.0897 [0.439]	0.0606 [0.601]	0.0308 [1.080]	0.153 [1.166]		
ln(Mkt Val) _{<i>i,t-1</i>}	0.0075*** [0.001]	0.0099*** [0.000]	0.0023*** [0.001]	0.0034*** [0.001]	0.0077*** [0.001]	0.0120*** [0.001]	0.0129*** [0.002]	0.0124*** [0.003]		
ln(Price) _{<i>i,t-1</i>}	-0.0112*** [0.002]	-0.0008* [0.000]	-0.0030*** [0.001]	-0.0046*** [0.001]	-0.0102*** [0.002]	-0.0167*** [0.002]	-0.0192*** [0.003]	-0.0221*** [0.005]		
Regime 2 _{<i>i,t</i>}	0.0035** [0.002]	0.0009 [0.001]	0.0005 [0.001]	0.0002 [0.001]	0.0044*** [0.002]	0.0063** [0.003]	0.0082*** [0.003]	0.0106* [0.006]		
Regime 3 _{<i>i,t</i>}	0.0117*** [0.002]	0.0113*** [0.001]	0.0008 [0.001]	0.0025* [0.001]	0.0118*** [0.002]	0.0211*** [0.004]	0.0268*** [0.004]	0.0325*** [0.007]		
Reg NMS _{<i>i,t</i>}	-0.0177*** [0.002]	-0.0011** [0.001]	-0.0032*** [0.001]	-0.0055*** [0.001]	-0.0172*** [0.002]	-0.0277*** [0.003]	-0.0353*** [0.004]	-0.0433*** [0.006]		
Analyst Cov. _{<i>i,t-1</i>}	-0.0004** [0.000]	-0.0001 [0.000]	-0.0002* [0.000]	-0.0002 [0.000]	-0.0002 [0.000]	-0.0005** [0.000]	-0.0007** [0.000]	-0.0005 [0.001]		
Option Vol. _{<i>i,t-1</i>}	0.0022* [0.001]	0.0027* [0.001]	0.0021 [0.002]	0.0021* [0.001]	0.0025* [0.001]	0.0016 [0.003]	-0.0015 [0.004]	0.001 [0.006]		
Option OI _{<i>i,t-1</i>}	-0.0003*** [0.000]	-0.0002** [0.000]	-0.0001 [0.000]	-0.0002** [0.000]	-0.0003*** [0.000]	-0.0004** [0.000]	-0.0002 [0.000]	-0.0004 [0.000]		
Quotes/ Δ Quotes _{<i>i,t-1</i>}	0.0059 [0.005]	-0.0005 [0.001]	-0.0016 [0.002]	-0.0019 [0.004]	0.0084 [0.007]	0.0109 [0.011]	0.0200* [0.012]	0.0455** [0.022]		
Quotes/Trades _{<i>i,t-1</i>}	0.0001** [0.000]	0.0000 [0.000]	0.0000 [0.000]	0.0000* [0.000]	0.0001*** [0.000]	0.0002** [0.000]	0.0002** [0.000]	0.0006** [0.000]		
Constant	-0.0202* [0.011]	-0.0173* [0.010]	-0.0130** [0.005]	-0.0143** [0.007]	-0.0351*** [0.009]	-0.0367*** [0.013]	-0.0216 [0.019]	0.0024 [0.029]		
Property dummies	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ² / Pseudo-R ²	0.074	0.072	0.007	0.015	0.041	0.07	0.083	0.085		

Note: Dependent variable is |1 - Variance Ratio|. For OLS, we report clustered, robust standard errors in brackets with statistical significance as follows, *** p<0.01, ** p<0.05, * p<0.1. We generate standard errors for the quantile estimates using bootstrap methods with 250 replications. Sample size is 8,104. The values of the dependent variable at each quantile are as follows: 5%: 0.003, 10%: 0.007, 20%: 0.014, 50%: 0.040, 80%: 0.083, 90%: 0.109, and 95%: 0.134.

