Geographic Proximity and Managerial Alignment: Evidence from Asset Sell-offs by Real Estate Investment Trusts[1]

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Abstract

While the relation between geographic dispersion and firm value has been extensively studied, there are intriguing aspects that we do not yet understand. For example, Bernile, Kumar and Sulaeman (2015) report that, "local investors may perceive an informational advantage where there is in fact none." Additionally, when we talk of local assets versus distant assets, there is little data showing what that means. REITs offer a unique and more complete data source of evidence about the proximity issue and value. In our unique panel dataset of more than 800,000 property-year observations, we find that local must be carefully evaluated as in most cases these REITs own a wide pool of geographically diversified assets.

We apply a two-stage sequential choice model to mitigate selection bias at the firm-level and property-level. We find that REITs tend to dispose of distant properties and there is a negative relation between distance and cumulative abnormal returns. The top-ten MSAs in our disposition sample were over 860 miles (1,388 kilometers) from their REIT headquarters (HQs). The average cumulative abnormal return (CAR) was over three times as large and statistically significant for those dispositions that were below the median distance compared to those farther. However, further analyses show that headquarters that were in smaller areas (below the mean by population) were the only REITs to have positive abnormal returns. Thus, the gain is to firms that are located in smaller areas and who dispose of properties closer to their HQs. The gains are monotonically declining by distance from their HQs. This evidence is supportive of managerial alignment theory in the literature.

Further, informational and social factors explain corporate decisions on asset sell-offs: this social interaction effect exists for those HQs located in less-populated areas. Consistent with the hypothesis of Landier, Nair and Wulf (2009), we find a positive and significant relation between aggregated proximity of a firm's property holdings (Geographic HHI) and employee friendliness, indicating proximity between a particular firm's headquarters and its underlying properties is associated with poor shareholder protection due to better employee protection. Together, these findings suggest a dominant role for the managerial alignment hypothesis. We find in particular that for HQs in less-populated MSAs, the *managerial alignment effect* dominates the *information asymmetry effect*.

JEL classification: G34, D82

1. Introduction

The relation between geographic dispersion and firm value has been extensively studied. However, two key hypotheses predict different outcomes. On the one hand, geographic proximity mitigates information asymmetry and improves firm performance (*information asymmetry hypothesis*; see John and Ofek, 1995; Lerner, 1995; Coval and Moskowitz, 1999, 2001; Grinblatt and Keloharju, 2001; Peterson and Rajan, 2002; Giroud, 2013). On the other hand, Landier, Nair and Wulf (2009) suggest that social concerns could affect the conflict with shareholder wealth maximization when firms are more concerned about nearby operating assets due to reputational concern and the management of geographically dispersed firms align their interests better with nearby employees rather than with shareholders (*managerial alignment hypothesis*).

Asset sales are considered as effective channels to examine the relation between geographic dispersion and corporate decision making (Jovanovic and Rousseau, 2002; Yang, 2008; Warusawitharana, 2008; Boot, 1992; Lang, Poulsen and Stulz, 1995; Kose, Sodjahin 2010). In the context of asset sales, information asymmetry effect predicts a *positive* relation between distant sales and post sell-off stock market reaction (measured by cumulative abnormal return, or CAR) while managerial alignment effect suggests a *negative* relation between distant sales and post sell-off stock market reaction.[2] In this study, we examine the asset sell-offs by equity real estate investment trusts (REITs), which provides an ideal setting to investigate the two competing but *not* mutually exclusive effects. REITs operate within a single asset class (because REITs must have at

[2] Cumulative abnormal return (CAR) is also known as the cumulative prediction error (CPE) used in Glascock, Davidson and Sirmans (1991). It is noted that although the two hypotheses generate opposite predictions, they are not necessarily mutually exclusive. All else equal, if information asymmetry effect (managerial alignment effect) dominates, we should observe a positive (negative) reaction to distant sell-offs.

least 75%, of assets and income from real estate related assets), have similar dividend payout policies (because they are required to pay out 90% of taxable income as dividends), have high institutional ownership (see Chan, Erickson, and Wang, 2003), and have similar antitakeover provisions (because 5-50 rule and excess share provision). These features help mitigate the likelihood of alternative explanations to asset sell-offs such as changes in corporate strategy (Kaplan and Weisbach, 1992), financing needs (Lang, Poulsen, and Stulz, 1995) and corporate governance (John and Sodjahin, 2010; John, Knyazeva and Knyazeva, 2011).

Real estate is heterogeneous and illiquid with slow market mechanism (Ling and Archer, 2013; Levitt and Syverson, 2008). Based on the link between distance and information flows, soft information might play an important role in the real estate market as information on potential rental growth and local market conditions cannot be cheaply hardened.[3] Managers might tend to dispose of distant properties and to keep the nearby properties because information in the real estate market is more costly to communicate to distant agents.

Landier, Nair and Wulf (2009) suggest that distance creates a potential distortion between managerial incentives and shareholder interests because managers react differently to economic shocks to underlying operating assets and business divisions through social interactions.[4] For example, managers of geographically concentrated firms are more concerned about nearby operating assets due to reputational concern and about employees with whom they interact more frequently. When information is soft, personal interactions are important. More frequent social interactions

[3] This argument has its root in Petersen (2004), in which soft information is defined as information that is difficult to quantify. This implies that the cost of soft information, compared with that of hard information, is much higher for operating assets that are distant from the management (usually measured by firm headquarters). Bank lending related studies provide extensive discussions on the link between distance and information flows (Petersen and Rajan, 2002; Liberti, 2005; Agarwal and Hauswald, 2010; Knyazeva and Knyazeva, 2012). As a result, small banks are found to have information advantage in lending to less transparent firms using soft information.

[4] In a different context of individual decisions, Glaeser, Sacerdote and Scheinkman (1996) find a relation between proximity and social interactions.

with nearby employees and reputational concerns would likely affect a firm's decision on asset allocation and disposition.

The sources of uncertainty in the real estate sector mainly come from property type and location, both are considered as highly rigid and relatively permanent. This relative simplicity makes it a plausible benchmark to evaluate information asymmetry through geographic dispersion.[5] To mitigate information asymmetry, market participants tend to purchase nearby properties (Garmaise and Moskowitz, 2004) and REITs tend to be geographically focused (Cronquist, Hogfeldt, and Nilsson, 2001; Hartzell, Sun, and Titman, 2009). While this may be expected, our sample shows that REITs have a large dispersion of properties that are not close by conventional measurement. For example, the top-ten MSAs in our disposition sample were over 860 miles (1,388 kilometers) from their REIT headquarters (HQs).

We manually collect a sample of property sell-offs by REITs from 2003 to 2013 based on an extensive search of news articles. We are able to construct a panel sample of underlying properties with detailed information on type and location, taking sales, purchases, mergers and acquisitions into consideration. Constructing these data sets is not a trivial task as there are about 36,528 underlying properties held by REITs and non-REIT firms in each year, adding to 840,150 during the entire sample period and much of the information has to be hand collected and verified due to missing data, renovations and changes of usage.[6] The sample of property-year observations is

[5] Some studies examine manufacturing industries (Edmans and Mann, 2015; Arnold, Hackbarth, and Puhan, 2015). We argue that real estate might be better suited in testing the information asymmetry effect because the production at plant locations could be quite dynamic, depending on firm's strategy which is less observable.
[6] We include both to account for the property transactions and M&As between REITs and non-REIT firms. The total number of properties held by REITs from 2003-2013 is 344,010.

merged with a comprehensive list of U.S. public equity REITs from 1993-2015 identified by NAREIT.[7]

We start our analysis by investigating the impact of property-headquarter distance on investor reactions to property sell-offs by REITs. As a cluster of properties was sold in most of sell-off transactions, our distance proxies include mean and median distances from the properties being sold to the sell-off firm headquarter. By defining nearby (distant) sell-offs as distance below (above) median, our univariate analysis suggests that CARs of distant sell-offs are significantly lower. By controlling for firm-level characteristics, including fundamentals, sources of fund and use of fund, as well as deal-level characteristics in multivariate analyses, we find that positive reactions are associated with nearer property sales.[8]

The sell-off decisions at *firm-level* are endogenous and subject to selection bias as firms are self-selected to be sellers. One commonly used approach to mitigate this concern is to construct a matched sample of non-sell-off firms by using propensity score matching to control for firm characteristics. However, selection bias may also occur at *property-level* because assets being sold might be fundamentally different than those being held. We address this problem with a two-stage *sequential* decision making process. In the first stage, we estimate the likelihood of firm-level asset sell-offs. In the second stage we estimate the likelihood of property-level sell-offs, conditional on firm-level sell-off decision. Our matched sample is constructed based on joint probabilities, which is the product of the firm-level sell-off probability and the property-level conditional probability.

[7] A comprehensive list of U.S. equity REITs identified by NAREIT can be downloaded from Dr. S. McKay Price's website: http://www.mckayprice.com/research.html. We construct our dataset in a similar manner to Feng, Price and Sirmans (2011).

[8] To be sure that this is not driven by outliers, we sort the data by quartiles: the positive reactions uniformly declined as distance increases.

This research design could help mitigate the double selection bias at both firm-level and property-level.

The univariate investigation of firm and property characteristics confirm that there is a large heterogeneity between sell-off firms and control firms. Within sell-off firms, the properties that being sold are quite different than those being held. We find consistent results with Landier et al (2009) that firms adopt a "pecking order" and are more likely to sell distant properties than nearby properties. Based on a matched sample controlling for both firm-level and property-level heterogeneity, we conclude that investors react more negatively to distant sales and managerial alignment effect dominates. Our results are robust to different discrete choice models (logit and probit), different matched samples (i.e. based on firm-level, and both firm-level and property-level only), different weights (by number of sell-off and by holding properties), and different model specifications.

To investigate how managerial alignment effect plays a role in the relation between asset sales and firm value, we employ two potential explanations. First, we investigate the employee friendliness (based on union power measures, including union coverage density and union membership density in Hirsch and Macpherson (2003)) as measures of misalignment of interest between managers and shareholders. We find a positive and significant relation between aggregated proximity of a firm's property holdings (measured by Geographic HHI) and employee friendliness, suggesting that the proximity between a firm's headquarter and its underlying properties is associated with poor shareholder protection due to the better employee protection. Second, to further examine the role of social factors, we divide our matched sample into subsamples of large- and small-population. Consistent with Landier et al. (2009), we find that social factors only affect post sell-off stock performance of firms headquartered in less populated counties, where managers are more visible.[9]

Lastly, market participants could be confident with negotiating deals from further distance because more observable settled deals are available to the market participants mitigate information concern. This possible link between market depth and distance would be driven by information asymmetry but could also predict a negative relation between market reaction to property sale and sell-off distance to HQs. We take advantage of our property-level dataset and find that there is virtually no relation between selloff distance and market depth.

This study makes several important contributions. First, although the effects of information asymmetry have been extensively examined, the effects of managerial alignment have not. Information asymmetry hypothesis and managerial alignment hypothesis offer opposite predictions on the relation between geographic dispersion and firm value. The setting of REIT sell-offs is uniquely suited in testing these two competing effects as real estate is a sector subject to high information asymmetry and soft information plays an important role when cash flows are driven by local market with high idiosyncratic risks and when information about the true value cannot be cheaply hardened. Although these two hypotheses are not mutually exclusive, our findings favor managerial alignment effect, and complement Landier et al (2009)'s finding suggesting that the managerial decisions are crucial in determining the balance between shareholders and social concerns on reputation and employees.

[9] This confirms our prediction that *managerial alignment effect* and *information asymmetry effect* are not mutually exclusive. In less populated areas, *managerial alignment effect* dominates *information asymmetry effect*.

