The Dynamics of REIT Market Efficiency*

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Abstract

We study the dynamics of pricing efficiency in the equity REIT market from 1993 to 2011. We measure pricing efficiency at the firm level using variance ratios calculated from quote midpoints in the TAQ database. We find five main results. First, on average the market is efficient, with variance ratios close to one. However, in any given year, there is considerable cross-sectional variation in variance ratios, suggesting at least some firms are priced inefficiently. Second, pricing efficiency is related to changes in the market microstructure over the sample period. Changes from 1/8th to 1/16th tick sizes improved pricing efficiency, while 1/16ths to decimals did not. Third, higher institutional ownership, especially ownership by institutions that trade frequently, is related to better pricing efficiency. Fourth, REITs that are included in the S&P 500 and S&P 400 are priced more efficiently than other REITs. For the S&P 500 firms we find evidence that this was purely driven by sample selection, while for S&P 400 firms, we find evidence that it is inclusion in the index that drives efficiency. Finally, we find evidence that firm investment activity can influence pricing efficiency. Firms engaged in greater asset expanding activity tend to be priced more efficiently than other firms.

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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. Price discovery is no less important for the companies themselves. The capital constrained nature of the REIT industry makes efficient access to capital a critical issue for the industry. As such, understanding the determinants of efficient pricing in the REIT level is important to both investors and managers alike.

Although there is a literature examining the efficiency of REITs, these papers either exclusively examine index returns,[1] or where they do use asset level data, they don't examine the cross-section.[2] In this sense they are really interested in examining market level efficiency. While this is interesting, efficiency at the asset level is more fundamental. Many investors trade individual names not indices, and even index investors care about asset level efficiency because it is these stocks that create the indexes they trade. Furthermore, from a managerial perspective, managers are more concerned about the efficient pricing of their stock than the pricing of the market in general.

With this motivation in mind, there have been studies examining asset level efficiency in the broader equities markets.[3] However, these studies typically exclude REITs and other securities such as ADRs and ETFs.[4] This leads to a gap in direct evidence on the issue of firm level efficiency in REITs. The question then becomes, are REITs different enough from the rest of the equities markets to warrant a separate investigation? We believe this is the case, because efficiency is one dimension along which REITs are plausibly different from a regular sample of equities for several reasons. First, REITs are typically small to midcap companies that are heavily dependent on capital markets to fund investment. The size of the firms suggests that a poor market microstructure may play a role in their pricing efficiency. Their reliance on capital markets to fund investment suggests that they may face higher levels of monitoring from capital markets which could improve efficiency.

[1] See, for example, Stevenson (2002), and Jirasakuldech and Knight (2005).
[2] See for example, Nelling and Gyourko (1998), and Kuhle and Alvayay (2000).
[3] See Boehmer and Kelley (2009), and Conrad, Wahal, and Xiang (2015) for recent examples.
[4] For recent examples of this sample selection, see O'Hara and Ye (2011) and Conrad, Wahal, and Xiang (2015).

Second, part of the requirements to maintain REIT tax status are restrictions on what assets the REIT can own and on what sources its income comes from.[5] The end result of these restrictions is that the equity REITs in our sample hold commercial properties as their assets. Furthermore, REITs tend to specialize by property type and/or location. The ability to examine the company's underlying assets and to also find comparable pricing of these assets (although in a somewhat illiquid market) provides a degree of transparency not observed in a regular sample of firms. This greater transparency should lead to greater price efficiency. Finally, although the REIT tax structure has existed in the US since the early 1960s, the industry has gone through massive structural changes since the early 1990s. Prior to this time there were restrictions on institutional ownership and the industry was viewed as fairly unsophisticated. Probably the best indication of this is that it wasn't until 2001 that REITs were even eligible to join the major S&P indexes. Taken together, these factors all suggests that REIT efficiency warrants its own investigation.

The first contribution of our paper is to provide a comprehensive assessment of REIT market efficiency at the level of the individual REIT over the modern REIT era. Prior asset level studies typically focused on time periods before 1993. At this time the REIT market was characterized by micro cap stocks and limited investor attention. A vast change from what we view as the REIT market today. We construct the empirical distribution of market efficiency using REIT-level variance ratios estimated using quarterly samples of 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 average 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 at any given point in time.

We also document 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.[6] In addition, the SEC rule, Reg NMS, went into effect in 2007, and this

[5] See 26 U.S.C §856 for details.

[6] A careful treatment is Foucault, Pagano, and Röell (2013).

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, and largely unaffected by shifting to decimal quotes and by Reg NMS.

The second 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 (2009)), there is, to the best of our knowledge, no comparable investigation in the REIT literature. We find several main characteristics that drive REIT efficiency. First, as in Boehmer and Kelley (2009) we find that higher institutional ownership is related to better pricing efficiency. A one standard deviation increase is institutional ownership is related to a 6.3% in measured efficiency. Interestingly, we find that it is ownership by institutions that tend to actively trade their portfolios that is driving this result. Approximately 75% of the benefit of institutional ownership is attributable to these funds.

Second, REITs that are included in the S&P 500 and S&P 400 trade more efficiently than other REITs, while there is no effect for the small cap S&P 600. In terms of economic magnitude, S&P 500 firms are 25% more efficient and S&P 400 firms are 19% more efficient than other firms. To address the issue of identification - that indexes may choose to only include efficient firms - we examine pre- and post-inclusion efficiency in small windows around the index inclusion date. We find that there is no significant difference in efficiency for S&P 500 firms, but there is a significant improvement in efficiency for S&P 400 firms. This suggests that the REITs that were added to the S&P 500 were already trading quite efficiently before they were added to the index. Inclusion in the midcap S&P 400 is however a significant event. The likely explanation for this is that addition to this index takes a firm from small cap obscurity and places it on the investment screens of more investors. We don't observe this effect for the S&P 600 simply because these firms are still small caps even after addition to the index.

Finally, we document that firm investment activity can impact efficiency. In our sample, asset expanding activities tend to improve efficiency, while asset contracting activities tend to decrease efficiency. Although the economic magnitude of the effect is small.

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 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 explore the efficiency of both US and international REIT markets, although these papers almost exclusively focus on market level implications and make no real examination of the cross-section. The results in this literature have been mixed. Seck (1996) examines the substitutability of direct and securitized real estate and finds that while direct real estate is inefficient, securitized real estate is priced efficiently at the index level. Nelling and Gyourko (1998) examine runs tests for a sample of REITs and find that although some REITs appear to be priced inefficiently, the market as a whole appears efficient. Jirasakuldech and Knight (2005) examine REIT index level returns and are unable to reject the null hypothesis of a random walk using variance ratio tests, and Schindler, Rottke, and Füss (2010) also supports this conclusion for US data, but show that internationally, most securitized real estate markets reject the null hypothesis of a random walk. These results contrast with Kuhle and Alvayay (2000), who find that the majority of individual REITs deviate significantly from a random walk, suggesting large scale inefficiency in the market. In general, the results reported in the literature are quite sensitive to the frequency of data employed, the time period examined, and the form of tests used.

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.[7] Much of the published research on securitized real estate market efficiency was completed nearly 20 years ago, well before changes in market structure and the establishment of the national market system in 2007 (Reg NMS).[8] The evidence from these early studies on REIT market efficiency is somewhat mixed, but generally points to rising efficiency over time.[9]

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 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.[10] For example, sophisticated analyses at the nexus of equity market efficiency and market quality such as Chordia, Roll, and Subrahmanyam (2011) and O'Hara and Ye (2011) explicitly exclude REITs from their data samples. An interesting study of market efficiency and

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

[8] Indeed, 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).

[9] See, for example, Nelling and Gyourko (1998).

[10] Somewhat 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.

market quality in the post-Reg NMS world by Conrad, Wahal, and Xiang (2015) also excludes REITs.

The paper most closely related to this one is Boehmer and Kelley (2009). They examine the cross-section of measured price efficiency for an extensive sample of regular equities. Their focus is on the relationship between institutional ownership and price efficiency. They find that higher institutional ownership leads to better pricing efficiency.

There is a thriving literature focused on REIT market quality analysis that draws on the market microstructure literature. Cannon and Cole (2011) focused on changes in REIT market liquidity over time, concluding that it has improved in 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 important theme in these studies is the differences between transaction costs and liquidity in securitized (i.e., public) vs. private markets.[11] 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, Roll, and Subrahmanyam (2011), see O'Hara and Ye (2011)).

[11] See 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, Roll, and Subrahmanyam (2011). In his other work, REITs are not part of the data used in the analysis.

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. We then exploit the model of proposed in Boehmer and Kelley (2009) to study the cross-section of market efficiency in the REIT market. In this section, we describe our data sources and aspects of our measurements.

3.1 Quotes

To examine firm level efficiency in the REIT market, we start with a comprehensive list of equity REITs that have existed between 1993 to 2011. We then match this list to the TAQ dataset. The TAQ dataset begins in 1993, so this places a limit on the historic sample. However, given that 1993 also represents essentially the start of the modern REIT era, it is also the logical starting point from any examination of REIT efficiency. The structural and economic differences that have occurred in the modern REIT are likely to have significant affects on efficiency. So limiting our focus to the post-1993 period not only limits these confounding effects, but also makes our results more applicable to the REIT industry that we observe today.