Table 8: Marginal Impact of SIO-Type Institutional Investors on Efficiency

RHS Variables	OLS	Quantile (Bootstrap SE)						
		0.05	0.1	0.2	0.5	0.8	0.9	0.95
SIO _{<i>i,t-1</i>}	-0.0011 [0.008]	0.0011 [0.003]	-0.0008 [0.004]	0.0002 [0.005]	-0.0066 [0.008]	0.005 [0.015]	0.0003 [0.017]	0.0098 [0.025]
TIO _{<i>i,t-1</i>}	-0.0088** [0.004]	-0.0016 [0.002]	-0.0019 [0.002]	-0.0039 [0.003]	-0.0071 [0.005]	-0.0167* [0.009]	-0.016 [0.010]	-0.0165 [0.013]
11-VR _{<i>i,t-1</i>}	0.1451*** [0.018]	0.0073 [0.005]	0.0260*** [0.007]	0.0436*** [0.009]	0.1419*** [0.018]	0.2087*** [0.027]	0.2414*** [0.032]	0.2763*** [0.047]
QSpread/Depth _{<i>i,t-1</i>}	0.0611 [0.047]	-0.1592 [0.170]	-0.3017 [0.334]	-0.2211 [0.538]	-0.0889 [0.499]	0.0604 [0.661]	0.0304 [1.141]	0.5794 [1.255]
ln(MktVal) _{<i>i,t-1</i>}	0.0075*** [0.001]	0.0010*** [0.000]	0.0023*** [0.000]	0.0034*** [0.001]	0.0075*** [0.001]	0.0120*** [0.002]	0.0129*** [0.002]	0.0128*** [0.003]
ln(Price) _{<i>i,t-1</i>}	-0.0112*** [0.002]	-0.0009** [0.000]	-0.0030*** [0.001]	-0.0046*** [0.001]	-0.0101*** [0.001]	-0.0169*** [0.002]	-0.0191*** [0.003]	-0.0219*** [0.005]
Regime 2 _{<i>i,t</i>}	0.0035** [0.002]	0.0009 [0.001]	0.0004 [0.001]	0.0002 [0.001]	0.0040** [0.002]	0.0060** [0.003]	0.0082*** [0.003]	0.0105* [0.006]
Regime 3 _{<i>i,t</i>}	0.0116*** [0.002]	0.0011 [0.001]	0.0007 [0.001]	0.0025* [0.002]	0.0110*** [0.002]	0.0208*** [0.004]	0.0269*** [0.004]	0.0327*** [0.007]
Reg NMS _{<i>i,t</i>}	-0.0177*** [0.002]	-0.0012** [0.001]	-0.0034*** [0.001]	-0.0055*** [0.001]	-0.0172*** [0.002]	-0.0277*** [0.003]	-0.0352*** [0.004]	-0.0433*** [0.006]
Analyst Cov _{<i>i,t-1</i>}	-0.0004** [0.000]	-0.0001 [0.000]	-0.0002* [0.000]	-0.0002 [0.000]	-0.0002 [0.000]	-0.0005** [0.000]	-0.0007** [0.000]	-0.0005 [0.001]
Option Vol _{<i>i,t-1</i>}	0.0022* [0.001]	0.0030** [0.001]	0.0021 [0.001]	0.0023* [0.001]	0.0022 [0.001]	0.0017 [0.003]	-0.0015 [0.004]	0.0012 [0.006]
Option OI _{<i>i,t-1</i>}	-0.0003*** [0.000]	-0.0002*** [0.000]	-0.0001 [0.000]	-0.0002** [0.000]	-0.0003*** [0.000]	-0.0004*** [0.000]	-0.0002 [0.000]	-0.0004 [0.000]
Quotes/ Δ Quotes _{<i>i,t-1</i>}	0.0060 [0.005]	-0.0005 [0.001]	-0.0018 [0.002]	-0.0017 [0.004]	0.0084 [0.007]	0.0098 [0.012]	0.0200 [0.013]	0.0421 [0.026]
Quotes/Trades _{<i>i,t-1</i>}	0.0001** [0.000]	0.0000 [0.000]	0.0000 [0.000]	0.0000* [0.000]	0.0001*** [0.000]	0.0002** [0.000]	0.0002** [0.000]	0.0006** [0.000]
Constant	-0.0200* [0.010]	-0.0065** [0.003]	-0.0129** [0.005]	-0.0145** [0.006]	-0.0333*** [0.009]	-0.0360** [0.015]	-0.0221 [0.018]	-0.0043 [0.031]
Property dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ² / Pseudo-R ²	0.074	0.007	0.01	0.015	0.041	0.07	0.083	0.085

Note: Dependent variable is |1 - Variance Ratio|. For OLS, we report clustered, robust standard errors in brackets with statistical significance as follows, *** p<0.01, ** p<0.05, * p<0.1. We generate standard errors for the quantile estimates using bootstrap methods with 250 replications. Sample size is 8,104. The values of the dependent variable at each quantile are as follows: 5%: 0.003, 10%: 0.007, 20%: 0.014, 50%: 0.040, 80%: 0.083, 90%: 0.109, and 95%: 0.134.