Second, our unique sample of asset sell-offs by REITs with detailed information on more than 800,000 property-year observations spanning a ten-year sample period provides us an opportunity to investigate the *double* endogeneity and selection bias problems at both firm-level and property-level using a sequential choice model. We believe this is the first study to address this issue in the literature of asset sales and the REIT literature.

Third, although prior studies in real estate suggest that REITs tend to be more property-type focused and location-focused, and many find that more property-type focused REITs value more than property-type diversified firms, they fail to find that it is the case in location-focused firms (see, for example, Cronqvist, Hogfeldt, and Nilsson, 2001). Our findings propose a new perspective and suggest that one should take into consideration managerial alignment with shareholders' benefit.

The reminder of the paper is organized as follows. In section 2, we briefly discuss the relevant literature. In section 3, sample construction and variable measurement are described. In Section 4, empirical results that test the two effects' implications are reported. Section 5 concludes the paper.

2. Literature Review

This study is related to several strands of literature. First, information concern has long been recognized as an important driving force of individual and corporate decisions. The effect of information asymmetry have received much attention since Peterson (2004), which classified information sources into hard vis-a-vis soft information. He argues that information concern arises when soft information, which cannot be easily quantified and is personal, dominates in a particular market. For example, in the banking industry, credit decisions are made based upon information collected over time through frequent and personal contacts with the borrower (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010; Knyazeva and Knyazeva, 2012). Since the term, "soft information", is innovated by Petersen (2004), its existence and effect have been noticed and discussed in many prior studies. For instance, issues such as "Home Bias" and "Local Bias" have received a lot of attention in the finance literature (French and Poterba, 1991; Huberman, 2001; Bodnaruk, 2009). A central argument of these studies is that investors tend to ignore diversification benefits and invest in the familiar.

One may doubt if such facts still exist as technologies that facilitate information transmission become more mature nowadays. Based on the recent literature such as Bernile, Kumar and Sulaeman (2015), however, the hardening of information doesn't fully resolve the "Home Bias" and "Local Bias".[10] One potential explanation is that certain components of soft information are heavily dependent on social interactions, which is personal and hard to quantify. This is especially true for the real estate industry, where assets are highly illiquid and information consideration is significant (Garmaise and Moskowitz, 2004).

Second, our evidence suggest that social factors are important and shape corporate decisions (Wang, 2012; John, Knyazeva, and Knyazeva, 2011). Introduced by geographical locations, these social factors affects firms' operation and thus shareholder wealth. For instance, Landier, Nair and Wulf (2009) argue that proximity to employees lead to misalignment of managerial incentives with shareholder objectives because managers interact more frequently with nearby employees. They find that in-state divestitures of a firm's entities lead to positive and significant *ex post* stock performance when the firm's headquarter is located in a less populated county. They

[10] Hardening of information refers to the question of whether information can be interpreted and coded into a numeric score (or scores) is a hard question (Petersen, 2004, pp. 6). For a comprehensive review of possible consequences of the hardening of information on both financial markets and institutions, one can refer to Petersen (2004).

give rise to the conflict of interest between stakeholders and shareholders, which is further explored in John, Knyazeva, and Knyazeva (2011). In addition, the amount of population affect firm's corporate governance through proximity to the firm's headquarter because of larger pools of director talent. Knyazeva, Knyazeva, and Masulis (2013) find that population is positively correlated with local director pool and thus the monitoring effect on firm's management. A recent paper by Ang, Jong, and Poel (2014) find that CEOs' divestments of familiar segments generate 1.2% higher abnormal returns and the greater returns are particularly pronounced for divestments of direct-experience segments by more entrenched CEOs.

Finally, our study contributes to the mixed evidence found on diversification discount of listed firms. "Diversification discount" attracts a lot of attentions in the finance and real estate literature. It is defined as "the fact that the average diversified firm has been worth less than a portfolio of comparable single-segment firms" (Lang and Stulz, 1994, pp. 36). Several explanations to diversification discount are proposed. First, firm-level diversification may provide more benefits to managers than it does to shareholders (Amihud and Lev, 1981). Second, internal capital markets in conglomerates transfer funds across divisions in a suboptimal manner (Lamont, 1997; Whited, 2001). Third, diversified firms are less transparent and more difficult to analyze. Therefore, their underlying stocks are less liquid and have lower value. REITs provide a suitable laboratory to study the "diversification discount" issue because REITs are less heterogeneous than conventional firms and the underlying assets, real estate, are less opaque than other revenue generating assets. The "diversification discount" on property type has been found in several recent studies such as Cronquist, Hogfeldt, and Nilsson (2001) and Ro and Ziobrowski (2012). However, evidence on the "diversification discount" on geographic dispersion of REITs' underlying properties is mixed (Hartzell, Sun, and Titman, 2009). Moreover, failure to notice endogeneity issue and could potentially bias the results found in previous studies.[11]

3. Sample Construction and Variable Measurement

3.1. Sample Construction

3.1.1. Sell-off Events

We search in Factiva to collect news announcements on property sales by REITs. Factiva applies Intelligent Indexing® in order to assign unique company codes to Dow Jones News Search (DJNS) articles that represent the companies that are the subject of the articles. Because of the Intelligent Indexing, Factiva is considered effective in identifying articles relevant to specific companies. By conducting rigours search in (1) Wall Street Journal, (2) Dow Jones Newswire and (3) Business Wires, we gather 1,271 articles on property sell-offs from January 1, 2003 to December 31, 2013 by all the US Equity REITs included in the FTSE National Association of Real Estate Investment Trusts (NAREIT) US equity REIT Index.

We follow Campbell et al. (2006) and focus on property sell-offs with total value greater than $20 million. For each property sale, we define an event date as the first trading day that the sell-off announcement appears in any of the three forth-mentioned publications if the announcement is made prior to 3:59 pm. If the announcement is made after 3:59 pm, we use the next trading

[11] For instance, Lamont and Polk (2001) argue that poor performers may be more likely to diversify in an attempt to increase value. Similarly, Campbell, Petrova and Sirmans (2003) also notice that a weakness of the diversification literature in Real Estate is that there are few studies that examine the relationship between shareholder wealth and events that significantly alter expectations regarding the firm's level of diversification or focus. Such studies are required to address the possible problem of self-selection and endogeneity in the data similar to those that have been noted in the finance literature. Therefore, using well-specified self-selection models to capture ex-ante expectations on firms' self-selection process and to mitigate endogeneity issue is important.

day as the event date. Events are deleted if there are any other major corporate announcements during the event window. The sample selection process gives us 161 property sell-offs. We delete 8 observations without property-level information. 154 sell-offs are used in our baseline regressions.

3.1.2. REIT Underlying Properties

We construct a comprehensive panel data of historical property holdings at REIT-property-year level based on the SNL Financial database, Factiva news search on property acquisitions and dispositions and on REITs mergers and acquisitions. Specifically, we start with the most current property holdings by all the REITs and track backward with historical property acquisitions and dispositions. To account for delisted and newly listed REITs, we follow Feng, Price and Sirmans (2011) and manually construct a comprehensive list of US public equity REITs identified by NAREIT from 1993-2015. Our sample is comprised of all equity REITs that are included in the calculation of the FTSE NAREIT US equity REIT Index.[12]

Our final sample includes 3,797 firm-year observations and 344,010 firm-property-year observations from 2003 to 2013. We further divide our sample into two groups, sell-off firms and non-sell-off firms. Our non-sell-off sample for testing the propensity of firm-level asset sell-offs includes all REIT-years except REITs that are in the sell-off sample. There are 100 firm-year and 1,157 property-firm-year observations (3,697 firm-year and 332,853 property-firm-year observations) in the sell-off sample (non-sell-off sample).[13]

[12] The FTSE NAREIT US Real Estate index contains all Equity REITs not designated as Timber REITs or Infrastructure REITs.
[13] 206 property-firm-year observations without information regarding properties held by the sellers available are dropped from the full sample of 1,363 property-firm-year observations.

3.1.3. Cumulative Abnormal Returns (CARs) and Control Variables

We compute CARs using CRSP value weighted market index, excess returns of small caps over big caps (SMB), excess returns of value over growth (HML), and momentum factor as systemic risk factor loadings. We follow Wiley (2013) and use an estimation period that includes one year of stock returns and ends 50 trading days before the event window. Event windows include (1) a trading day before the asset sale until the trading day (-1, 0), (2) the trading day when the asset sale occurs (0, 0), (3) the trading day when the asset sale occurs until the trading day after (0, +1), (4) the trading days before the asset sale until the trading day after (-1, +1), (5) five trading days before the asset sale until the trading day before (-5, -1), and (6) five trading days before the asset sale until five trading days after the asset sale (-5, +5).

Data on deal sizes are verified manually by matching Factiva search results with EDGAR SEC filings. We obtain stock price data from CRSP and financial data from COMPUSTAT-CRSP Merged database, respectively.

3.2. Distance Proxies

We calculate a firm-property-year distance, d_{ijt}, for each underlying property j sold or held by firm i in year t. Firm-property distances need to be aggregated for each transaction as there are more than one underlying property for each REIT-year and multiple properties sold in a sell-off transaction. Firm-year distance is calculated by taking the arithmetic mean and median of all firm-property distances for each firm-year or sell-off using the following expressions

$$AggregateDistance_{i,t} = \frac{1}{n}\sum_{j=1}^{n} d_{ijt}$$

$$MedianDistance_{i,t} = median_i(d_{ijt}), \tag{1}$$

where d_{ijt} represents the firm-property distance in year t, n equals to the number of properties sold or held by firm i.

4. Results

4.1. Asset Sell-offs and Market Reactions

Table 1 summarizes the annual frequency of property sell-offs, total value and average deal size from 2003 to 2013. There are 161 transactions with a total value of approximately $33 billion. The average deal size is $204 million. The number of sell-offs and the average deal size plummeted around the Global Financial Crisis (GFC) in 2008 and 2009. In unreported results, there are 68 unique sellers (defined by their CRSP PERMNO), of which 32 appear only once and 17 appear more than three times.

In Table 2, we divide our sample by property type and by their stated use of proceeds announced in the publications. The largest group by property type is office and industrial properties (41%). Most of the sell-off firms (45%) do not announce the use of sale proceeds. Among sell-offs with stated purposes, the largest group is to reduce debt (18.6%). Only 2.5% (1.9%) of sell-offs are to distribute dividends (to repurchase shares). In our sample, the breakdown by property type is qualitatively similar to Campbell et al. (2006), which examine equity REIT property sell-offs between 1992 and 2002. However, the breakdown by the use of sale proceeds is different from Campbell et al. (2006) as the largest group in our more recent sample is fund acquisition.

Panel A of Table 3 shows summary statistics CARs based on six different event windows, (-1,0), (0,0), (0,1), (-1,1), (-5,5) and (-5,0), which represent the one-day before, one-day, one-day ahead, three-day, eleven-day, and six-day windows, respectively. All CARs are positive and significant at 1% level except for the six-day window. Compared the CAR magnitude with prior studies, the mean in three-day window (-1, 1) is 1.18%, which is very close to the finding in Glascock, Davison and Sirmans (1991) and is greater than 0.8% reported in Campbell, Petrova and Sirmans (2006.).[14]

In Panel B, we separate our asset sales into two groups based on the distribution of distances from disposed properties to their headquarters. If the distance of a disposed property is greater than the sample median, it is assigned to the below-median group. Otherwise, it is assigned to the above-median group. If the deal consists of multiple properties, we use the average distance.

By comparing CARs of sell-offs with relatively short distance (in the below-median group) and that with relatively large distance (in the above-median group), we find that CARs of nearby sell-offs are positively significant while that of distant sell-offs are statistically insignificant. The *t*-statistics (=2.00) of mean difference and *z*-statistics (=1.69) of rank-sum tests (for median difference) between these two groups are significant. Unreported results suggest a similar pattern in all windows.[15] It reveals that the abnormal returns of sell-offs are higher if disposed properties are located in a relatively short distance from the headquarter location of its holding company, in favor of the managerial alignment explanation. By further separating our asset sales into four distance quartiles, Panel C confirms the negative relation between distance and CAR as we observe a monotonically decreasing pattern across distance quartiles.