The intra-day TAQ data includes both the complete record of trades and the quote history for each day for each REIT. It is possible to calculate variance ratios using either traded prices or quote midpoints. The potential problem with using traded prices is going to be induced negative serial correlation in prices because of bid/ask bounce. Given the small to midcap nature of the sample, especially in the early part of the sample, this problem is likely to be quite severe.[12] For this reason we follow Boehmer and Kelley (2009) and Conrad, Wahal, and Xiang (2015) and employ quote midpoints to estimate variance ratios rather than prices. To calculate the series of quote

[12]This may in part explain the mixed results in the prior literature on REIT efficiency. These papers use realized prices, and depending on the frequency of prices and time period examined, much of the deviation from random walks may be explained by bid/ask bounce. In unreported analysis we did calculate variance ratios using traded prices and do observe severe serial correlation, especially in the start of the sample examined.

midpoints, we employ the methodology of Holden and Jacobsen (2014).[13]

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 and Ye (2011), Boehmer and Kelley (2009), and Conrad, Wahal, and Xiang (2015), by relying on a variance ratio calculation. As developed in Lo and Mackinlay (1988), 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). If an asset 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, Wahal, and Xiang (2015) define their sampling intervals in 15 seconds, which we could mimic, but only for the years 2006 -2011. Instead, we follow O'Hara and Ye (2011) 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 an reasonable balance, and it permits us to track efficiency consistently over our entire sample.

The basic test designed by Lo and Mackinlay (1988) 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 Lo

[13]This eliminates quotes from outside normal trading hours, quotes with abnormal conditions, crossed quotes on the same exchange, one-sided bid quotes, quotes with abnormally large spreads, and withdrawn quotes.

and Mackinlay (1988) 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 and i.i.d. increments.[14] 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 i.i.d. assumption.

We recognize the vast literature documenting the weaknesses involving inferences based on a standard VR test.[15] 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 and in the cross-section. As such, the main body of our methodology should mitigate such concerns.

4 REIT Efficiency Over Time

In this section we document the time-series 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. For each 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. In total there are 233 REITs in the sample between 1993 and 2011. The number of REITs trading in a given year varies between 51 in 1993 up to 137 in 1998, dropping to 87 in 2008, and then rising to 100 in 2011, the last year of our data. This pattern reflects the REIT IPO waves of the early and mid-1990s, and then the consolidation of the industry in the early to mid-2000s.

[14] See Lo and Mackinlay (1988) for details.

[15] See, Charles and Darne (2009), for an overview.

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 quarterly variance ratios for each REIT trading in a given year, and repeat for each year from 1993-2011. For each year in the sample, these distributions are depicted in Figure 1. The first thing to note is that the center mass of these distributions is consistently near one, indicating that the typical REIT appears efficient. However, we do observe that the distribution of variance ratios appears to differs across years. Some years, such as 2009, are very tightly centered around one, while other years, such as 2010 have long left tails. Even within a year like 2009 where the distribution is heavily centered at one, we still observe considerable cross sectional variation. This suggests that efficiency is dynamic in nature. 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 1995. The p-value K-S test statistic for that comparison is 0.083, suggesting that we fail to reject the null of equal empirical distributions. 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 13 of the 18 pairwise comparisons (e.g, 1996 vs. 1997, etc.). These test results suggest that the distributions do indeed change over time.[16]

The visual findings in Figure 1 are corroborated by the summary statistics provided in Table 1. In Table 1 we report the descriptive statistics of the quarterly variance ratios by year. In the column headed 'significant' we report the number of variance ratio tests for that year that can reject the null hypothesis of a random walk at the 5% level of significance. In each year we observe that the mean variance ratio is close to one. The lowest average variance ratio occurs in 2003 with a value of 0.946, while the highest average occurs in 2009 with an average variance ratio of 0.998. In each year we observe a significant range in variance ratios, with the lowest and highest variance ratios in any given year differing by approximately 0.5. So while the average suggests efficiency, there are numerous firms each period that are priced inefficiently. This notion is further supported

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

by the variance ratio tests. In total, 24.2% of the variance ratio tests reject the null hypothesis of a random walk at the 5% level of significance. Notice that this level is not constant across years. With a low of 10.9% rejecting in 2001 and a high of 39.9% rejecting in 2003. While there are well known issues with variance ratio tests, the tests do provide further evidence that efficiency in the REIT market is dynamic in nature.

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. 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 2, 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 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. This might impact the efficiency of price discovery by linking order flow across individual exchanges.[17] In Panel C of Figure 2, 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.

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, the data in the second subsection, followed by presentation of panel results in the final subsection.

5.1 Model and Estimation

The empirical approach we adopt to examine the determinants of efficiency is largely predicated on the work of Boehmer and Kelley (2009). The main empirical obstacle in examining firm efficiency

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

is the obvious potential for endogeneity. For instance, it is possible that institutional ownership leads to higher levels of efficiency through a standard information production. However, it is also possible that institutions just have a preference for investing in efficient firms. Lacking a clean natural experiment, the standard approach in the literature has been to regress current measures of efficiency on the lagged dependent variable and lagged explanatory variables:

$$|1 - VR|_{i,t} \quad = \quad \alpha + \beta|1 - VR|_{i,t-1} + \Sigma_{k=1}^{K}\gamma_k X_{k,i,t-1} + \epsilon_{i,t}, \tag{1}$$

where $|1 - VR|_{i,t}$ is the absolute value of one minus the variance ratio of firm i in period t, and $X_{k,i,t-1}$ is a vector of K explanatory variables in period $t-1$. Given the unbalanced panel nature of the sample, we estimate (1) using a standard fixed effect panel model.

Employing raw variance ratios as the dependent variable in (1) is problematic because variance ratios both greater and less than one signal inefficiency. What we expect is that a variable that improves efficiency should lead to variance ratios closer to one. So the relationship could be negative or positive depending on if the variance ratio is greater or less than one. To solve this problem we employ |1-Variance Ratio| (multiplied by 100) as our dependent variable. For this variable, larger values are related to higher levels of inefficiency. The only limitation is that it treats inefficiency symmetrically - deviations above one are the same as deviation below one. Given we have no *a priori* reason to expect asymmetry, we believe this is a reasonable assumption.

In Table 1 we report descriptive statistics for |1-VR|*100, by year. The quarterly variance ratios are calculated as $VR = \frac{Var[r_t(30minutes)]}{2Var[r_t(15minutes)]}$, where $Var[r_t(30minutes)]$ is the variance of 30 minute returns calculated over the quarter and $Var[r_t(15minutes)]$ is the variance of 15 minute returns calculated over the quarter. Returns are calculated from quote midpoint and quote midpoints are calculated from TAQ data using the methods of Holden and Jacobsen (2014). Like for the case of the raw variance ratios in Table 1, we observe both time series and cross sectional variation. We observe the lowest level of average pricing inefficiency in 2009 and the highest level in 2004. In each year we observe considerable variation in inefficiency, once again indicating that not all REITs are being priced efficiently at all points in time.

There are several candidates for explanatory variables, X_K, in this framework. We divide them into four groups: institutional ownership, index inclusion, market microstructure, and information production.

5.1.1 Ownership

One dimension along which REITs potentially differ from regular firms is institutional ownership. Part of the requirements in 26 U.S.C. §856(a)(6) for a REIT to maintain its REIT status and hence preferential tax treatment is diverse ownership.[18] The requirement is that at no time during the second half of the year can five or fewer individuals own, directly or indirectly, 50% or more of the REIT. This effectively limits the ability of owners to build large block positions in the firm. In 1993 a look-through provision was enacted with regards to the five or fewer rule, which relaxed this restriction for pension funds.[19] Although not as binding a constraint as it once was due to the 1993 look-through provision, typically REITs will have ownership restrictions as part of their corporate charter to avoid conflicting with the closely held stock rule. The one place where this is likely to become an issue for institutional owners is in forming controlling stakes in the firm, although it could also be an issue for small firms if institutions were interested in investing large dollar amounts in the firm.

Although the regulation related to institutional ownership is different in REITs compared to regular firms, the role of institutional investors is the same. In our context, informed trading refers to the trader's ability to acquire and accurately assimilate information regarding the asset. All else equal, 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 Boehmer and Kelley (2009) 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.

[18]See Boudry (2011) for a discussion of REIT taxation.
[19]See Downs (1998) for a discussion of the rule change and the situation that lead up to it.

To measure institutional ownership, we follow the methodology proposed by Yan and Zhang (2009), and calculate four institutional ownership variables; we rely on the underlying ownership data from Thomson Financial's 13(f) database. Total Institutional Ownership (TIO) is the level of ownership by all institutions. We then decompose the total level of institutional ownership into three components based on the frequency of trading of the underlying institutions. 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, and Medium-term Institutional Ownership (MIO) is the percentage of ownership of the REIT held by funds in the middle tertile of portfolio turnover. If information is impounded into asset prices through active trading, it is possible that what matters for efficiency is the level of ownership held by active traders.