Table 9: Marginal Impact of LIO-Type Institutional Investors on Efficiency

RHS Variables	Quantile (Bootstrap SE)							
	OLS	0.05	0.1	0.2	0.5	0.8	0.9	0.95
LIO _{<i>i,t-1</i>}	-0.0262*** [0.010]	-0.0049* [0.003]	-0.0110** [0.005]	-0.0170** [0.007]	-0.0256** [0.012]	-0.0519*** [0.017]	-0.0519*** [0.018]	-0.0872*** [0.029]
TIO _{<i>i,t-1</i>}	-0.0057 [0.004]	-0.0002 [0.001]	-0.0006 [0.002]	-0.0010 [0.002]	-0.0071* [0.004]	-0.0063 [0.005]	-0.0072 [0.007]	-0.0001 [0.010]
1-VR _{<i>i,t-1</i>}	0.1443*** [0.018]	0.0079* [0.004]	0.0246*** [0.008]	0.0419*** [0.010]	0.1413*** [0.017]	0.2159*** [0.026]	0.2446*** [0.029]	0.2651*** [0.042]
QSpread/Depth _{<i>i,t-1</i>}	0.0603 [0.047]	-0.1443 [0.167]	-0.2976 [0.336]	-0.2033 [0.505]	-0.0954 [0.374]	0.0577 [0.699]	0.0292 [1.090]	1.7329 [1.232]
ln(MktVal) _{<i>i,t-1</i>}	0.0077*** [0.001]	0.0010*** [0.000]	0.0025*** [0.000]	0.0037*** [0.001]	0.0078*** [0.001]	0.0124*** [0.001]	0.0138*** [0.002]	0.0143*** [0.003]
ln(PPrice) _{<i>i,t-1</i>}	-0.0113*** [0.002]	-0.0009** [0.000]	-0.0033*** [0.001]	-0.0050*** [0.001]	-0.0104*** [0.001]	-0.0172*** [0.002]	-0.0201*** [0.003]	-0.0255*** [0.004]
Regime 2 _{<i>i,t</i>}	0.0031* [0.002]	0.0008 [0.001]	0.0003 [0.001]	0.0001 [0.001]	0.0036** [0.002]	0.0060** [0.003]	0.0064** [0.003]	0.0084 [0.006]
Regime 3 _{<i>i,t</i>}	0.0122*** [0.002]	0.0011* [0.001]	0.0009 [0.001]	0.0030** [0.002]	0.0115*** [0.002]	0.0227*** [0.004]	0.0276*** [0.004]	0.0315*** [0.007]
Reg NMS _{<i>i,t</i>}	-0.0162*** [0.002]	-0.0009 [0.001]	-0.0027*** [0.001]	-0.0044*** [0.001]	-0.0152*** [0.002]	-0.0248*** [0.003]	-0.0322*** [0.004]	-0.0427*** [0.006]
Analyst Cov _{<i>i,t-1</i>}	-0.0003* [0.000]	-0.0001 [0.000]	-0.0001 [0.000]	-0.0002 [0.000]	-0.0001 [0.000]	-0.0005** [0.000]	-0.0007** [0.000]	-0.0004 [0.000]
Option Vol _{<i>i,t-1</i>}	0.0021* [0.001]	0.0027* [0.001]	0.0020 [0.001]	0.0019* [0.001]	0.0019 [0.001]	0.0018 [0.003]	-0.0005 [0.004]	-0.0016 [0.006]
Option OI _{<i>i,t-1</i>}	-0.0003*** [0.000]	-0.0002** [0.000]	-0.0001* [0.000]	-0.0002** [0.000]	-0.0002** [0.000]	-0.0004** [0.000]	-0.0003 [0.000]	-0.0002 [0.000]
Quotes/ Δ Quotes _{<i>i,t-1</i>}	0.0047 [0.005]	-0.0007 [0.001]	-0.0024 [0.002]	-0.0015 [0.005]	0.0079 [0.006]	0.0088 [0.011]	0.0239* [0.012]	0.0333 [0.024]
Quotes/Trades _{<i>i,t-1</i>}	0.0001** [0.000]	0.0000 [0.000]	0.0000 [0.000]	0.0000 [0.000]	0.0001*** [0.000]	0.0002** [0.000]	0.0002** [0.000]	0.0006** [0.000]
Constant	-0.0216** [0.011]	-0.0065** [0.003]	-0.0136*** [0.005]	-0.0176*** [0.007]	-0.0361*** [0.009]	-0.0402*** [0.014]	-0.0306* [0.017]	-0.0089 [0.029]
Property dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ² / Pseudo-R ²	0.075	0.007	0.011	0.015	0.042	0.072	0.084	0.087