[14] In unreported results, we find that, consistent with Campbell et al (2006), the average CAR in three-day window is significantly positive for sales that are not structured as Section 1031 transactions while there is no evidence of CAR for Section 1031 transactions.

[15] In unreported results, for each property-year, we define Distant as an indicator variable that takes value of one if it is located above median distance of the other underlying properties. For multiple property sales, we calculate aggregate this variable at deal level by taking the average. We investigate the sub-sample of CARs with Distant above median and that below median and find similar results.

The finding of a negative relation between market reaction to property sales and the distance of sell-off properties to their HQs is new and complements previous studies such as Hartzell, Sun, and Titman (2009), who find evidence of regional diversification discount of REITs utilizing a sample of equity REITs over the 1995-2003 period.

Hartzell, Sun, and Titman (2009) also suggest that the regional diversification discount is mitigated when institutions have a greater equity stake as institutions monitor the REITs more effectively than retail investors. We predict that firms located in areas with larger population has stronger monitoring effect as population can be used as an approximation of the size of potential director pool (Knyazeva, Knyazeva, and Masulis, 2013); therefore, benefits to the shareholders associated with local selloffs is smaller. To test this prediction, we sort CARs over three-day window into different subgroups based upon four distance quartiles and median local population, which is measured by the population of the county where a REIT is headquartered.[16]

In Panel D, our results suggest that the positive relation between selloff CARs and geographic proximity only exists among REITs headquartered in counties with population below sample median (*Small Population*). There is no such relation for REITs headquartered in counties with population above sample median (*Large Population*). Moreover, CARs are larger for *Small Population* group than for *Large Population* group in the first three distance quartiles.

In an alternative measure of monitoring based on population, we follow Loughran and Schultz (2005) and define a REIT as in a "top-ten" MSA if its headquarters is in one of the ten

[16] We also divide the selloff CARs into different subgroups four distance quartiles and small-, medium-, and large-population groups. We find that the monotonic declining relation between CARs and distance only exists among the small-population group. The results are reported in Panel E.

largest metropolitan areas of the U.S. according to the 2010 Census.[17] We define the rest of the REITs in our sample as in “non-top-ten” MSAs. Information asymmetry concern is likely to be more severe among firms in smaller MSAs than those in larger ones due to the lack of monitoring effect. Consistent with Panel D, results in Panel E suggest that the negative relation between CARs and distance only exists among property selloffs by non-top-ten-MSA REITs.

As business cycle might exert different effects on small and on big MSAs and potentially drive the previously documented results, in Panel F, we use the fall of Lehman Brothers (May 28, 2009) as the cutting point. Selloffs occur prior to May 28, 2009 are defined as Pre-Recession selloffs; the rest of the selloffs are defined as Post-Recession selloffs. We did not find too much evidence that our previous findings are affected by business cycle: Small (non-top-ten) MSA selloffs experienced a decline in CARs during the post-recession period but such effect does not exist in large (top-ten) MSA selloffs.

4.2. The Impact of Distance on Market Reactions – OLS Regressions of CARs on the Determinants of Abnormal returns

To further investigate the heterogeneity among sell-off firms, our next step is to conduct multivariate analysis controlling for firm-level and deal-level characteristics. We follow Wiley (2013) and perform three sets of tests based on firm-level determinants of CARs: (1) fundamentals, (2) source of fund and (3) use of fund. In addition, we add tests based on deal-level characteristics as documented in the literature (Lang, Poulsen, and Stulz, 1995; Campbell, Petrova, and Sirmans,

[17] Loughran and Schultz (2005) define firms as urban, small-city or rural based on their location relative to the largest MSAs in terms of population.

2006; Wiley et al., 2010; Wiley, 2013). We report summary statistics of these determinants in Table 4 Panel A and regression results in Panel B, C and D.

4.2.1 Fundamentals

The difference in market reactions are driven by differences in firm fundamentals. The model of the impact of distance on market reactions with firm fundamentals is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Cash + \beta_3 Firm\ Size + \beta_4 ROA + \beta_5 Debt + \beta_6 Coverage + \beta_7 Tobin's\ Q + \beta_8 DC + \varepsilon, \quad (2)$$

where *Distance Proxies* include average and median firm-property distance described in Equation (1). *Cash* is cash and short-term investments (CHE) divided by total assets (AT). *Firm Size* is the annual reported book value of total assets (AT) in millions of USD. Return on assets (*ROA*) is expressed as the annual net income (NI) over total assets (AT). *Debt* equals to the sum of total long-term debt (DLTT) and debt in current liabilities (DLC) divided by total assets (AT). *Coverage* is interest coverage ratio, which equals income before extraordinary items (IB) divided by the sum of preferred dividends (DVP) and interest and related expenses (XINT). *Tobin's Q* equals total book assets (AT) plus the market cap (PRCC_C*CSHO) minus common equity (CEQ), all divided by total book assets (AT). *DC* is an indicator variable which equals one if a firm's coverage ratio is below the sample median in the last fiscal year prior to the announcement, and zero otherwise. All the fundamental variables are lagged.

Table 4 Panel A presents summary statistics and Panel B includes regression results of the relation between investor reactions and underlying property distance to the selling REIT's head-quarter. In both Model (1) and (2), the coefficient estimates of distance proxies are negative and statistically significant, controlling for firm fundamentals. The effect is also economically significant: one standard deviation increase in average (median) distance decreases CARs by 117 (114) basis points from the mean (median).[18]

Coefficient estimates of control variables have expected signs and are consistent across model specifications. Since we restrict our analysis to the short event window (3 days) and avoid property selloffs coincide with other events, i.e., mergers and acquisitions, coefficient estimates on most *ex ante* fundamental return predictors are insignificant. There is a positive and statistically significant relation between CAR and pre-announcement debt ratio. Lang, Poulsen and Stulz (1995) suggest that asset sale may help avoid recapitalization costs that would have to be paid to raise funds on capital markets when the firm's debt overhang is large. Therefore, lower cost of refinancing might explain the positive relation between CAR and pre-announcement debt ratio. On the other hand, the positive relation between CAR and pre-announcement debt ratio could also be explained by lower agency cost if debt plays a useful role in disciplining management.

The results based on continuous distance measures might be driven by outliners. As a result, we use an alternative binary measure of distance, *Nearby*, which equals to 1 if *median distance* in Equation (1) is less than the sample median of the 154 selloff observations and 0 otherwise. In Model (3), we find that *Nearby* dummy is positively associated with the abnormal returns. This finding indicates that our previous results based on the other distance measures are robust and supports the managerial alignment hypothesis.

4.2.2 Sources of Fund and Use of Fund

[18] From Table 4, Panel A, the standard deviation of average (median) distance is 0.961 (1.001); from Table 4, Panel B, the coefficient estimate on average (median) distance is -1.216 (-1.142). Therefore, one standard deviation change in average (median) distance leads to -1.216 * 0.961= 1.17 (-1.142 * 1.001= 1.14) percent, or 117 (114) basis points from the mean (median), decrease in CAR.

In addition to ex ante firm's fundamentals, sources of funds and use of funds are also likely to affect ex post sell-off stock performance. For instance, Lang, Poulsen, and Stulz (1995) find that firms paying out the proceeds are typically poor performers and highly levered firms. Lang, Poulsen, and Stulz (1995) address the importance of both sets of variables. They suggest that managers are self-interest individuals who pursue their own objectives and are likely to be empire builders. Empirically testing managerial alignment involves both sources of funds and use of funds. Therefore, including these two sets of variables as control variables help disentangle the effects of our distance measures, firm's fundamentals, and firm's financing and investment activities.

Consistent with the literature (e.g. Wiley, 2013), we conduct analysis with sources of funds and use of funds as control variables separately. We control for funding generated from the proceeds of an asset sale and/or from the capital markets. The model of the impact of distance on market reactions with sources of funds is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Selloff + \beta_3 Gain + \beta_4 DebtIssues + \beta_5 EquityIssues + \varepsilon, \tag{3}$$

where *Distance Proxies* and *Selloff* are defined the same as Section 4.2.1. *Gain* is the reported gain or loss generated from the sale of property (SRET). *Debt Issues* is the total new long-term debt issued (DLTISY). *Equity Issues* is the total proceeds from the sale of common and preferred stock (SSTKY). All the sources of fund variables are lagged.

Next, we address the question how funding raised in the previous step is spent. Funding can be used to retire debt, to distribute as preferred and/or common dividends, and/or to invest in new projects. Therefore, we follow Wiley (2013) and include potential usage of funds as control variables in our analysis. The model of the impact of distance on market reactions with use of funds is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Selloff + \beta_3 DeltaDebt + \beta_4 DeltaPreferredEquity + \beta_5 DeltaCommonEquity + \beta_6 DeltaInvestment + \varepsilon, \quad (4)$$

where *Distance Proxies* and *Selloff* are defined the same as Section 4.2.1. *Delta Debt* is the difference in debt reduction (DLTRY) from the previous fiscal year (t-2) divided by total long-term debt (DLTTY), in the last fiscal year prior to the sell-off announcement (t-1). *Delta preferred* equals the difference in preferred dividends paid (DVPY) from the previous fiscal year (t-2) divided by total liabilities (LT). *Delta common equity* equals the difference in cash dividends paid (DVY) from previous fiscal year (t-2), divided by the market cap (PRCC_C*CSHO). *Delta investment* equals the difference in increased investments (IVLTY).

Results in Panel C and D of Table 4 conform the negative relation between property-HQ distance and market reaction to property sell-offs: the coefficient estimates of different distance measures are negative in all the model specification. The coefficients of continuous distance measures are smaller compared with those in Panel B. The coefficient estimates of control variables associated with the sources of funds and use of funds have consistent signs as in Wiley (2013) but are statistically insignificant.[19]

4.2.3 Deal-level Characteristics

[19] There are two potential explanations for this. First, Wiley (2013) use abnormal returns over intermediate window (5 weeks) as dependent variable but we follow Campbell et al. (2006) and use abnormal returns over the short horizon (3days) as dependent variable. Second, Wiley (2013) focus on apartment and office properties through 2010, but our sample covers all major types of properties through 2013.

For each transaction, we hand collected detailed information on the purpose of the sale and the usage of sale proceeds which is unarguably important as it affects investors' prospect on the asset sell-off and thus can affect post sell-off stock performance. The model of the impact of distance on market reactions with deal-level dummies and firm's fundamentals is

$$CAR = \beta_0 + \beta_1 Distance\ Proxies + \beta_2 Deal\ Size + \beta_3 Geographic\ Focus + \beta_4 URSTD + \beta_5 URLTD + \beta_6 EXCH + \beta_7 Recession + \beta_8 Pay\ Dividend + \beta_9 Cash + \beta_{10} lnrsize + \beta_{11} ROA + \beta_{12} dassets + \beta_{13} Coverage + \beta_{14} Tobin's\ Q + \beta_{15} DC, \quad (5)$$

where *Distance Proxies*, *Selloff*, and fundamental variables (*Cash*, *lnrsize*, *ROA*, *dassets*, *Coverage*, *Tobin's Q*, and *DC)* are defined the same as Section 4.2.1. *Deal Size* equals to the transaction price divided by total book assets (AT). *Geographic Focus* is an indicator variable equals to 1 if the stated goal of a particular asset sale is geographic focus and 0 otherwise. *URSTD (URLTD)* is an indicator variable equals to 1 if proceeds from sale are announced to be used to reduce short-term (long-term) debt. *Pay_Div* is an indicator variable equals to 1 if proceeds from sale are announced to be distributed as dividends. Prior studies suggest that distributing dividends to shareholders may signal either the seller's financial solvency, or a less-entrenched management team, or both. *EXCH* is an indicator variable equals to 1 if 1031 tax-free exchange is used. *Recession* is an indicator variable equals to 1 if announcement date is in the recession period defined by NBER US Business Cycle Expansions and Contractions (http://www.nber.org/cycles.html).