Figure 3 plots the average level of institutional ownership through time for the sample. As is evident in the figure, all three measures of institutional ownership have increased through time. Part of the explanation for this at least early in the sample is the relaxation of the closely held stock rule discussed above. Although this wouldn't explain the long term trend. The more likely explanation for the long term trend is that our sample covers what is commonly referred to as the new REIT era. During this period of time, REITs have become more integrated with the broader capital markets. Because REITs are capital constrained due to their high payout requirements, they need to raise capital to invest.[20] Thus integration with broader capital markets has become a critical component of the industry's expansion.

In Table 3 we report descriptive statistics for *SIO*, *MIO*, and *LIO* by year for the sample. In Table 3, the overall increasing trend in institutional ownership among REITs is quite evident, but so it the high degree of cross-sectional variation. Even in the early part of the sample when the REIT industry was quite small, we still observed firms with high institutional ownership. Interestingly, this tended to be because of short term institutional owners as opposed to medium or long term owners. The rise in long term owners coincides with inclusion of the REITs in the S&P indices in 2001. Between 2001 and 2011, the average level of *LIO* more than doubled going from 9.6%

[20]See Ott, Riddiogh, and Yi (2005) for a discussion of REIT investment and Boudry (2011) and Boudry, Kallberg, and Liu (2013) for a discussion of REIT payout policy.

to 23.2%. During the same time period the growth in ownership by short-term and medium-term owners was much more modest. The average level of *SIO* increased from 13.1% to 21.7%, while the average level of *MIO* increased from 16.7% to 23.8% The net result being that ownership by the three groups is fairly similar in 2011, with each group on average holding approximately 20-25% of the outstanding shares of a REIT. Notice that although the average level of ownership by each group is similar, at the individual firm level we observe far more concentration, especially for short-term and medium-term owners.

5.1.2 Index Inclusions

One of the substantial changes in the REIT industry over the sample period has been the inclusion of REITs in major market indices.[21] REITs first became eligible to enter the major S&P indices in 2001. Prior to this time, REITs were excluded from all S&P indices. In that year, Equity Office Properties was the first REIT added to the S&P 500. In some sense this was a watershed moment for the REIT industry, because it was the first time that REITs became part of the broader universe of stocks. Since that time, the indexation of the market has been quite dramatic. By 2015, 22 REITs were included in the S&P 500, 31 were included in the mid cap S&P 400, and 31 were included in the small cap S&P 600. As discussed above, inclusion in these indices may explain part of the large increase in long-term institutional owners after 2001, as REITs entered the portfolios of passive index funds. Inclusion in major market indices is likely to improve efficiency by not only improving microstructure fundamentals, but also increasing information production through higher analyst coverage and institutional ownership. It also likely expands the REIT investor base from those focussed on real estate to a larger audience of general equity investors. We obtain S&P index constituents and addition dates from COMPUSTAT, NAREIT, and press releases.

5.1.3 Microstructure

The quality of the trading environment in which a REIT trades is also likely to have a material impact on how efficiently the company is priced. To capture this effect, we include several measures

[21] See Ambrose, Lee, and Peek (2007) for a discussion of REIT index inclusions.

from the microstructure literature to control for this effect in addition to dummy variables related to the quote regime and Reg NMS change discussed earlier.

QS to QD is the ratio of the quoted spread to the quoted depth, both of which are calculated daily from the underlying TAQ data and averaged over the quarter. As Boehmer and Kelley (2009) note (pg. 3755, fn. 18), this combined measure is superior to either individual measure entered alone: "...a decline in quoted spreads is often associated with a contemporaneous decline in quoted size. In this case, a trader benefits from the decline in spread for part of his intended trade. But for a given trade size, he may be worse off if the supply schedule 'behind' the best quote has become steeper. Alternatively, a trader may simply prefer a larger quoted size at a slightly wider spread. " We use the methods outlined in Holden and Jacobsen (2014) to calculate spreads and depth using the TAQ data.

High frequency traders may also impact efficiency. Our first high-frequency trading proxy is *Quote Changes*, the ratio of NBBO quote changes to total NBBO quotes each day (averaged over the quarter). The idea is that a large number of changes in NBBO quotes relative to the total number of NBBO quotes implies changes in demand and supply conditions in the market for shares in a particular REIT. If the number of quote changes is small relative to the total number of quotes, this is typically regarded as evidence of the presence of high-frequency traders in the market. If the number of quote changes is high relative to the number of quotes, this indicates high information flow in the market.

Our second proxy for HFT trading, is *Quotes to Trades*, the ratio of quotes to trades. Our measure is similar to an approach taken in Boehmer, Fong, and Wu (2012). In settings where HFT is important, traders offer quotes and cancel them at very high rates, so that the ratio of quotes to actual trades may be very high. We compute our quarterly measure by taking the average of the number of NBBO quotes each day (from TAQ) to the number of trades (from the CRSP tape).

Illiquidity is also likely to negatively impact the efficiency of pricing. Stocks that are hard to trade are less likely to be targeted by arbitrageurs. To capture this effect, we include *Amihud*, the Amihud (2002) measure as an inverse proxy for the quality of the market in shares for a particular REIT. By definition, the Amihud illiquidity measure is given by $|r|/DVOL$, where the numerator is the absolute value of the return on a given day and the denominator is the dollar volume of trade that same day (and is equal to the firms total market equity value times the firms share turnover on that day). Using CRSP tape data, we calculate the average of this measure over the quarter for each REIT in the sample.

To capture the effect of trading volume, we include *Turnover*, the average daily turnover for the company for the quarter from CRSP. If efficiency and institutional ownership are simply driven by trading volume, then this should hopefully control for that effect.

Finally, firms that are larger or with higher stock prices may be less costly to trade. To control for this we include *Size*, the log of firm market capitalization, and *Price* the log of the firms stock price.

5.1.4 Information Production

Institutions are just one potential avenue of information production for a company. It is also reasonable to expect that the level of information production is not likely to be constant over the life of a REIT. Information production is likely to be higher around the issuance of securities to the market. 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.[22] From NAREIT, we gather a complete record of REIT-specific debt and equity issues during the 1993-2011 period. We use this to construct two dummy variables, *Issued Equity* and *Issued Debt*, 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. *Analysts* is the number of analysts providing coverage for the REIT in a given quarter. Compared to regular firms, the level of analyst coverage in the REIT universe is quite low.[23] Higher analyst coverage should be related to more information production related to the firm, although exactly what effect this will have on pricing efficiency is unclear. Boehmer and Kelley (2009) find evidence that analyst coverage may improve pricing efficiency, but potentially counteracting this effect in REITs is the

[22]See Boudry, Kallberg, and Liu (2011) for a discussion of REIT security issuance decisions.
[23]See Downs and Güner (1999), Downs and Güner (2000), and Boudry, Kallberg, and Liu (2011).

finding of Downs and Güner (1999) and Downs and Güner (2000) that unlike for regular firms, increased analyst attention in REITs leads to lower liquidity. Lower liquidity should, all things equal, lead to less pricing efficiency.

REITs that are engaged in significant investment or divestment activity are also likely to have a different informational environment from other REITs. To proxy this effect, we include Δ *Assets*, the firm's percentage change in total assets during the quarter in our analysis. We obtain the firm's total assets from SNL Financial. We do not lag this variable because the direction of causality is fairly clear. Changes in investment policy should affect firm efficiency, while the opposite is a much harder story to tell.

The final measure of informational transparency we employ is *Rated*, a dummy variable indicating whether the firm has a credit rating with any of the three major rating agencies (S&P, Moody's, and Fitch.) Firms with credit ratings should, all things equal, have greater information transparency. Although the recent literature casting doubt on the information content of ratings is well taken.[24] We obtain rating agency information from SNL Financial.

5.2 Descriptive Statistics

Table 4 reports descriptive statistics for the variables used in the analysis. The sample period covers 1993 to 2011, contains 233 unique REITs, and an unbalanced panel of 7771 firm/quarter observations. As expected from Table 3 the average level of total institutional ownership is 49%, with this being comprised of 17.6% short term owners, 11.7% long term owners, and the remainder being medium term owners. For each ownership variable we observe considerable cross-sectional variation.

On average approximately 3-4% of the sample is in the S&P 500, the midcap S&P 400, and the small cap S&P600 in any quarter. Given that REITs only entered these indices in 2001, those percentages are roughly doubled if you considered only the period of time in which REITs were eligible for the indices. In fact, by the end of our sample period, approximately half the REITs in the sample are in one of those indices. In total, 71 of the 233 REITs in the sample have been

[24] See, for example, Bolton, Frexias, and Shapiro (2012).

part of a major S&P index between 1993 and 2011. We conduct difference in means t-tests of the REITs included in an index versus those not, and find the included REITs tend to be more efficient. For S&P 500 REITs the mean difference in |1-Variance Ratio| (multiplied by 100) is 1.00 with a t-statistic of 3.64, for the S&P 400 it is 0.89 with a t-statistic of 4.1, and for the S&P 600 it is 0.88 with a t-statistic of 4.58.