Note: Dependent variable is |1 - Variance Ratio|. For OLS, we report clustered, robust standard errors in brackets with statistical significance as follows, *** p<0.01, ** p<0.05, * p<0.1. We generate standard errors for the quantile estimates using bootstrap methods with 250 replications. Sample size is 8,104. The values of the dependent variable at each quantile are as follows: 5%: 0.003, 10%: 0.007, 20%: 0.014, 50%: 0.040, 80%: 0.083, 90%: 0.109, and 95%: 0.134.

Table 10: Mean and Quantile Estimates of Simple Dynamic Model

RHS Variables	Quantile Estimates					
	OLS Estimates	0.05	0.1	0.5	0.9	0.95
$VR_{i,t-1}$	0.0878*** [0.014]	0.1210*** [0.039]	0.0942*** [0.024]	0.0943*** [0.014]	0.0334* [0.018]	0.0497*** [0.017]
$ 1-VR _{i,t-1}$	0.6966*** [0.035]	0.6217*** [0.064]	0.6824*** [0.035]	0.6817*** [0.034]	1.2687*** [0.080]	1.3848*** [0.101]
$Pos* 1-VR _{i,t-1}$	-1.1260*** [0.025]	-1.1292*** [0.083]	-1.2024*** [0.045]	-1.0907*** [0.024]	-1.5637*** [0.070]	-1.7180*** [0.087]
Regime $2_{i,t}$	-0.001 [0.002]	-0.0097* [0.005]	-0.0017 [0.003]	-0.0027* [0.001]	0.0041* [0.002]	0.0056 [0.003]
Regime $3_{i,t}$	-0.0059*** [0.002]	-0.0248*** [0.005]	-0.0177*** [0.003]	-0.0072*** [0.002]	0.0055*** [0.002]	0.0117*** [0.003]
Reg NMS $_{i,t}$	0.0094*** [0.002]	0.0237*** [0.005]	0.0194*** [0.003]	0.0094*** [0.002]	0.0004 [0.002]	-0.0072** [0.003]
Constant	0.8927*** [0.014]	0.8949*** [0.039]	0.8392*** [0.024]	0.8933*** [0.014]	0.9790*** [0.018]	0.9791*** [0.016]
R^2 / Pseudo- R^2	0.360	0.363	0.178	0.243	0.259	0.250

Note: Dependent variable is the variance ratio. We include dummy variables for the period when quotes were in 1/16ths (Regime 2), quotes are in decimals (Regime 3), and for the period when Reg NMS is in place (Reg NMS). For OLS, we report clustered, robust standard errors in brackets with statistical significance as follows, *** p<0.01, ** p<0.05, * p<0.1. We generate standard errors for the quantile estimates using bootstrap methods with 250 replications. Sample size is 8,375. The values of the dependent variable at each quantile are as follows: 5%: 0.871, 10%: 0.897, 20%: 0.925, 35%: 0.953, 50%: 0.975, 65%: 0.995, 80%: 1.018, 90%: 1.043, and 95%: 1.066.

Table 11: Efficiency Adjustments Across Microstructure Regimes

RHS Variables	Baseline	Regime 2	Regime 3	Reg NMS
$VR_{i,t-1}$	0.0521 [0.0377]	0.1557*** [0.0232]	0.0947*** [0.0163]	-0.0059 [0.0532]
$ 1-VR_{i,t-1}^- $	0.5788*** [0.0737]	0.7429*** [0.0688]	0.7520*** [0.0403]	0.5285*** [0.1217]
$ 1-VR_{i,t-1}^+ $	-0.4047*** [0.0591]	-0.3778*** [0.0386]	-0.4340*** [0.0305]	-0.3663*** [0.0890]

Note: Dependent variable is variance ratio (VR). We indicate the period when quotes were in 1/8ths as the Baseline, quotes in 1/16ths as Regime 2, quotes decimals as Regime 3, and the period when Reg NMS is in place as Reg NMS. Standard errors in brackets are clustered, robust standard errors. Statistical significance as follows, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.