In Panel E with more controls of deal level characteristics, we find that the negative relation between CAR and the proximity of sell-off properties to their HQs is still robust. The magnitude of the coefficients are very similar to those in Panel C and D, even controlling for *Geographic Focus*, whether the purpose of a particular sale is to increase the geographic focus of the selling

REIT. Regarding deal-level indicators, we find that market reactions are positively associated with the application of sale proceeds to the retirement of short-term debt (*URSTD*), deal size (*Deal Size*) and *Pay Dividend* dummy.

4.3. Matched Sample based on Two-stage Sequential Model of Asset Sell-off Decisions

Although our cross-sectional regression results in Section 4.2 suggest that investors react more positively to sell-offs of nearby assets, controlling a large set of aspects that might affect the abnormal returns of asset sell-offs, selection bias may occur at firm-level because we only observe the market reaction-distance relation among firms that self-select to be sellers. For example, firms that are more financially constraint, holding more geographically dispersed properties are more likely to become sellers. A possible solution is to construct a matched sample of firms with similar characteristics of sell-off firms.

However, one complication arises because, given that a sell-off is likely at *firm-level*, selection bias may occur at *property-level* because assets being sold maybe fundamentally different than those being hold. For example, it is well-documented in literature that REITs tend to specialize in operating a single type of property or in a more focused geographic area (Capozza and Seguin (1999), Campbell, Petrova, and Sirmans (2003), Hartzell, Sun, and Titman (2009), Ro and Ziobrowski (2012)). If an underlying property is of a different type from the majority of the other holding properties or is located in a distant area compared with the majority, it is more likely to be sold. As a result, the typical firm-level matching is not sufficient to mitigate this endogeneity problem.

Our matching sample is constructed based on a two-stage *sequential* decision making process, in which the first stage is to estimate the likelihood of asset sell-off occurs at firm-level and the second stage is to estimate, conditional on the firm-level sell-off, the likelihood of a property being sold within the firm. Next, the joint probability is the production of firm-level sell-off probability and the property-level conditional probability as follows

$$\begin{aligned} P(seller = 1)_{i,t} = {} & \beta_0 + \beta_1 Size_{i,t-1} + \beta_2 FFO_{i,t-1} + \beta_3 Debt_{i,t-1} + \beta_4 TobinQ_{i,t-1} + \\ & \beta_5 Cash_{i,t-1} + \beta_6 SaleGrowth_{i,t-1} + \beta_7 Coverage_{i,t-1} + \\ & \beta_8 Momentum_{i,t-1} + \beta_9 DC_{i,t-1} + \ Firm\ Fixed\ Effects\ + \\ & Year\ Fixed\ Effects\ +\ \varepsilon, \end{aligned} \tag{6}$$

$$\begin{aligned} P(ppty\ sold = 1|seller = 1)_{i,j,t} = {} & \gamma_0 + \gamma_1 Nearby_{i,j,t-1} + \gamma_2 Diverse_{i,j,t-1} + \\ & \gamma_3 Office_j + \gamma_4 Retail_j + \gamma_5 Multifamily_j + \gamma_5 Industrial_j + \\ & \gamma_6 Leisure_j + \gamma_7 HealthCare_j + \gamma_8 OtherType_j + \\ & Property\ Fixed\ Effects\ +\ Year\ Fixed\ Effects\ +\ \varepsilon, \end{aligned} \tag{7}$$

where $P(ppt\ sold = 1, seller = 1)_{i,j,t}$ is the joint probability that property *j* is disposed by firm *i* in year t, $P(seller = 1)_{i,t}$ is the probability of sell-off by firm *i* in year *t*, $P(ppty\ sold = 1|seller = 1)_{i,j,t}$ is the conditional probability that property *j* hold by firm *i* is disposed, given that $P(seller = 1)_{i,t} = 1$.

Firm-level determinants of asset sale are constructed based on prior studies and include *Size*, *FFO*, *Debt*, *Tobin's Q*, *Cash*, *Sale Growth*, *Coverage*, *Momentum* and *DC*. *FFO* is funds from operations (FFO) divided by total assets (AT). *Sales Growth* is the annual percentage change in total revenue (REVT). The remaining variables are the same as in Equation (2). For property-level characteristics, *Nearby* is a dummy variable that takes one if the distance of a deal is less than the sample median and 0 otherwise. *Diverse* is a dummy variable that equals 1 if the property type of the property been disposed is different from the property type of a particular firm identified by

CRSP permanent security identification number (PERMNO) and 0 otherwise. *Hold Time* describes how many years has a property been held by a particular company. *Office*, *Retail*, *Multifamily*, *Industrial*, *Health Care*, *Hotel* and *Others* are indicator variables of property types.

Table 5 presents the comparison between firm-level and property-level characteristics of sell-off firms with that of non-sell-off firms. The last two columns report *t*-test statistics of the mean differences between sell-off firms and non-sell-off firms and their significance. The "*Firm-level*" comparison suggests a stark difference between these two groups: sell-off firms are larger, have better operating performance prior to the sell-off, hold more debt and less cash, consistent with Campbell et al. (2006) and Warusawitharana (2008). These comparisons are statistically significant. The "*Property-level*" comparison suggests that the sell-off firms adopt a "pecking order" and tend to dispose distant properties (Landier, Nair and Wulf, 2009; Peterson and Rajan, 2002; and Peterson, 2004). If the underlying property is different from the majority, it is more likely to be disposed. In addition, sell-off firms tend to hold properties for a shorter period of time. Breaking down the underlying properties by type, there is a large discrepancy in property compositions between sell-off firms and control firms. REITs are more likely to dispose office and industrial properties. Together, both firm-level and property-level comparisons between sell-off REITs and control REITs suggest that it is important to control for heterogeneity at both firm-level and property-level.

Table 6 presents our results of two-stage sequential analysis with binary outcome variables. Results of the first stage of firm-level sell-off decision in Equation (6) and that of the second stage of property-level sell-off decision in Equation (7) are included in Panel A and Panel B, respectively. In Column (1), a selloff firm is firstly matched to a non-selloff firm with the closest holding distance. Holding distance is defined as the average geographic distance between firm headquarters and properties been held. Then we estimate Probit model with the selloff sample and distance-matched non-selloff sample (hereby distance-matched model). Therefore, there is no property matching corresponding to Column (1). Results based on logit model and Probit model are shown in Column (2) and (3), respectively. To accommodate repeated sales, we repeat our analysis with the number of properties sold as weights, shown in Column (4) and (5), respectively.

Results in Panel A suggest that REITs are more likely to become sellers if they are larger, have higher ROA, have high debt ratio and less cash. These results are largely consistent with Warusawitharana (2008). Based upon his theoretical framework, firms that are exposed to a negative profitability shock find themselves with more assets to reach optimal size.[20] In Panel B, consistent with REITs pursuing a focusing strategy, properties located near its headquarters and of a different type from the majority of the underlying properties are more likely to be sold. In addition, industrial properties are more likely to be disposed relative to the other types.

The results of the two-stage sequential model in Table 6 suggest that there are selection problems at both firm level and property level. Our next step is to construct a matched sample of properties based on the *predicted* joint probability that a property *j* is disposed by firm *i* in year *t*, which is the production of the *predicted* probability calculated based on the first-stage estimates in Equation (7) (shown in Panel A) and the *predicted* conditional probability based on the second-stage estimates in Equation (8) (shown in Panel B) as follow

[20] However, one of our findings contradicts his prediction. We find ex ante profitability positively predicts the probability of a property being disposed. One explanation for this is that our sample period coincides with the capital recycling phase of REITs (2003-2007), through which REITs became net sellers. Although REITs enjoyed high growth and profitability due to property appreciation during this period, the majority of the managers of REITs realized the upcoming threat brought by overvalued properties and actively disposed those particular properties.

$$P(\widehat{ppt\ sold = 1, seller} = 1)_{i,j,t} = P(\widehat{seller =} 1)_{i,t} \times P(ppty\ sold \widehat{= 1|} seller = 1)_{i,j,t} \tag{9}$$

For a given firm-year, we then calculate our propensity score for a given firm-year by aggregating the predicted joint probabilities at property-level as an average predicted probability as shown below.

$$Propensity\ Score_{i,t} = \frac{\sum_{j=1}^{J} P(ppt\ sold{=}1, seller{=}1)_{i,j,t}}{J}, \tag{10}$$

Next, we calculate absolute differences between the average predicted probabilities (propensity scores) of firms in our sell-off sample (treatment group) and that in the non-sell-off firms. We then rank the absolute differences and keep firms in the non-sell-off sample using the nearest neighborhood 1:3 with replacement (Rosenbaum and Rubin, 1983).[21] The match is performed in year *t*-1, prior to the sell-off.

Results based on propensity score matched sample are presented in Table 7. Tests based on firm fundamentals, source of fund and use of fund are presented in Panel A, B and C, respectively. In Panel A, we include the sell-off sample (treatment group, as in Panel B of Table 4) and the control groups constructed using five different propensity score matching methods. We use lagged fundamental variables and sell-off dummy as control variables. We regress three-day cumulative abnormal returns on *Average Distance*, *Sell-off dummy*, and firm's fundamentals.

[21] We repeat our tests using (1) nearest neighbor 1:1 with replacement, (2) nearest neighbor 1:1 without replacement, (3) nearest neighbor 1:3 without replacement and (4) a sample including all firms within the region of common support of their propensity scores. Results are qualitatively similar.

The coefficient estimates of return predictors (fundamentals, sources of funds, and use of funds) are largely consistent with results reported in Table 4. It is worthwhile noting that the distance measure, *Average Distance*, is the average of all the firm-property distances prior to the asset sell-off. The coefficient estimates for *Average Distance* are negative and statistically significant. *ROA*, which is defined the same as previously, has negative and significant coefficient only when distance-matched model is applied to construct our control sample. This is potentially due to the bad match by simply distance-matched model, which ignores property-level information. *Dassets* has positive and significant coefficient estimates under distance-matched and Probit Model weighted by the number of underlying properties. This is consistent with the financing hypothesis of asset sales to some extent. We use sources and use of funds variables as control variables in Panel B and C, respectively, and find that our results on distance are robust to the inclusion of different control variables.

4.4. What Explains the Negative Relation between Distance and CARs

In the previous sections, we conclude a negative relation between post sell-off stock return and distance measures, suggesting a dominant role of managerial alignment. In this section, we investigate the role of social factors and managerial concern for employees as documented in Landier, Nair and Wulf (2009). First, we examine whether high ex ante local union power (employee friendliness) leads to high geographic concentration of a firm's property holdings (or, aggregated proximity of all properties held by a firm) ex post. Second, we follow Landier, Nair and Wulf (2009) and evaluate if the effect of proximity on post sell-off stock performance varies by size of community. In other words, we explore if the proximity-firm value linkage is stronger when the manager is more visible in the community.