For all of the microstructure variables, we observe a high degree of variation in the sample. Mean level of *Amihud* is 0.794, on average 14.4% of quotes are related to quote changes, and there are 12.44 quotes per trade. The average daily turnover in the sample is 0.515%.

Following Boehmer and Kelley (2009) we control of share price and firm size in our analysis. The small/mid-cap nature of the REIT universe is evident in Table 4, with the average firm size being $1.2B. Notice that although we concentrate on only one industry, there is a great deal of cross-sectional variation firm size in the sample. The one caveat is that even the largest firm in the sample has a market cap of only $17.8B. So this is very much a small/midcap sample, but that is also interesting in that most microstructure studies tend to focus on larger firms.

Turning to the information production proxies, we observe that on average 36.2% of firms in any given quarter have a credit rating with one of the three major rating agencies. 10.5% of firms will issue equity in any given quarter and 8% will issue debt. While the level of security issuances may seem high, it must be remembered that REITs are capital constrained firms due to their dividend payout requirements and must come to the capital markets to raise capital to invest.[25]

On average a REIT in the sample is covered by 6.3 analysts in any given quarter. Although some REITs are not covered at all, while others have over 20 analysts covering them. The level of coverage has definitely not been constant over the sample period. In fact analyst coverage is virtually non-existent in the sample prior to the late 90s. This is not overly surprising given this is the same period for which REITs generally lacked what are thought of as the common drivers of analyst coverage.[26]

The average quarterly change in total assets is 5.4% in the sample. The extremes of Δ *Assets*

[25]See Ott, Riddiogh, and Yi (2005) for a discussion of REIT investment and Boudry, Kallberg, and Liu (2010) for a discussion of REIT security issuance decisions.

[26]See Boudry, Kallberg, and Liu (2011) for a discussion of the economic determinants of analyst coverage in REITs.

are also interesting because they represent true economic events. The minimum value of a -94.8% change in total assets reflects a planned liquidation of a firm in the sample, while the maximum is related to the merger of a small firm with a much larger one. While these transactions are not the norm for most firms in most periods, if the goal of the exercise is to understand what drives pricing efficiency, then events such as these are likely to be important in understanding this phenomenon.

5.3 Principal Results

Table 5 reports our main quarterly estimation results. The dependent variable for all regressions is |1- Variance Ratio| (multiplied by 100). The explanatory variables in the analysis related to institutional ownership, analyst coverage, and microstructure are all lagged one period. The remaining variables are contemporaneous, because the direction for causality for these variables is more apparent. We include both firm and year fixed effects as specified.[27] Firm clustered t-statistics are reported in parentheses.

In Model 1 of Table 5 we include only the total level of institutional ownership in the regression. In Model 2, we include the decomposition of *TIO* into *SIO*, *MIO*, and *LIO* to examine the effect of active versus passive institutional owners. Models 3, 4, and 5 examine the effect of firm and year fixed effects on the estimation.

Turning to Model 1 in Table 5 we observe the result in Boehmer and Kelley (2009) that higher institutional ownership tends to related to better pricing efficiency. The economic magnitude of the effect is only modest however. A one standard deviation increase in *TIO* leads to a 6.3% improvement in absolute pricing. The causal interpretation of this finding is predicated on the careful work of Boehmer and Kelley (2009).

We also observe the significant effect of index inclusion on efficiency, especially for the S&P 500 and midcap S&P 400. S&P 500 firms are 25% more efficient then non-index firms, while S&P 400 firms are 19% more efficient. Notice that there is a potential identification issue involved. It is possible that efficiency is one characteristic that S&P considers when choosing firms to add

[27]We have also estimated the models removing the microstructure regime dummy variables and including with quarter fixed effects. The results are similar to those reported. We have also removed firm fixed effects and included property type effects for each REIT. The results are similar and none of the property type dummy variables was significant.

to one of their indices. This would lead to the same result that we observe - firm sin an index trade more efficiently than other firms - although the causal interpretation would be completely different. To try and disentangle causality, we examine changes in efficiency around index inclusion dates. We calculate variance ratios in 15-, 30-, and 60-day windows before and after the index addition date. To avoid any potential information leakage issues, we exclude the 15 days around the announcement date from our analysis. We then calculate the change in efficiency, $|1-VR|$, between the two estimation windows. If indexes simply add firms that are already efficient, then we would expect to see no significant change between the two estimation windows. On the other hand, if index inclusion does increase efficiency, then we would expect $|1-VR|$ to be smaller in the post-addition window. Our selection in the size of the estimation windows was driven by two motivations. First, smaller windows around the announcement date, should enable stronger identification because it gives less time for confounding events to occur. Second, smaller estimation windows are likely to lead to noisier estimates of variance ratios. The windows we estimate hopefully balance these two forces.

For the overall sample of index additions (S&P 500, S&P 400, and S&P 600), we find that the change in $|1-VR|$(multiplied by 100) is -0.815, -0.974, and -1.45 in the 15-, 30-, and 60-day windows respectively. These are significantly different from zero at the 5% for the 30- and 60-day windows and significant at the 10% level for the 15-day window. Given that the average level of $|1-VR|$ reported in the sample is 5.104, they also represent economically meaningful changes. So at a first pass, it appears that inclusion in a major S&P index improves efficiency. To see if this effect is consistent across indices, we then repeat this exercise for each index. For the S&P 500, the 15-, 30-, and 60-day changes are 0.31, -0.35, and -1.3. None of these were significantly different from zero at conventional levels. For the S&P 400, the 15-, 30-, and 60-day changes are -2.1, -2.03, and -2.0. All three are significantly different from zero at the 5% level. These all represent a near 40% improvement in pricing for the average firm in the sample. Finally, for the S&P 600, the 15-, 30-, and 60-day changes are -0.52, -0.51, and -1.07. None of these were significantly different from zero at conventional levels.

The results for the changes in efficiency around index inclusions point to an interesting conclusions. Joining the S&P 500 isn't in and of itself beneficial. It appears that the REITs joining this index were already priced efficiently. This may not be surprising given the unique situation the REIT industry went through in being added to the S&P 500. The REITs that were sequentially added to the S&P 500 were considered the best and brightest of the REIT market. They were all large, or at least large for the REIT market, and well known. The first REIT added to the S&P 500 was Equity Office Properties, which was the largest and probably best known REIT in 2001. In this sense it isn't difficult to think that perhaps these firms were just always priced efficiently. Similarly, joining the S&P 600 small cap index has minimal effect. Joining this index isn't going to change the fact that these are still very small firms. On the other hand, joining the S&P 400 midcap index appears to be a much more efficiency changing event. These firms experience significant improvements in their pricing efficiency around being added to the index. The results from our panel analysis suggest that these improvements are persistent, even controlling for a myriad of factors (such as turnover, liquidity, institutional ownership) that could explain why being added to the index improves efficiency. A potential explanation for this is simply that being added to the S&P 400 midcap index means that the firm is now in the investment opportunity set of a different set of investors. In this sense the firm is lifted up from small cap obscurity. While we do try and control for this increased attention with institutional ownership and analyst coverage, it is possible that these proxies do not fully capture the changing information environment that being added to this index entails.[28]

In Table 5, we also find some evidence of the impact of market microstructure on pricing efficiency. The positive coefficient on *QS to QD* suggests that worse market conditions (higher spreads/lower depth) are related to more pricing inefficiency. This is intuitive because worse trading conditions should make it harder for arbitrageurs to trade the firm's stock. The positive and significant coefficient on *Quote Changes* suggests that a more dynamic information environment (a high number of quote changes relative to the number of quotes) is related to worse pricing efficiency. As expected, higher stock prices are associated with better efficiency, because higher prices means

[28]Notice that controlling for the levels of institutional ownership or analyst coverage is potentially only part of the story. It could also be that the composition of those groups are changing. Becoming a more high profile firm may attract the attention of better analysts and institutional investors, and also possibly better financial intermediaries likes banks and investment banks.

lower percentage transaction costs for fixed tick size. Also notice that controlling for other factors, the transition to the decimal quote regime tended to have a negative impact on efficiency.

From an information production perspective we find little evidence of efficiency effects. Neither *Analysts*, *Issued Equity*, *Issued Debt*, nor *Rated* are statistically significant. The insignificant effect for analyst coverage may be due to this variable being highly correlated with both firm size and institutional ownership. The correlation between analyst coverage and firm size is 75.2%, while the correlation with institutional ownership is 52.9%. When we remove these variables from the regression, but leave in analyst coverage, we find that higher analyst coverage is associated with better efficiency and the effect is statistically significant at the 10% level. Although an alternative explanation can be found in Downs and Güner (1999) and Downs and Güner (2000). They find that increased analyst coverage tends to lead to lower liquidity in the REIT market. This contradicts the pattern found for regular equities. The insignificant result for analyst coverage may simply reflect offsetting effects. They may increase information production helping efficiency, but if they reduce liquidity this is likely to reduce efficiency.

The final result from Model 1 is the negative and significant coefficient on $\Delta Assets$. Notice however that the effect is fairly small in economic terms on average. A one standard deviation increase in $\Delta Assets$ is associated with a 1.2% increase in pricing efficiency. Although given the extreme range of the variable, there is the potential for large economic effects.