4.4.1. Labor Union Power and Geographic Concentration

In Landier, Nair, and Wulf (2009), geographic dispersion of firms is related to corporate actions such as employee friendliness and divestitures. The proximity between a firms' HQ location and its division locations is associated with interest misalignment between managers and shareholders because of more frequent interactions between managers and nearby employees. The proximity might have a detrimental effect on shareholder wealth. In this section, we tests whether geographical concentration and employee friendliness are related. Similar to Landier et al. (2009), we regress *Geographic HHI,* a geographic concentration measure, on *Union Power*, a measure of employee friendliness. *Union Power* is the state-level union coverage (membership) density adopted from Hirsch and Macpherson (2003). *Geographic HHI* is a Herfindahl-Hirschman index that measures the geographic concentration of a firm's property holdings. We calculate this measure based on Hartzell, Sun and Titman (2014) as,

$$\text{Herfindahl Index (HHI)} = \sum_{i=1}^{I} P_I^2, \tag{11}$$

where P_i is the proportion of a REIT's properties located in geographic location (city) *i*. In other words, we examine how property management teams can exert influence on managers ex post via its proximity to the firm's headquarter location. The regression coefficient estimates are reported in Table 8.

We find a positive and significant relation between *Geographic HHI* and *Union Power*, which confirms our prediction that high *Union Power ex ante* is associated with a potential misalignment of between managers and shareholders, whereby managers are more likely to dispose distant assets relative to nearby ones. The outcome of this misalignment of interest is captured by the higher geographic proximity between a particular firm headquarters location and properties held ex post.

4.4.2. Population and Effect of Distance on CAR

To explore the driving force behind the negative relation between CAR and distance measures, we focus on population around a particular firm's headquarter location. There are at least two reasons for us to examine population. First, as mentioned in Landier, Nair, and Wulf (2009), managers are more visible in small population communities where social factors are likely to play an important role. If the effect of distance on CAR is purely information driven, one should not expect to find different results. Second, monitoring effect on managers is stronger in large population communities relative to small ones because population are positively correlated with director pool. The monitoring effect from directors strengthens corporate governance and mitigates misalignment of interest between managers and shareholders (Knyazeva, Knyazeva, and Masulis (2013)). Both reasons indicate that the effect of distance on CAR should be more prominent in small population communities relative to large ones.

To empirically test these implications, in Table 9 we divide our matched sample into high and low population sample (Less population=0 and 1, respectively) by comparing the population around a particular firm's headquarter to the sample median population. Population data is obtained from the U.S. Census Bureau in the year 2010 at county level. Consistent with our predictions, the effect of distance on CAR becomes more negative and significant for low population sample. However, we didn't find any evidence for high population sample. This finding further supports our previous results that both informational and social factors are important in affecting post sell-off stock returns via proximity and this effect is more robust among low population firms relative to high population ones.

4.4.3. Market Depth as an Alternative Explanation that Supports Information Asymmetry

Our results is supportive of managerial alignment theory in the literature, especially for firms that are located in less-populated MSAs. However, one could argue that the negative relation between market reaction to asset sales and property-HQ distance might be affected by market depth, which is essentially driven by information asymmetry. For example, even when the sell-off properties are far from the HQ, the information asymmetry could be low in an active market if there are abundant sales transactions and comparables. If it is the case, finding a negative relation between CAR and distance of disposed properties to their HQs becomes a story about information dissemination and is irrelevant to managerial alignment.

To investigate this issue, we take advantage of our property-level dataset and conduct analysis to see whether the selloff distance is determined by market depth. In Appendix 1, Panel A and B, we use two proxies for market depth (total appraisal value and total number of properties sold). We would expect a positive relation between market depth and average selloff distance within a certain MSA if more observable settled deals available to the market participants mitigate information concern, and market participants are confident with negotiating deals from further distance.

Based upon Appendix 1, Panel A and B, we do not observe a clear pattern that average selloff distance increases with more properties sold, either in terms of total appraisal value or total number of properties. For instance, New York-Newark-Jersey City, NY-NJ-PA MSA ranked highest in terms of total appraisal value ($2,538 million). However, the average selloff distance is only around 848 kilometers (or 527 miles), which is much less than the sample mean of 1,322 kilometers (or 821 miles). Washington-Arlington-Alexandria, DC-VA-MD-WV MSA ranked second (third) in terms of total appraisal value (total number of properties sold), and the average distance for Washington-Arlington-Alexandria, DC-VA-MD-WV MSA is about 557 kilometers (or 346 miles). In Panel C and D, we didn't observe a clear relation between distance and market depth at least for top MSA of properties selloffs in each year.

Together, results in Appendix 1 suggest that there is virtually no relation between selloff distance and market depth. Moreover, most MSAs listed among the top MSAs for property selloffs are among the top 10 MSAs ranked by population. It is likely that REITs headquartered in non-top 10 MSAs (which are considered as distant investors to the top 10 MSAs) are not able to invest in top 10 MSAs due to market frictions, such as higher cost of obtaining capital, etc. In Appendix 2, we listed all selloffs that are conducted by REITs headquartered in non-top 10 MSAs.

5. Discussions and Conclusion

In this research, we investigate how geographic dispersion of asset dispositions and of REIT Headquarters affect shareholder wealth through the vendor of property sell-offs by the U.S. equity REITs. We find evidence that the geographic distance between a firm's headquarter location and property (properties) been disposed negatively affects sell-off stock performance of the firm's shareholders. Our major findings are threefold.

First, using different distance measures and different sets of sell-off controls, we find distance measures have negative and significant effect on post sell-off stock performance.

Second, we conduct propensity score matching based on a sequential choice process to mitigate potential self-selection and endogeneity concerns. Specifically, we estimate the firm-level sell-off likelihood in the first stage and the property-level likelihood of being sold, given a sell-off decision is made, in the second stage. The matched sample is constructed based on propensity scores by multiplying the predicted probability in the first stage and the conditional probability in the second stage. Results based on the two-step sequential choice matched sample using different model specifications and models suggest that that the effect of distance on CAR is still negative and significant and managerial alignment effect plays a dominant effect.

Finally, we analyze the potential driving force(s) behind the managerial alignment effect by examining the role of distance on CAR using union power and population. We find that the geographic proximity between property management teams of a particular firm and the firm's headquarter are affected by the misalignment of interest between firm's managers and shareholders. Moreover, when we divide firms into large and small population subsamples, we find that the effect of distance on CAR only exists among firms headquartered in less populated areas. Therefore, we identify that informational and social factors together determine post sell-off shareholder wealth through geographic proximity only in less populated areas, in favor of the managerial alignment explanation.

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Table 1: Property Sell-offs by Equity REITs, 2003-2013

This table describes a sample of property sell-offs by U.S. equity REITs from 2003 to 2013 with sale price exceeding USD 20 million.

Year	Total Number of Transactions	Total Value (Million USD)	Average Deal Size (Million USD)
2003	16	1676	105
2004	18	1839	102
2005	17	2608	163
2006	24	7556	315
2007	19	4391	231
2008	3	293	98
2009	8	514	64
2010	4	2578	645
2011	15	2892	193
2012	17	3582	211
2013	20	4914	246
Total	161	32843	204

Table 2: Property Sell-offs by REIT Type and Stated Use of Proceeds, 2003-2013

This table presents property sell-offs by REIT property type and by stated use of proceeds based on a sample of property sell-offs by U.S. equity REITs from 2003 to 2013 with sale price exceeding USD 20 million. Sell-offs are divided into different groups based on property type, including multi-family, office and/or industrial, diversified, and shopping center or regional mall. Sell-offs are divided into different groups based on stated use of proceeds from property sales. Information on selling REITs' property type is from SNL Financial and information on the stated use of proceeds is obtained from press releases.

Category	N	%
Sell-offs by REIT Property Type		
Multi-Family	20	12.4
Office and/or Industrial	66	41
Diversified	16	9.9
Shopping Center or Regional Mall	24	14.9
Other	35	21.7
Total	161	100
Sell-offs by Stated Use of Proceeds		
Fund acquisitions	11	6.8
Mixed use	15	9.3
Reduce debt (General)	30	18.6
Reduce long-term debt	2	1.2
Reduce short-term debt	8	5.0
Repurchase shares	3	1.9
Distribute dividends	4	2.5
Other	15	9.3
Not stated	73	45.3
Total	161	100

Table 3: Market Reactions to Equity REIT Property Sell-offs

This table presents summary statistics of cumulative abnormal returns (CARs). Panel A presents CARs based on six event windows, (-1,0), (0,0), (0,1), (-1,1), (-5,5), (-5,-1), which represent respectively the one-day before, one-day, one-day ahead, three-day, eleven-day, and six-day windows. In Panel B, we divide 3-day CARs, our main variable of interest, into (1) distance below median and (2) distance above median subsamples based on the comparison between average firm-property distance of a particular firm and the sample median of firm-property distances. In Panel C, we divide 3-day CARs, number of properties sold (held), deal size, and property appraisal value into 4 quartiles based on firm-property distances. In Panel D, we sort 3-day CARs into different subgroups based upon firm-property distance and population. In Panel E, we sort 3-day CARs into different subgroups based upon firm-property distance and REIT headquarter locations. We follow Loughran and Schultz (2005) and define an REIT as in "top-ten MSA" if its headquarters is in one of the ten largest metropolitan areas of the U.S. according to the 2010 Census. We define the rest of the REITs in our sample as in "non-top-ten MSAs". In Panel F, we sort 3-day CARs into different subgroups based upon REIT headquarter locations and pre- & post-recession periods (the fall of Lehman Brothers on May 28, 2009 is used as the cutting point). The symbols *, ** and *** denote statistical significance at the 10%, 5% and 1% level of Portfolio Time-Series (CDA) *t* statistics, respectively.

Panel A: Cumulative Abnormal Returns (CARs)

	N	CAR	% Negative	*t*-stat	*z*-stat
CAR (-1, 0)	161	0.74***	40.99	4.06	1.99
CAR (0)	161	0.71***	41.61	5.52	2.21
CAR (0,1)	161	1.15***	40.99	6.29	2.20
CAR (-1, +1)	161	1.18***	43.48	5.26	2.14
CAR (-5, +5)	161	1.49***	42.86	3.49	1.08
CAR (-5, -1)	161	0.44	44.10	1.52	-0.48

Panel B: CAR (-1, 1) by Nearby Sell-offs versus Distant Sell-offs

Distance to HQs	Mean	Std Dev	Q1	Median	Q3
Below Median	2.047	5.926	-0.72	1.45	3.51
Above Median	0.465	3.447	-1.29	-0.04	2.36

Panel C: CAR (-1,1) by Distance Quartile

Distance to HQs	# sell-offs	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat	# Ppties Sold	Deal Size (USD mil)	# Ppties Held	Appraisal Value (USD mil)
Q1 (0-25 percentile)	39	132.15	2.19*	1.804	139	6058	8871	393039.8
Q2 (25-50 percentile)	38	917.24	1.93**	2.673	210	5318	12396	234084.6
Q3 (50-75 percentile)	39	1631.90	0.93	0.616	880	10690	17822	335486.1
Q4 (75-100 percentile)	38	2629.15	0.12	1.076	147	6485	13617	316032.4

Panel D: CAR (-1,1), sort by Distance and HQ County Population (Small and Large)

	Small Population			Large Population		
Distance Quartile	Avg. distance(in km)	CAR (-1,1)	CDA *t*-stat	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat
Q1 (0-25 percentile)	183.69	2.73***	5.424	83.18	1.42	0.489
Q2 (25-50 percentile)	890.10	2.10**	2.378	944.37	1.43	1.324
Q3 (50-75 percentile)	1599.21	1.59	0.413	1662.95	1.00	0.414
Q4 (75-100 percentile)	2682.59	-0.50	-0.129	2575.71	0.61	1.434

Panel E: CAR (-1,1), sort by Distance and HQ MSA Population (Non-top-ten MSAs and Top-ten MSAs)

	Non-top-ten MSAs			Top-ten MSAs		
Distance Quartile	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat	Avg. distance (in km)	CAR (-1,1)	CDA *t*-stat
Q1 (0-25 percentile)	348.47	4.35**	2.60	88.44	2.04***	3.381
Q2 (25-50 percentile)	1197.10	3.26***	3.24	767.37	0.21	0.819
Q3 (50-75 percentile)	1642.48	2.10***	10.12	1656.21	0.93	1.091
Q4 (75-100 percentile)	2368.71	0.00	-1.56	2747.05	-0.11*	-2.109

Panel F: CAR (-1,1), sort by sub-periods and HQ MSA Population (Non-top-ten MSAs and Top-ten MSAs)

	Non-top-ten MSAs		Top-ten MSAs	
Sub-period	Avg. distance (in km)	CAR (-1,1)	Average distance (in km)	CAR (-1,1)
Pre-Recession	1522.47	2.04	1472.86	-0.17
Post-Recession	1132.57	1.17	1077.26	0.66

Table 4: Determinants of CARs

This table includes summary statistics and regression results of determinants of CARs. Panel A presents summary statistics on distance proxies, firm-level characteristic and deal-level characteristics. Panel B presents regression results based on firm fundamentals. Panel C (D) presents regression results based on source of fund (use of fund). Panel E presents regression results based on deal-level determinants. The dependent variable is three-day window cumulative abnormal returns, CAR (-1,+1). *Average distance* (*Median distance*) is the average (median) distances of all the properties disposed by a particular firm (in 1,000 kilometers). We scaled the distance measures in order to better interpreting its economic meaning. Since our historical property portfolios are constructed such that they were rebalanced annually, we compute the *Average (Median) Holding distances* at firm-year level instead of deal level for each seller (in 1,000 kilometers). *Number of Properties Sold (Held)* is defined as the total number of properties sold (held) in an average firm-year. *Firm Size* (*lnrsize*) is the natural logarithm of the quarterly total assets of the firm in millions of dollars (ATQ). *ROA* (Return on assets) is expressed as the quarterly net income (NIQ) over total assets (ATQ). *Debt Ratio* (dassets) equals to the sum of total long-term debt (DLTTQ) and debt in current liabilities (DLCQ) divided by total assets (ATQ). *Coverage* is interest coverage ratio, which equals income before extraordinary items (IBQ) divided by the sum of preferred dividends (DVPQ) and interest and related expenses (XINTQ). *Tobin's Q* equals total book assets (ATQ) plus the market cap (PRCCQ*CSHOQ) minus common equity (CEQQ), all divided by total book assets (ATQ). *Gain* is the reported quarterly gain or loss generated from the sale of property (SRETQ). *Debt Issues* is the total new long-term debt issued (DLTISY). *Equity Issues* is the total proceeds from the sale of common and preferred stock (SSTKY). *Delta Debt* is the difference in debt reduction (DLTRY) from the previous fiscal quarter (t-2) divided by total long-term debt (DLTTQ), in the last fiscal quarter prior to the sell-off announcement (t-1). *Delta preferred* equals the difference in preferred dividends paid (DVPQ) from the previous fiscal quarter (t-2) divided by total liabilities (LTQ). *Delta common equity* equals the difference in cash dividends paid (DVY) from previous fiscal quarter (t-2), divided by the market cap (PRCCQ*CSHOQ). *Delta investment* equals the difference in increased investments (IVLTQ). *Deal Size* is the transaction price of the selloff divided by the total book assets (ATQ). *Geographic Focus* is an indicator variable equals to 1 if the stated goal of a particular asset sale is geographic focus and 0 otherwise. *URSTD* is an indicator variable equals to 1 if proceeds from sale are announced to be used to reduce short-term debt. *URLTD* is an indicator variable equals to 1 if proceeds from sale are announced to be used to reduce long-term debt. *Pay Dividend* is an indicator variable equals to 1 if proceeds from sale are announced to be distributed as dividends. *EXCH* is an indicator variable equals to 1 if 1031 tax-free exchange is used. *DC* is an indicator variable equals to 1 if a particular firm's interest coverage ratio is below the sample median at the end of the last fiscal quarter prior to the announcement. *Recession* is an indicator variable equals to 1 if announcement date is in the recession period defined by NBER US Business Cycle Expansions and Contractions (http://www.nber.org/cycles.html). All quarterly variables are lagged. Robust standard errors are used and *t*-statistics are shown in parentheses. *, ** and *** stand for 10%, 5% and 1% significance level, respectively.

Panel A: Summary Statistics

	N	Mean	Median	Std. Dev.
Distance Proxies				
Average Distance (dmean, in 1,000 km)	154	1.322	1.296	0.961
Median Distance (dmedian, in 1,000 km)	154	1.293	1.199	1.001
Nearby	154	0.025	0.500	0.160
Distance Proxies and Number of Properties (Firm-Year)				
Average Holding Distance (in 1,000 km)	100	0.945	0.684	0.835
Median Holding Distance (in 1,000 km)	100	0.772	0.497	0.845
Number of Properties Sold	100	156	94	159
Number of Properties Held	100	12	3	34
Firm-level Characteristics				
Fundamentals				
Cash	154	0.032	0.016	0.047
Firm Size (lnrsize)	154	7.850	8.105	1.713
ROA	154	0.007	0.004	0.021
Debt Ratio (dassets)	154	0.472	0.542	0.215
Coverage	154	0.671	0.284	2.336
Tobin’s Q	154	1.234	1.236	0.338
DC	154	0.610	1	0.489
Source of Fund				
Gain	154	5.145	0	26.18
Debt Issues	154	700.2	303.2	1598.3
Equity Issues	154	133.5	12.28	292.3
Use of Fund				
Delta Debt	154	0.0362	0.0331	0.2245
Delta Preferred	154	0.0002	0	0.0016
Delta Common Equity	154	0.0031	0.0107	0.0328
Delta Investment	154	0.0047	0.0121	0.0948
Deal-level Characteristics				
Geographic Focus	154	0.214	0	0.412
URSTD	154	0.013	0	0.114
URLTD	154	0.045	0	0.209
EXCH	154	0.065	0	0.247
Pay Dividend	154	0.026	0	0.160
Recession	154	0.110	0	0.314

Panel B: Firm Fundamentals

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-1.216**		
	(-2.54)		
Median distance		-1.142***	
		(-2.62)	
Nearby			1.944**
			(2.09)
Cash	-10.855	-10.816	-10.074
	(-1.41)	(-1.40)	(-1.25)
Firm Size (lnrsize)	-0.462	-0.458	-0.444
	(-1.31)	(-1.29)	(-1.23)
ROA	14.436	15.960	21.082
	(0.70)	(0.78)	(0.96)
Debt Ratio (dassets)	5.708*	5.673*	5.193*
	(1.89)	(1.90)	(1.75)
Coverage	-0.078	-0.086	-0.138
	(-0.47)	(-0.52)	(-0.81)
Tobin's Q	0.155	0.156	0.155
	(0.13)	(0.13)	(0.12)
DC	0.075	0.052	-0.025
	(0.07)	(0.05)	(-0.02)
Intercept	3.907**	3.771**	1.464
	(2.14)	(2.11)	(0.90)
R Squared	10%	10%	9%
Number of Obs	154	154	154

Panel C: Source of Fund

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-0.941**		
	(-2.18)		
Median distance		-0.893**	
		(-2.24)	
Nearby			1.644**
			(1.98)
Gain	0.002	0.002	0.002
	(0.38)	(0.35)	(0.30)
Debt Issues	-0.00007	-0.00007	-0.00011
	(-0.73)	(-0.72)	(-1.27)
Equity Issues	-0.001	-0.001	-0.001
	(-1.35)	(-1.40)	(-1.36)
Intercept	2.731***	2.649***	0.699
	(3.08)	(3.17)	(1.49)
R Squared	4%	3%	3%
Number of Obs	154	154	154

Panel D: Use of Fund

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-0.984**		
	(-2.48)		
Median distance		-0.919**	
		(-2.53)	
Nearby			1.629**
			(2.01)
Delta Debt	0.412	0.442	0.530
	(0.25)	(0.27)	(0.32)
Delta Preferred	-242.7	-238.9	-236.5*
	(-1.49)	(-1.47)	(1.74)
Delta Common	17.074	16.555	14.578
	(0.52)	(0.50)	(0.45)
Delta Investment	-3.393	-3.451	-3.255
	(-0.93)	(-0.95)	(-0.92)
Intercept	2.588***	2.476***	0.475
	(3.15)	(3.21)	(1.10)
R Squared	5%	4%	4%
Number of Obs	154	154	154

Panel E: Deal-level Determinants

CAR (-1, 1)	(1)	(2)	(3)
Average distance	-0.985**		
	(-2.44)		
Median distance		-0.924**	
		(-2.46)	
Nearby			1.819**
			(2.06)
Deal Size	0.000	0.000	0.000*
	(1.53)	(1.52)	(1.71)
Geographic Focus	-0.883	-0.900	-1.104
	(-1.13)	(-1.15)	(-1.32)
URSTD	2.366*	2.488*	2.973**
	(1.97)	(1.96)	(2.35)
URLTD	0.147	0.194	-0.132
	(0.05)	(0.07)	(-0.05)
EXCH	0.466	0.526	0.549
	(0.40)	(0.45)	(0.49)
Recession	4.154**	4.077**	4.134**
	(2.13)	(2.09)	(2.11)
Pay Dividend	8.554*	8.758*	8.546*
	(1.76)	(1.80)	(1.73)
Cash	-17.104**	-17.248**	-17.492**
	(-2.42)	(-2.47)	(-2.42)
Firm Size (lnrsize)	-0.615	-0.596	-0.500
	(-1.53)	(-1.48)	(-1.25)
ROA	36.590	37.800	40.502
	(1.44)	(1.50)	(1.52)
Debt Ratio (dassets)	3.134	3.131	3.045
	(1.53)	(1.54)	(1.44)
Coverage	-0.140	-0.144	-0.159
	(-0.68)	(-0.70)	(-0.74)
Tobin's Q	-0.835	-0.833	-0.897
	(-0.55)	(-0.55)	(-0.60)
DC	1.272*	1.251*	1.109
	(1.71)	(1.69)	(1.49)
Intercept	5.989	5.740	3.032
	(1.40)	(1.34)	(0.67)
R Squared	30%	29%	29%
Number of Obs	154	154	154

Table 5: Firm-level and Property-level Comparisons between Sell-off Firms and Non-sell-off Firms

This table compares firm-level and property-level descriptive statistics of a sample of REITs with asset sales from 2003 to 2013 and a sample of REITs without asset sale (control sample) during the same period. *Firm Size* is the annual reported book value of total assets (AT) in millions of USD. *ROA* (Return on assets) is expressed as the annual net income (NI) over total assets (AT). *FFO/Total Assets* equals to funds from operations (FFO) divided by total assets (AT). *Debt Ratio* (*dassets*) equals to the sum of total long-term debt (DLTT) and debt in current liabilities (DLC) divided by total assets (AT). *Cash* is expressed as cash and short-term investments (CHE) divided by total assets (AT). *Sales Growth* is the most recent annual percentage change in total revenue (REVT). *Coverage* is interest coverage ratio, which equals income before extraordinary items (IB) divided by the sum of preferred dividends (DVP) and interest and related expenses (XINT). *Momentum* is the aggregated stock return from month t-12 to t-2. *DC* is an indicator variable which equals 1 when a firm's coverage ratio is below the sample median in the last fiscal year prior to the announcement, 0 otherwise. *Nearby* is a dummy variable that takes one if the distance of a deal is less than the sample median and 0 otherwise. *Diverse* is a dummy variable that equals 1 if the property type of the property been disposed is different from the property type of a particular firm identified by CRSP permanent security identification number (PERMNO) and 0 otherwise. *Hold Time* describes how long has (had) a property been held by a particular company. Health care, hotel, industrial, office, retail, multifamily, and other are indicator variables of major property types. "N.A." means that the median of a variable is not shown if it's a dummy. The last column reports t-test statistics and significance. *, ** and *** stand for 10%, 5% and 1% significance level, respectively.