To examine if all institutional owners have the same effect on efficiency, we split *TIO* into *LIO*, *MIO*, and *SIO* in Model 2. The coefficient on *SIO* is statistically significant, while the coefficients on *LIO* and *LIO* are not. Economically, a one standard deviation increase in *SIO* is related to a 4.7% improvement in efficiency. This suggests that approximately 75% of the benefit from institutional owners found in Model 1 is related to ownership by institutions who trade frequently. So while passive indexers do improve efficiency, it appears that the largest effect comes from institutions who are active traders.

In Models 3, 4, and 5, we remove year effects, firm fixed effects, and then both year and firm effects. The removal of these effects doesn't change the results we have previously discussed, but it does highlight some new relationship. When year effects are removed, we observe that *Turnover* and *LIO* become significant. As noted before, we observe a large time trend in *TIO*, especially after 2001. Similarly we observe a large increase in *Turnover* through time. When we remove the firm fixed effects, *Amihud* becomes statistically significant with a negative coefficient. The negative coefficient is unexpected because it implies as the firm becomes less liquid, its pricing efficiency improves.

6 Conclusion

Using individual REIT pricing data, we estimate the time-varying distribution of REIT-level variance ratios covering the 1993-2011 period. Our motivation for examining the REIT market is twofold. First, there is scant evidence on the asset level efficiency of the market. Those papers that do exist focus primarily on market level efficiency. While this is interesting in and of itself, both participants in the market and managers face asset level decisions. So it is efficiency at this level that is important to these groups. Second, while the finance literature has examined efficiency for general stocks, these studies exclude REITs at the sample selection stage. Given the unique nature of both the REIT business model compared to regular equities and also the extreme changes that have occurred in the industry during the sample period, it not obvious that prior results can be easily extended to the REIT market.

Our estimates show that the average individual REIT is efficiently priced, but there are many REITs which are clearly not efficiently priced at any given point in time. We find examples of both mean aversion and mean reversion in the prices of individual REITs. 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.

Following the approach of Boehmer and Kelley (2009), we also examine determinants that explain deviations from pricing efficiency. Consistent with their result, we find that higher institutional ownership is related to better pricing efficiency. We find that this efficiency improvement is more strongly related to ownership by institutions that trade frequently. Approximately 75% of efficiency gains from institutions is generated by these institutions that trade frequently.

One of the unique changes in the REIT market during our sample period has been the inclusion of REITs in major market indices. Prior to 2001, REITs were excluded from all S&P indices. We find that REITs that are part of the S&P 500 or S&P 400, but not the S&P 600, are more efficiently priced than other REITs. Examining changes in efficiency around index inclusion dates, we find that the result for the S&P 500 REITs is likely driven by sample selection. There is no significant change in efficiency for these firms. This is consistent with the notion that the REITs added to the S&P 500 are in some sense special REITs. They are large by REIT market standards and also have significant investor attention before they were added to the index. For example, Equity Office Properties was the first REIT added to the S&P 500, and it was the largest REIT at the time of that addition. For the midcap S&P 400, we find significant improvements in efficiency around index inclusion. The change in efficiency for these firms is likely due to the large change in investor exposure that entering this index provides. These firms go from small cap obscurity into the midcap universe of firms. We find no change in efficiency for the small firms in the S&P 600. This is likely because these firms really don't change significantly because of being added to the index. They are still only part of the small cap universe of stocks, and thus likely didn't have a significant change in their investor universe.

Finally, we find that firm investment activity has an effect of firm pricing efficiency. Firm's that are involved in asset expanding activity during a quarter tend to be priced more efficiently. Overall, our results add to our understanding of price efficiency in the REIT market, especially at the asset level.

References

Ambrose, B.W., D.W. Lee, and J. Peek, 2007, Comovement after joining an index: Spillovers of nonfundamental effects, *Real Estate Economics* 35, 57–90.

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Boehmer, E., Y.L. Fong, and J.J. Wu, 2012, International evidence on algorithmic trading, *Working Paper*.

Boehmer, E., and E. Kelley, 2009, Institutional investors and the informational efficiency of prices, *Review of Financial Studies* 22, 3566–3594.

Bolton, P., X. Frexias, and J. Shapiro, 2012, The credit ratings game, *Journal of Finance* 67, 85–111.

Boudry, W. I., 2011, An examination of REIT dividend payout policy, *Real Estate Economics* 39, 601–634.

——— , N. E. Coulson, J. G. Kallberg, and C. H. Liu, 2012, On the hybrid nature of REITs, *Journal of Real Estate Finance and Economics* 44, 230–249.

Boudry, W. I., J. G. Kallberg, and C. H. Liu, 2010, An analysis of REIT security issuance decisions, *Real Estate Economics* 38, 91–120.

——— , 2011, Analyst behavior and underwriter choice, *Journal of Real Estate Finance and Economics* 43, 5–38.

——— , 2013, Investment opportunities and share repurchases, *Journal of Corporate Finance* 23, 23–38.

Brounen, D., P. Eichholtz, and D. Ling, 2009, The liquidity of property shares: An international comparison, *Real Estate Economics* 38, 361–381.

Cannon, S. E., and R. A. Cole, 2011, Changes in REIT liquidity 1988-2007: Evidence from daily data, *Journal of Real Estate Finance and Economics* 43, 258–280.

Charles, A., and O. Darne, 2009, Variance-ratio tests of random walk: An overview, *Journal of Economic Surveys* 23, 503–527.

Chordia, T., R. Roll, and A. Subrahmanyam, 2011, Recent trends in trading activity and market quality, *Journal of Financial Economics* 101, 243–263.

Clayton, J., and G. MacKinnon, 2000, Measuring and explaining changes in REIT liquidity: Moving beyond the bid-ask spread, *Real Estate Economics* 28, 89–115.

Conrad, J., S. Wahal, and J. Xiang, 2015, High frequency quoting, trading, and the efficiency of prices, *Journal of Financial Economics*, Forthcoming.

Downs, D.H., 1998, The value in targeting institutional investors: Evidence from the five-or-fewer rule change, *Real Estate Economics* 26, 613–649.

——— , and Z.N. Güner, 1999, Is the information deficiency in real estate evident in public market trading?, *Real Estate Economics* 27, 517–541.

——— , 2000, Investment analysis, price formation and neglected firms: Deos real estate make a difference?, *Real Estate Economics* 28, 549–579.

Foucault, T., M. Pagano, and A. Röell, 2013, *Market Liquidity: Theory, Evidence, and Policy* (Oxford University Press: Oxford).

Glascock, J., and R. Lu-Andrews, 2014, An examination of macroeconomic effects on the liquidity of REITs, *Journal of Real Estate Finance and Economics* 49, 23–46.

Hardin, W., K. Liano, G-C. Huang, and G. Nagel, 2007, REITs, decimalization, and ex-dividend stock prices, *Journal of Real Estate Finance and Economics* 34, 499–511.

Holden, C., and S. Jacobsen, 2014, Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions, *Journal of Finance* 69, 1747–1785.

Huang, C-M., H-M. Su, and C-L. Chiu, 2009, REIT market efficiency before and after inclusion in the S&P 500, *Journal of Real Estate Portfolio Management* 15, 239–250.

Jain, P., M. Sunderman, and K. J. Westby-Gibson, 2013, REITs and market microstructure: A comprehensive analysis of market quality, Working Paper, Central Michigan University.

Jirasakuldech, B., and J.R. Knight, 2005, Efficiency in the market for REITs: Further evidence, *Journal of Real Estate Portfolio Management* 11, 123–132.

Kuhle, J.L., and J.R. Alvayay, 2000, The efficiency if equity REIT prices, *Journal of Real Estate Portfolio Management* 6, 349–354.

Lo, A., and A. C. Mackinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* 1, 41–66.

Nelling, E., and J. Gyourko, 1998, The predictability of equity REIT returns, *Journal of Real Estate Research* 16, 251–268.

O'Hara, M., and M. Ye, 2011, Is market fragmentation harming market quality?, *Journal of Financial Economics* 100, 459–467.

Ott, S.H., T.J. Riddiogh, and H.C. Yi, 2005, Finance, investment and investment performance: Evidence from the REIT sector, *Real Estate Economics* 33, 203–235.

Schindler, F., N. Rottke, and R. Füss, 2010, Testing the predicatbility and efficiency of securitized real estate markets, *Journal of Real Estate Portfolio Management* 16, 171–192.

Seck, D., 1996, The substitutability of real estate assets, *Real Estate Economics* 24, 75–95.

Stevenson, S., 2002, Momentum effects and mean reversion in real estate securities, *Journal of Real Estate Research* 23, 47–64.

Subrahmanyam, A., 2007, Liquidity, return and order-flow linkages between REITs and the stock market, *Real Estate Economics* 35, 383–408.

Yan, X., and Z. Zhang, 2009, Institutional investors and equity returns: Are short-term institutions better informed?, *Review of Financial Studies* 22, 893–924.

Figure 1: REIT Variance Ratio Densities, 1993-2011.

Figure reports kernel density plots of the distribution of quarterly variance ratios by year. Quarterly variance ratios are calculated as $VR = \frac{Var[r_t(30minutes)]}{2Var[r_t(15minutes)]}$, where $Var[r_t(30minutes)]$ is the variance of 30 minute returns calculated over the quarter and $Var[r_t(15minutes)]$ is the variance of 15 minute returns calculated over the quarter. Returns are calculated from quote midpoints and quote midpoints are calculated from TAQ data using the methods of Holden and Jacobsen (2014).

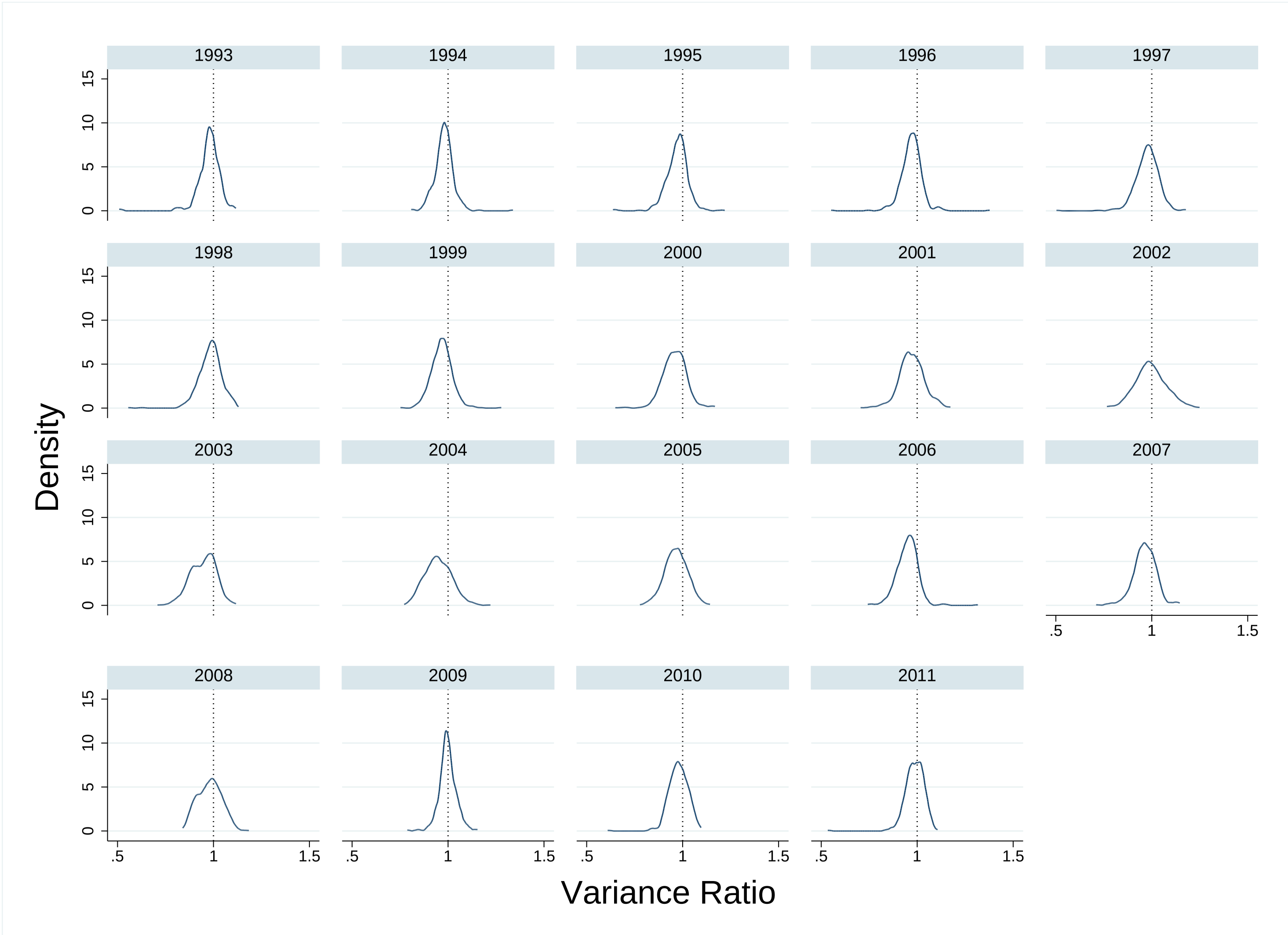
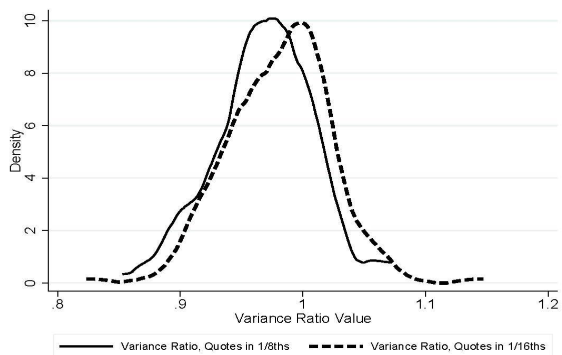
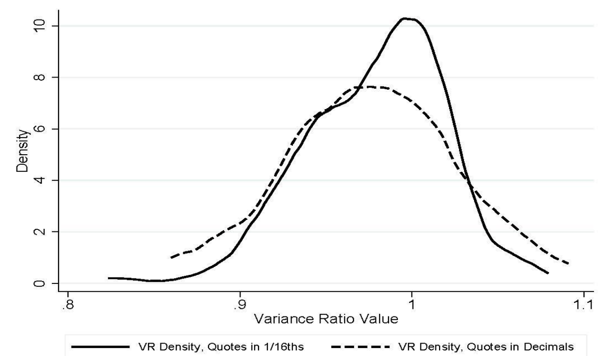


Figure 2: Event-Related REIT Variance Ratio Densities.

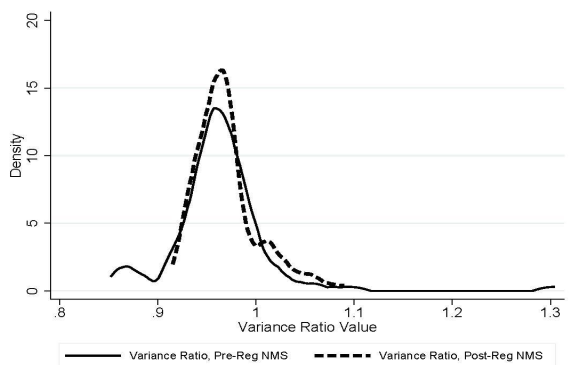
Figure compares kernel density plots of the distribution of variance ratios between adjacent microstructure regimes. Panel A compares June 23, 1997 change from 1/8ths to 1/16ths, Panel B compares the January 28, 2001 change from 1/16ths to decimals, and Panel C compares the July 1 - August 8, 2007 introduction of Regulation NMS. Variance ratios are calculated for the year before the event and the year after, excluding a 10-day window around the transition. Variance ratios are calculated as $VR = \frac{Var[r_t(30minutes)]}{2Var[r_t(15minutes)]}$, where $Var[r_t(30minutes)]$ is the variance of 30 minute returns and $Var[r_t(15minutes)]$ is the variance of 15 minute returns. Returns are calculated from quote midpoints and quote midpoints are calculated from TAQ data using the methods of Holden and Jacobsen (2014).



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.

Figure 3: Institutional Ownership.

Figure plots the average level of institutional ownership by quarter from 1993 to 2011. *TIO*(Black) is the percentage of the firm's shares held by all institutional owners. *SIO*(Red), *MIO*(Green), and *LIO*(Blue) are the percentage of shares held by owners in the top, middle, and bottom tertile of portfolio turnover. *SIO*, *MIO*, and *LIO* are calculated using the method proposed by Yan and Zhang (2009). Underlying ownership data comes from Thomson Reuter's 13(f) database.