	(1) Non-sell-off				(2) Sell-offs				(1)-(2)	
	N	Mean	Median	Std Dev	N	Mean	Median	Std Dev	*t*-stat	
Firm-level	(firm-year)				(firm-year)					
Firm Size	3,697	1803.358	666.803	3274.583	100	4919.646	2803.544	5862.672	-9.13	***
ROA	3,697	0.026	0.027	0.128	100	0.028	0.023	0.051	-0.14	
FFO/Total assets	3,697	0.025	0	0.090	100	0.039	0.044	0.031	-1.52	*
Debt Ratio	3,697	0.455	0.478	0.223	100	0.522	0.542	0.142	-3.04	***
Tobin's Q	3,697	1.252	1.184	0.475	100	1.272	1.227	0.281	-0.42	
Cash	3,697	0.045	0.017	0.092	100	0.028	0.017	0.039	1.80	**
Sales Growth	3,697	46.615	7.676	1057.434	100	6.025	2.735	24.893	0.38	
Coverage	3,697	6.614	0.606	93.387	100	0.580	0.429	1.112	0.65	
Momentum	3,697	0.14	0.136	0.880	100	0.124	0.157	0.309	0.19	
DC	3,697	0.492	0	0.500	100	0.5	1	0.503	-0.16	
Property-level	(property-year)				(property-year)					
Hold Time	332,853	11.880	10	7.298	1,157	6.790	6	4.572	23.71	***
Nearby	332,853	0.556	1	0.497	1,157	0.476	0	0.499	5.44	***
Diverse	332,853	0.285	0	0.451	1,157	0.656	1	0.475	-27.93	***
Health Care	332,853	0.085	0	0.279	1,157	0.008	0	0.088	9.42	***
Hotel	332,853	0.037	0	0.189	1,157	0.041	0	0.199	-0.75	
Industrial	332,853	0.107	0	0.309	1,157	0.273	0	0.446	-18.18	***
Office	332,853	0.130	0	0.336	1,157	0.186	0	0.389	-5.63	***
Retail	332,853	0.281	0	0.449	1,157	0.123	0	0.328	11.95	***
Multifamily	332,853	0.137	0	0.343	1,157	0.091	0	0.287	4.54	***
Other	332,853	0.156	0	0.363	1,157	0.249	0	0.433	-8.67	***

Table 6: Two-stage sequential model of property sell-offs

This table reports results of coefficient estimates used to calculate predicted probabilities of asset sell-offs at firm-level in Panel A and (conditional) predicted probabilities of asset sell-offs at property-level in Panel B. In Panel A of firm-level, the dependent variable is an indicator variable equals to one if a firm sells any properties in a specific year, and zero otherwise. Model (1) reports probit results based on a sample of firm-year with sell-offs and a sample of firm-year without sell-off matched with average firm-holding property distance. Model (2) ((3)) report coefficient estimates based on logit (probit) model without weights. Model (4) ((5)) report coefficient estimates based on logit (probit) model with weights of the inverse of the number of properties held by firm *i* in year *t*. In Panel B of property-level, the dependent variable is an indicator variable equals to 1 if a property is disposed in a specific year, given the holding company is a seller in that year; and zero otherwise. The estimation of firm-level propensity is indicated by P(seller = 1), and the estimation of property-level propensity is indicated by P(property sold = 1 | seller = 1). Model (1) ((2)) report results based on logit (probit) model. Coefficient estimates and *t* statistics (in parentheses) are reported. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A: The probability of property sell-offs at firm-level

Dependent variable:	(1) Probit, distance	(2) Logit	(3) Logit, weighted	(4) Probit	(5) Probit, weighted
Firm Size	0.00006***	0.0001***	0.0001***	0.00006***	0.00006***
	(7.58)	(6.17)	(8.07)	(6.00)	(9.13)
ROA	0.343	5.436*	8.766***	2.550*	4.689***
	(1.57)	(1.76)	(3.91)	(1.68)	(4.39)
FFO/Total Assets	0.757***	2.076	5.251***	1.048	3.071***
	(2.61)	(0.59)	(3.33)	(0.64)	(3.31)
Debt Ratio	0.545**	0.706	0.777***	0.329	0.644***
	(2.38)	(1.00)	(2.64)	(1.02)	(3.81)
Tobin's Q	0.023	-0.190	0.197	-0.071	0.075
	(0.26)	(-0.51)	(1.17)	(-0.40)	(0.74)
Cash	-1.756	-0.467	-10.659***	-0.161	-5.525***
	(-1.48)	(-0.21)	(-6.55)	(-0.16)	(-6.31)
Sales Growth	-0.00007	-0.00008	-0.00017	-0.00004	-0.0001
	(-1.63)	(-0.48)	(-1.35)	(-0.43)	(1.49)
Coverage	-0.00027	-0.097*	-0.207***	-0.051*	-0.054***
	(-0.93)	(-1.75)	(-3.21)	(-1.67)	(-2.66)
Momentum	-0.003	-0.239	0.030	-0.100	0.016
	(-0.11)	(-0.67)	(0.75)	(-0.60)	(0.66)
DC	-0.015	0.106	0.096	0.064	0.124**
	(-0.15)	(0.42)	(0.89)	(0.54)	(1.98)
Intercept	-2.357***	-3.596***	-1.174***	-1.999***	-0.853***
	(-16.13)	(-6.97)	(-4.79)	(-8.16)	(6.02)
Log likelihood	-432.61	-376.05	-1883.93	-374.44	-1892.25
Pseudo R-squared	6.43%	5.24%	8.59%	5.64%	8.19%
Number of Obs	3,797	2,055	3,120	2,055	3,120

Panel B: The conditional probability of property sell-offs at property-level

Dependent variable: P(property sold = 1 | seller =1)	(1) Logit	(2) Probit
Nearby	-0.408***	-0.212***
	(-6.26)	(-6.55)
Diverse	1.010***	0.422***
	(13.47)	(11.38)
Health Care	-1.027***	-0.443***
	(-2.67)	(-2.84)
Leisure	0.653***	0.302***
	(2.77)	(2.63)
Industrial	1.062***	0.524***
	(5.64)	(5.69)
Office	0.139	0.054
	(0.70)	(0.57)
Retail	0.068	0.045
	(0.34)	(0.47)
Multifamilty	0.356*	0.166*
	(1.72)	(1.66)
Other	2.621***	1.378***
	(13.32)	(13.85)
Intercept	-3.453***	-1.820***
	(-17.68)	(-19.24)
Log likelihood	-3555.84	-3584.75
Pseudo R-squared	14.54%	13.85%
Number of Obs	16,102	16,102

Table 7: OLS Regression of CAR on distance and fundamentals using matched samples

This table presents the regression results of determinants of CARs, using sell-off and matched samples from Model (1) – (5) in Table 6. Panel A presents regression results based on firm fundamentals. Panel B (C) presents regression results based on source of fund (use of fund). In Model (1) and Model (2) of Panel A, a sell-off firm is first matched with 10 non-sell-off firms using the nearest propensity scores, which are calculated as the predicted probabilities at firm-level based on Model (1) Panel A in Table 6. Next, the percentile of the (average) distance between the disposed property (properties) and headquarter of the sell-off firm is matched with the percentiles of the average distance between the holding properties and headquarter of the non-sell-off firms. The non-sell-off firm with the smallest absolute difference of percentile is selected. In Model (3) and Model (4) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (2) Panel A in Table 6 and the conditional predicted probability at property-level based on Model (1) Panel B in Table 6. In Model (5) and (6) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (4) Panel A in Table 6 and the conditional predicted probability at property-level based on Model (2) Panel B in Table 6. In Model (7) and (8) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (3) Panel A in Table 6 and the conditional predicted probability at property-level based on Model (1) Panel B in Table 6. In Model (9) and (10) of Panel A, a sample of sell-off firms is matched with a sample of non-sell-off firms using the nearest propensity score, which is calculated as a multiplication of the predicted probability at firm-level based on Model (5) Panel A in Table 7 and the conditional predicted probability at property-level based on Model (2) Panel B in Table 6. In Model (1) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (1) and (2) Panel A. In Model (2) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (3) and (4) Panel A. In Model (3) of Panel B and Panel C, a sample of sell-off firms is matched with is matched with the same control sample in Model (5) and (6) Panel A. In Model (4) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (7) and (8) Panel A. In Model (5) of Panel B and Panel C, a sample of sell-off firms is matched with the same control sample in Model (9) and (10) Panel A. The matching is conducted by using the nearest neighborhood 1:1 except for Model (1) and (2) of Panel A and Model (1) of Panel B and C. The dependent variable is cumulative abnormal return (CAR) over three days around sell-off announcements, CAR (-1,1). *Sell-off* is a dummy equals to 1 if a particular firm disposes properties on an even date, zero otherwise. *Average distance* is the test variable, which is defined as the arithmetic average firm-property distances of all the properties disposed by a selling firm. Other variables are defined in Table 4. Robust standard errors are used and *t*-statistics are shown in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels, respectively.

Panel A: Matched Sample – Fundamentals

CAR (-1, 1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Matched with	Probit, distance	Probit, distance	predicted prob. based on logit	predicted prob. based on logit	predicted prob. based on probit	predicted prob. based on probit	predicted prob. based on logit, weighted	predicted prob. based on logit, weighted	predicted prob. based on probit, weighted	predicted prob. based on logit, weighted
Sell-off	1.201**	1.452**	1.044*	1.046	1.059*	1.118	0.974*	1.260*	1.002*	0.869
	(2.28)	(2.25)	(1.89)	(1.51)	(1.93)	(1.65)	(1.77)	(1.89)	(1.88)	(1.38)
Average distance	-0.493*	-0.627**	-0.448*	-0.423*	-0.400*	-0.416*	-0.486**	-0.457**	-0.551**	-0.473**
	(-1.87)	(-2.45)	(-1.88)	(-1.87)	(-1.70)	(-1.76)	(-2.06)	(-2.05)	(-2.35)	(-2.17)
Cash		-9.304		5.840		-1.526		1.664		-2.373
		(-1.18)		(0.94)		(-0.70)		-0.31		(-0.43)
Firm Size		-0.276		-0.129		-0.392		-0.398		-0.380
		(-0.98)		(-0.44)		(-1.20)		(-1.40)		(-1.37)
ROA		-59.40*		-18.22		-0.479		-20.22		2.768
		(-1.71)		(-0.78)		(-0.02)		(-1.15)		(0.19)
Debt Ratio		4.951*		2.914		2.560		3.272		4.367**
		-1.93		(1.42)		(1.09)		(1.44)		(2.14)
Coverage		0.583		0.091		-0.131		-0.021		-0.102
		(1.45)		(0.36)		(-0.42)		(-0.25)		(-1.39)
Tobin's Q		0.042		-0.819		-1.008		-0.831		-0.532
		(0.05)		(-0.95)		(-0.89)		(-0.71)		(-0.57)
DC		-0.031		-0.192		-0.259		-0.953		-0.009
		(-0.03)		(-0.22)		(-0.25)		(-1.05)		(-0.01)
Intercept	0.568	0.576	0.678	1.343	0.615	4.077	0.787*	3.845	0.825*	2.588
	(1.53)	(0.28)	(1.58)	(0.54)	(1.37)	(1.38)	(1.74)	(1.60)	(1.89)	(1.15)
R squared	4%	12%	3%	6%	2%	6%	3%	7%	3%	10%
Number of Obs	247	247	252	252	252	252	252	252	252	252