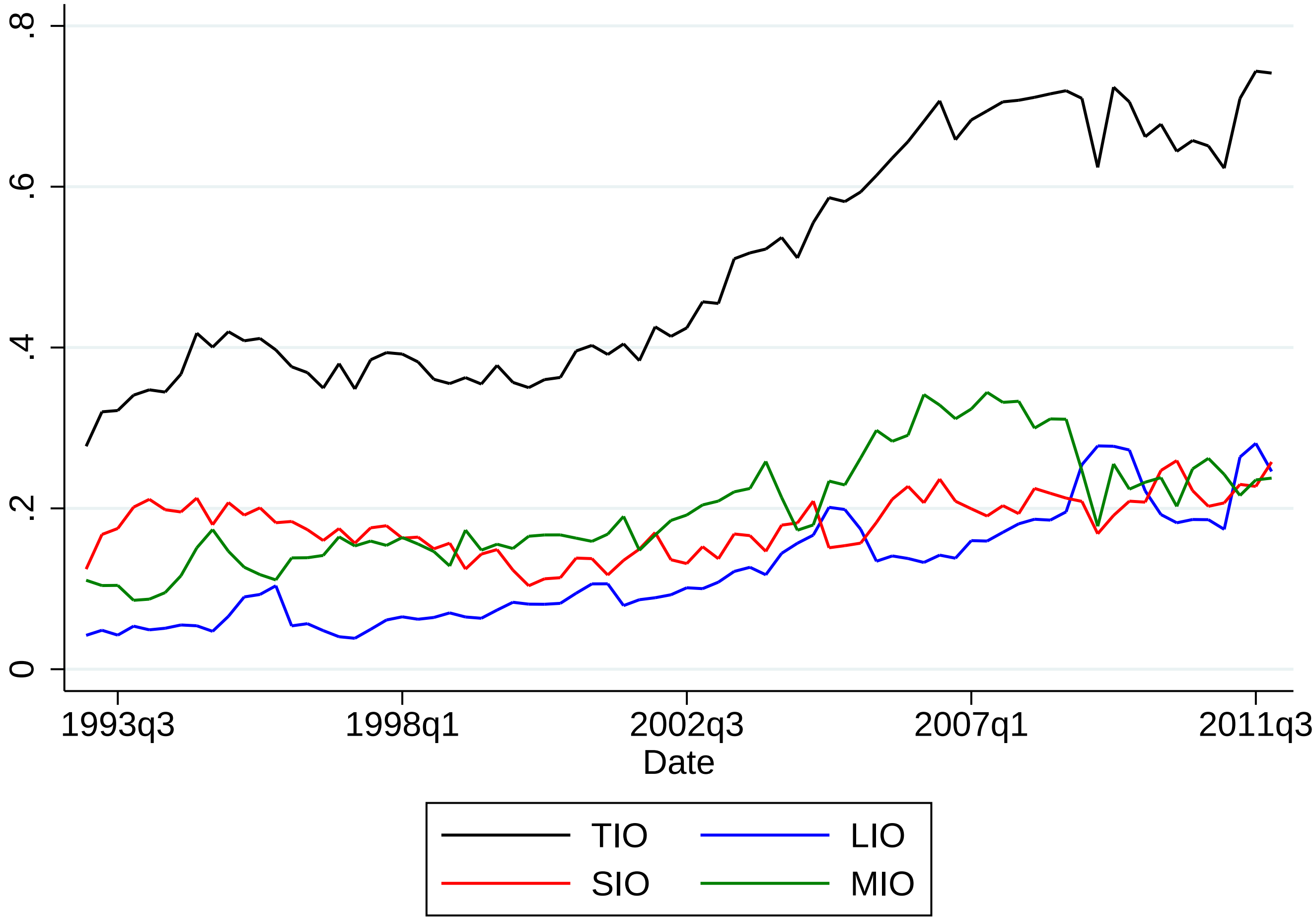


Table 1: Variance Ratios By Year

Table reports descriptive statistics of quarterly variance ratios by year. Quarterly variance ratios are calculated as $VR = \frac{Var[r_t(30minutes)]}{2Var[r_t(15minutes)]}$, where $Var[r_t(30minutes)]$ is the variance of 30 minute returns calculated over the quarter and $Var[r_t(15minutes)]$ is the variance of 15 minute returns calculated over the quarter. Test statistics are calculated using overlapping samples to increase power. Returns are calculated from quote midpoints and quote midpoints are calculated from TAQ data using the methods of Holden and Jacobsen (2014).

		Variance Ratio				
Year	Obs	Mean	Std	Min	Max	Significant
1993	126	0.977	0.064	0.509	1.117	18
1994	376	0.979	0.049	0.808	1.338	68
1995	471	0.971	0.058	0.637	1.219	110
1996	479	0.970	0.057	0.552	1.378	99
1997	497	0.976	0.061	0.504	1.178	99
1998	510	0.983	0.060	0.556	1.130	96
1999	505	0.967	0.055	0.752	1.277	124
2000	483	0.959	0.063	0.649	1.168	162
2001	457	0.971	0.066	0.705	1.173	99
2002	442	0.995	0.081	0.766	1.249	124
2003	421	0.946	0.067	0.709	1.118	168
2004	436	0.949	0.070	0.771	1.221	168
2005	462	0.966	0.060	0.778	1.143	123
2006	403	0.949	0.056	0.743	1.316	118
2007	346	0.964	0.060	0.711	1.146	61
2008	315	0.981	0.062	0.840	1.184	96
2009	318	0.998	0.044	0.788	1.153	38
2010	367	0.979	0.051	0.610	1.096	76
2011	357	0.987	0.051	0.534	1.106	39

Table 2: Pricing Efficiency By Year

Table reports descriptive statistics of quarterly pricing efficiency by year. Pricing efficiency is measured as |1-VR|*100, where VR is the quarterly variance ratio. Quarterly variance ratios are calculated as $VR = \frac{Var[r_t(30minutes)]}{2Var[r_t(15minutes)]}$, where $Var[r_t(30minutes)]$ is the variance of 30 minute returns calculated over the quarter and $Var[r_t(15minutes)]$ is the variance of 15 minute returns calculated over the quarter. Returns are calculated from quote midpoints and quote midpoints are calculated from TAQ data using the methods of Holden and Jacobsen (2014).

|1-Variance Ratio|*100					
Year	Obs	Mean	Std	Min	Max
1993	126	4.316	5.292	0.060	49.101
1994	376	3.920	3.599	0.000	33.830
1995	471	4.623	4.558	0.001	36.268
1996	479	4.605	4.458	0.006	44.771
1997	497	4.825	4.456	0.010	49.617
1998	510	4.597	4.230	0.020	44.385
1999	505	5.005	3.965	0.008	27.730
2000	483	5.828	4.796	0.022	35.074
2001	457	5.633	4.530	0.027	29.470
2002	442	6.376	5.024	0.017	24.870
2003	421	6.715	5.365	0.005	29.121
2004	436	7.024	4.958	0.010	22.856
2005	462	5.510	4.131	0.000	22.231
2006	403	5.995	4.714	0.050	31.610
2007	346	5.396	4.471	0.029	28.948
2008	315	5.265	3.750	0.020	18.450
2009	318	3.248	3.031	0.000	21.210
2010	367	4.257	3.534	0.004	39.030
2011	357	3.830	3.563	0.010	46.560

Table 3: Institutional Ownership By Year

Table reports descriptive statistics for the quarterly level of institutional ownership each year 1993 to 2011. *SIO*, *MIO*, and *LIO* are the percentage of shares held by owners in the top, middle, and bottom tertile of portfolio turnover. *SIO*, *MIO*, and *LIO* are calculated using the method proposed by Yan and Zhang (2009). Underlying ownership data comes from Thomson Reuter's 13(f) database.

	SIO				MIO				LIO			
Year	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
1993	0.163	0.124	0.000	0.721	0.106	0.069	0.000	0.320	0.046	0.044	0.000	0.307
1994	0.202	0.139	0.000	0.603	0.100	0.067	0.000	0.298	0.052	0.044	0.000	0.312
1995	0.198	0.136	0.000	0.602	0.149	0.092	0.000	0.427	0.067	0.056	0.000	0.324
1996	0.185	0.137	0.000	0.620	0.126	0.084	0.000	0.403	0.075	0.064	0.000	0.356
1997	0.171	0.122	0.000	0.762	0.158	0.104	0.000	0.613	0.045	0.036	0.000	0.281
1998	0.159	0.107	0.000	0.479	0.154	0.099	0.000	0.556	0.064	0.043	0.000	0.253
1999	0.143	0.096	0.000	0.472	0.151	0.106	0.000	0.491	0.069	0.047	0.000	0.275
2000	0.114	0.085	0.000	0.530	0.166	0.118	0.000	0.530	0.082	0.048	0.000	0.284
2001	0.131	0.104	0.000	0.585	0.167	0.117	0.000	0.559	0.096	0.061	0.000	0.333
2002	0.148	0.102	0.000	0.468	0.177	0.127	0.000	0.692	0.093	0.048	0.000	0.374
2003	0.155	0.095	0.000	0.382	0.212	0.130	0.002	0.663	0.117	0.056	0.000	0.369
2004	0.185	0.106	0.000	0.615	0.204	0.113	0.006	0.585	0.149	0.080	0.000	0.344
2005	0.161	0.098	0.000	0.499	0.263	0.123	0.001	0.606	0.176	0.089	0.000	0.397
2006	0.224	0.117	0.000	0.560	0.308	0.143	0.001	0.662	0.139	0.065	0.003	0.318
2007	0.196	0.090	0.000	0.443	0.330	0.148	0.005	0.630	0.158	0.057	0.004	0.352
2008	0.213	0.081	0.014	0.542	0.315	0.124	0.017	0.588	0.188	0.064	0.005	0.381
2009	0.196	0.082	0.005	0.442	0.229	0.122	0.005	0.505	0.272	0.071	0.018	0.438
2010	0.236	0.100	0.014	0.660	0.230	0.110	0.000	0.590	0.191	0.067	0.009	0.337
2011	0.217	0.105	0.006	0.573	0.238	0.104	0.000	0.656	0.232	0.096	0.000	0.471

Table 4: Descriptive Statistics

Table reports descriptive statistics of the explanatory variables used in the analysis. *TIO* is the percentage of the firm's shares held by all institutional owners, while *SIO*, *MIO*, and *LIO* are the percentage of shares held by owners in the top, middle, and bottom tertile of portfolio turnover. *SIO*, *MIO*, and *LIO* are calculated using the method proposed by Yan and Zhang (2009). Underlying ownership data comes from Thomson Reuter's 13(f) database. S&P 500, S&P 400, and S&P 600 are dummy variables equal to one if the firm is part of the S&P 500, S&P 400, or S&P 600 during the quarter. Index constituent data is obtained from NAREIT and COMPUSTAT. *Amihud* is the quarterly average of the daily ratio of absolute returns to dollar volume for each firm calculated from CRSP. *Turnover* is the quarterly average of daily share turnover calculated from CRSP. *QS to QD* is the quarterly average of the daily quoted spread to quoted depth for each firm calculated from TAQ data. *Quote Change* is the ratio of NBBO quote changes to the total NBBO quotes each day, averaged over the quarter. *Quote to Trade* is the ratio of quotes to trades each day, averaged over the quarter. *Size* is the firm's market capitalization, *Price* is the firm's share price. *Reg 2*, *Reg 3*, and *Reg 4* are dummy variables equal to one if the quarter falls under the 1/16ths, decimal, or Regulation NMS regimes. *Rated* is a dummy variable equal to one if the firm has a credit rating with one of the three major credit rating agencies. *Issue Equity* and *Issue Debt* are dummy variables equal to one if the firm issued equity or debt during the quarter. *Analysts* is the number of analysts covering the firm taken from IBES, and $\Delta Assets$ is the change in total assets for the firm over the quarter, taken from SNL Financial.

Variable	Obs	Mean	Std	Min	Max
TIO	7771	0.490	0.252	0.000	1.000
SIO	7771	0.176	0.113	0.000	0.762
LIO	7771	0.117	0.087	0.000	0.471
MIO	7771	0.197	0.129	0.000	0.692
S&P 500	7771	0.034	0.181	0.000	1.000
S&P 400	7771	0.040	0.195	0.000	1.000
S&P 600	7771	0.049	0.215	0.000	1.000
Amihud	7771	0.794	2.957	0.001	39.293
QS to QD	7771	0.000	0.006	0.000	0.492
Quote Changes	7771	0.144	0.141	0.002	1.000
Quote to Trade	7771	12.441	17.796	0.034	365.839
Turnover	7771	0.515	0.569	0.007	6.658
Size	7771	1.227	1.919	0.009	17.800
Price	7771	23.884	15.236	0.806	142.721
Regime 2	7771	0.226	0.418	0.000	1.000
Regime 3	7771	0.360	0.480	0.000	1.000
Regime 4	7771	0.197	0.397	0.000	1.000
Rated	7771	0.362	0.481	0.000	1.000
Issued Equity	7771	0.105	0.306	0.000	1.000
Issued Debt	7771	0.080	0.271	0.000	1.000
Analysts	7771	6.348	5.086	0.000	26.667
Δ Assets	7771	0.054	0.403	-0.948	29.653

Table 5: Estimation Results

Table reports estimation results from panel regressions. The dependent variable is |1-VR|*100. *TIO* is the percentage of the firm's shares held by all institutional owners, while *SIO*, *MIO*, and *LIO* are the percentage of shares held by owners in the top, middle, and bottom tertile of portfolio turnover. *SIO*, *MIO*, and *LIO* are calculated using the method proposed by Yan and Zhang (2009). Underlying ownership data comes from Thomson Reuter's 13(f) database. S&P 500, S&P 400, and S&P 600 are dummy variables equal to one if the firm is part of the S&P 500, S&P 400, or S&P 600 during the quarter. Index constituent data is obtained from NAREIT and COMPUSTAT. *Amihud* is the quarterly average of the daily ratio of absolute returns to dollar volume for each firm calculated from CRSP. *Turnover* is the quarterly average of daily share turnover calculated from CRSP. *QS to QD* is the quarterly average of the daily quoted spread to quoted depth for each firm calculated from TAQ data. *Quote Change* is the ratio of NBBO quote changes to the total NBBO quotes each day, averaged over the quarter. *Quote to Trade* is the ratio of quotes to trades each day, averaged over the quarter. *Size* is the firm's market capitalization, *Price* is the firm's share price. *Reg 2*, *Reg 3*, and *Reg 4* are dummy variables equal to one if the quarter falls under the 1/16ths, decimal, or Regulation NMS regimes. *Rated* is a dummy variable equal to one if the firm has a credit rating with one of the three major credit rating agencies. *Issue Equity* and *Issue Debt* are dummy variables equal to one if the firm issued equity or debt during the quarter. *Analysts* is the number of analysts covering the firm taken from IBES, and $\Delta Assets$ is the change in total assets for the firm over the quarter, taken from SNL Financial. S&P 500, S&P 400, S&P 600, *Issue Equity*, *Issue Debt*, *Rated*, and $\Delta Assets$ are contemporaneous to the dependent variable. All other variables are lagged one period. Firm clustered standard errors are reported in parentheses. Data is an unbalanced panel of quarterly observations from 1993 to 2001.

	1		2		3		4		5	
TIO	-1.273**	(-2.18)								
SIO			-2.113***	(-2.66)	-2.077***	(-2.63)	-1.537**	(-2.57)	-1.543***	(-2.63)
MIO			-0.383	(-0.49)	0.0602	(0.08)	-0.0615	(-0.11)	0.468	(0.87)
LIO			-0.949	(-0.70)	-2.437**	(-2.12)	-1.718*	(-1.67)	-2.848***	(-3.07)
$\lvert 1-VR\rvert_{t-1}$	0.0846***	(-4.36)	0.0845***	(4.36)	0.0956***	(4.91)	0.130***	(7.19)	0.140***	(7.73)
S&P 500	-1.317***	(-2.98)	-1.316***	(-2.88)	-1.217***	(-2.81)	-1.301***	(-3.85)	-1.223***	(-3.75)
S&P 400	-0.970***	(-3.16)	-0.994***	(-3.26)	-1.077***	(-3.92)	-0.485**	(-2.36)	-0.525***	(-2.77)
S&P 600	-0.365	(-0.97)	-0.378	(-0.99)	-0.45	(-1.25)	-0.393*	(-1.79)	-0.432**	(-2.12)
Amihud	-0.0487	(-1.51)	-0.0513	(-1.59)	-0.051	(-1.62)	-0.0834***	(-3.18)	-0.0829***	(-3.21)
QS to QD	5.674*	(1.77)	5.913*	(1.81)	4.496	(1.24)	7.159*	(1.82)	5.692	(1.35)
Quotes Changes	1.913**	(2.54)	1.954***	(2.62)	1.513**	(2.17)	1.943***	(2.97)	1.878***	(3.06)
Quotes to Trades	0.00532	(0.74)	0.00521	(0.73)	0.00657	(0.99)	0.0117*	(1.91)	0.0123**	(2.23)
Turnover	-0.0835	(-0.68)	-0.0705	(-0.56)	-0.240**	(-2.33)	-0.0781	(-0.69)	-0.262***	(-2.75)
Size	0.394*	(1.77)	0.387*	(1.75)	0.420**	(2.13)	0.651***	(5.63)	0.636***	(5.65)
Price	-0.683***	(-2.78)	-0.693***	(-2.82)	-0.604**	(-2.56)	-1.207***	(-7.88)	-1.140***	(-7.51)
Regime 2	-0.473	(-1.18)	-0.462	(-1.15)	0.345	(1.47)	-0.424	(-1.05)	0.312	(1.57)
Regime 3	2.406***	(3.68)	2.295***	(3.45)	1.453***	(4.65)	0.442	(0.63)	1.421***	(5.31)
Regime 4	1.727**	(2.2)	1.603**	(2.01)	0.415	(0.99)	-0.378	(-0.63)	0.0162	(0.05)
Rated	-0.193	(-0.73)	-0.205	(-0.77)	-0.0329	(-0.13)	-0.0403	(-0.25)	0.026	(0.16)
Issued Equity	0.057	(0.34)	0.0564	(0.33)	0.00101	(0.01)	0.185	(1.13)	0.134	(0.84)
Issued Debt	0.0884	(0.46)	0.0842	(0.44)	0.0294	(0.15)	0.111	(0.57)	0.0498	(0.25)
Analysts	-0.0154	(-0.64)	-0.0201	(-0.83)	-0.00394	(-0.18)	-0.0188	(-0.99)	-0.0113	(-0.65)
Δ Assets	-0.144***	(-4.08)	-0.144***	(-3.96)	-0.157***	(-4.41)	-0.145***	(-3.70)	-0.163***	(-4.51)
Constant	0.815	(0.36)	0.964	(0.43)	0.93	(0.46)	-0.919	(-0.73)	-0.693	(-0.59)
N	7771		7771		7771		7771		7771	
Adj. R^2	0.1005		0.1007		0.0904		0.092		0.0809	
Firm FE	Yes		Yes		Yes		No		No	
Year FE	Yes		Yes		No		Yes		No	

*** p< 0.01, ** p<0.05, and * p<0.1