Panel B: Matched Sample – Source of Fund

CAR (-1, 1)	(1)	(2)	(3)	(4)	(5)
	Probit, distance	Logit	Probit	Logit weighted	Probit weighted
Sell-off	1.393**	1.153*	0.707	1.148*	1.050*
	(2.50)	(1.93)	(1.19)	(1.92)	(1.85)
Average distance	-0.495*	-0.425*	-0.407*	-0.446*	-0.532**
	(-1.86)	(-1.78)	(-1.73)	(-1.89)	(-2.28)
Gain	-0.015	-0.012	-0.014	-0.014	-0.006
	(-1.50)	(-1.43)	(-1.49)	(-1.48)	(-0.79)
Debt Issues	-0.000	-0.000	-0.000	-0.000	0.000
	(-0.57)	(-0.22)	(-0.09)	(-0.73)	(0.09)
Equity Issues	-0.002**	-0.001	-0.002	-0.002**	-0.002
	(-2.16)	(-0.82)	(-1.54)	(-2.29)	(-1.51)
Intercept	0.742*	0.728*	1.231***	0.952**	0.956**
	(1.86)	(1.65)	(2.90)	(2.02)	(2.09)
R squared	5%	3%	2%	4%	4%
Number of Obs	247	252	252	252	252

Panel C: Matched Sample – Use of Fund

CAR (-1, 1)	(1)	(2)	(3)	(4)	(5)
	Probit, distance	Logit	Probit	Logit weighted	Probit weighted
Sell-off	1.221**	1.118*	0.936*	0.969*	0.962*
	(2.28)	(1.96)	(1.81)	(1.74)	(1.80)
Average distance	-0.538**	-0.492**	-0.533**	-0.473*	-0.582**
	(-1.97)	(-2.02)	(-2.32)	(-1.93)	(-2.44)
Delta Debt	-0.693	-0.438	-2.015*	-1.571	-0.578
	(-0.65)	(-0.28)	(1.93)	(-1.40)	(-0.66)
Delta Preferred	-102.86*	-128.3	-95.63	-87.45	19.95
	(-1.92)	(-1.39)	(-1.05)	(-0.92)	(0.23)
Delta Common Equity	23.853	27.948	32.81***	20.02	5.521
	(0.77)	(0.92)	(2.70)	(1.29)	(0.75)
delta investment	-3.558	-3.345	-0.462*	-0.823	-3.252**
	(-0.93)	(-1.21)	(-1.90)	(-0.73)	(-2.40)
Intercept	0.566	0.602	0.839**	0.785*	0.921**
	(1.41)	(1.36)	(2.15)	(1.68)	(2.10)
R squared	6%	6%	13%	6%	5%
Number of Obs	247	252	252	252	252

Table 8: Regression of local (state) union power on property holding's geographic concentration index

This table presents the regressions for the local (state) union power factors, using sell-off and matched samples from Model (2) – (5) in Table 6. The dependent variable is *Geographic HHI*, which is the Herfindahl-Hirschman Index that measures the geographic concentration of a particular firm at city level (Hartzell, Sun, and Titman 2014). Local union power is measured by state union coverage density or union membership density. Data on union power measures are obtained from Hirsch and Macpherson (2003). *Sell-off* is defined in Table 7. Column 1 to 4 report OLS regression results based on matched samples from different PSM analysis. Robust standard errors are used and *t*-statistics are shown in parentheses. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A

Geographic HHI (City)	(1)		(2)		(3)		(4)	
Union Coverage Density	0.007	***	0.006	***	0.008	***	0.008	***
	(3.32)		(2.63)		(3.29)		(3.40)	
sell-off	0.025		0.025		0.053	***	0.069	***
	(1.19)		(1.08)		(2.60)		(3.04)	
Intercept	-0.023		-0.003		-0.050		-0.073	*
	(-0.71)		(-0.09)		(-1.47)		(-1.96)	
Model	Logit		Probit		Logit - Weighted		Probit - Weighted	
R squared	8%		5%		13%		14%	
Number of obs	281		264		226		231	

Panel B

Geographic HHI (City)	(1)		(2)		(3)		(4)	
Union Membership Density	0.007	***	0.006	***	0.008	***	0.009	***
	(3.31)		(2.62)		(3.26)		(3.40)	
sell-off	0.024		0.025		0.053	***	0.069	***
	(1.17)		(1.08)		(2.60)		(3.04)	
Intercept	-0.014		0.004		-0.041		-0.063	*
	(-0.46)		(0.10)		(-1.28)		(-1.83)	
Model	Logit		Probit		Logit - Weighted		Probit - Weighted	
R squared	8%		5%		13%		14%	
Number of obs	281		264		226		231	

Table 9: OLS Regression of low and high populated counties

This table presents the OLS regressions for CAR in different subsamples. Firms are separated into different subsamples based upon the population around their headquarters. The dependent variable is cumulative abnormal return (CAR) over three days around sell-off announcements, CAR (-1,1). Sell-off and Average distance are defined as Table 7. Panel A to D presents results with respect to average distance, our main test variable, using sell-off and matched samples from sequential logit, sequential Probit, sequential logit with weights, and sequential Probit with weights, respectively. In each panel, we report regression results for the full sample, for firms headquartered in less-populated counties, and for firms headquartered in highly-populated counties separately in Column 1 to 3. Less-populated counties are defined as counties with population below the sample median. *, **, and *** indicate significance for the coefficient at the 10%, 5%, and 1% levels.

Panel A: matched sample from logit

Variables	All	Less Populated=0	Less Populated=1
Sell off	1.044*	0.637	1.494*
	(1.89)	(0.76)	(1.85)
Average distance	-0.448*	-0.296	-0.847**
	(-1.88)	(-0.91)	(-2.19)
Intercept	0.678	0.324	1.394**
	(1.58)	(0.60)	(2.06)
R squared	3%	1%	7%
Number of Obs	252	111	123

Panel C: matched sample from logit with weights

Variables	All	Less Populated=0	Less Populated=1
Sell off	0.974*	1.361	0.995*
	(1.77)	(1.50)	(1.25)
Average distance	-0.486**	-0.034	-0.951**
	(-2.06)	(-0.09)	(-2.53)
Intercept	0.787*	-0.633	2.008***
	(1.74)	(-0.85)	(3.07)
R squared	3%	2%	6%
Number of Obs	252	113	125

Panel B: matched sample from Probit

Variables	All	Less Populated=0	Less Populated=1
Sell off	1.059*	0.386	1.737**
	(1.93)	(0.41)	(2.25)
Average distance	-0.400*	-0.148	-0.798**
	(-1.70)	(-0.37)	(-2.30)
Intercept	0.615	-0.443	1.096*
	(1.37)	(-0.53)	(1.84)
R squared	2%	1%	8%
Number of Obs	252	114	121

Panel D: matched sample from Probit with weights

Variables	All	Less Populated=0	Less Populated=1
Sell off	1.002*	0.183	1.906**
	(1.88)	(0.20)	(2.54)
Average distance	-0.551**	-0.251	-0.942***
	(-2.35)	(-0.68)	(-2.65)
Intercept	0.825*	0.738	1.087*
	(1.89)	(0.92)	(1.95)
R squared	3%	1%	11%
Number of Obs	252	116	124

Appendix 1: Top MSA of Property Dispositions

This table presents top MSAs of property holdings and dispositions ranked by total appraisal value (of all properties disposed within a particular MSA) and total number of properties sold within a particular MSA from 2003 to 2013. Average REIT-properties sold distances (in kilometers) are included for top MSAs. In Panel A and B, top 10 MSAs with the highest number of total appraisal value or highest total number of properties sold are listed, respectively. In Panel C and D, for each year during 2003 – 2013, top 1 MSA with the highest number of total appraisal value or highest total number of properties sold are listed, respectively. Panel E includes all selloffs that occurred in small towns (non-top 10 MSAs). MSAs are ranked by population according to 2010 Census.

Panel A: Top 10 MSAs by Total Appraisal Value of Property Dispositions

MSA Name	Avg. Distance (in kilometers)	Property Value (millions of USD)	# Properties Sold
New York-Newark-Jersey City, NY-NJ-PA	847.70	2538.20	37
Washington-Arlington-Alexandria, DC-VA-MD-WV	557.59	1631.85	66
Atlanta-Sandy Springs-Roswell, GA	1296.57	1437.78	134
Dallas-Fort Worth-Arlington, TX	1157.62	729.77	94
San Francisco-Oakland-Hayward, CA	1259.65	626.69	8
Houston-The Woodlands-Sugar Land, TX	1345.41	521.09	46
Baltimore-Columbia-Towson, MD	555.48	508.95	55
Jacksonville, FL	2968.49	403.54	46
Los Angeles-Long Beach-Anaheim, CA	1317.92	390.55	13
Nashville-Davidson-Murfreesboro-Franklin, TN	2581.17	388.48	41

Panel B: Top 10 MSAs by Total Number of Properties Disposed

MSA Name	Avg. Distance (in kilometers)	# Properties Sold	Property Value (millions of USD)
Atlanta-Sandy Springs-Roswell, GA	1296.57	132	1437.78
Dallas-Fort Worth-Arlington, TX	1157.62	91	729.77
Washington-Arlington-Alexandria, DC-VA-MD-WV	557.59	66	1631.85
Baltimore-Columbia-Towson, MD	555.48	55	508.95
Houston-The Woodlands-Sugar Land, TX	2968.49	46	403.54
Jacksonville, FL	1345.41	46	521.09
Minneapolis-St. Paul-Bloomington, MN-WI	1370.99	45	252.23
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	491.41	44	360.82
Nashville-Davidson-Murfreesboro-Franklin, TN	2581.17	41	388.48
Chicago-Naperville-Elgin, IL-IN-WI	471.58	38	278.10

Panel C: Top MSA by Total Appraisal Value of Property Dispositions

Year	CBSA Code	MSA Name	Avg. Distance (in kilometers)	# Properties Sold	Property Value (USD million)
2003	31080	Los Angeles-Long Beach-Anaheim, CA	1386.26	4	303.02
2004	41860	San Francisco-Oakland-Hayward, CA	2460.92	2	202.86
2005	12060	Atlanta-Sandy Springs-Roswell, GA	1411.55	81	292.46
2006	35620	New York-Newark-Jersey City, NY-NJ-PA	1084.99	7	850.09
2007	35620	New York-Newark-Jersey City, NY-NJ-PA	1078.84	10	292.59
2008	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	1269.15	1	104.96
2009	28140	Kansas City, MO-KS	2574.83	6	168.97
2010	41940	San Jose-Sunnyvale-Santa Clara, CA	2980.54	1	84.77
2011	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	272.20	20	365.09
2012	35620	New York-Newark-Jersey City, NY-NJ-PA	238.08	3	970.95
2013	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	433.64	31	610.36

Panel D: Top MSA by Total Number of Properties Disposed

Year	CBSA Code	MSA Name	Avg. Distance (in kilometers)	# Properties Sold	Property Value (USD million)
2003	33100	Miami-Fort Lauderdale-West Palm Beach, FL	1321.60	6	67.57
2004	16980	Chicago-Naperville-Elgin, IL-IN-WI	278.58	29	108.78
2005	12060	Atlanta-Sandy Springs-Roswell, GA	1411.55	81	292.46
2006	19820	Detroit-Warren-Dearborn, MI	855.89	19	256.55
2007	19100	Dallas-Fort Worth-Arlington, TX	199.31	38	208.64
2008	19100	Dallas-Fort Worth-Arlington, TX	514.64	4	40.03
2009	28140	Kansas City, MO-KS	2574.83	6	168.97
2010	35380	New Orleans-Metairie, LA	1789.26	1	84.77
2011	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	272.20	20	365.09
2012	26420	Houston-The Woodlands-Sugar Land, TX	227.19	25	123.25
2013	27260	Jacksonville, FL	3050.26	32	183.43

Appendix 2: Selloffs in the non-Top 10 HQ MSAs

Event date	Company name	CAR(-1,1)	Avg. disntance	Headquarter MSA	Rank (by population)
10/18/2010	ProLogis	3.87	1789.25	San Francisco–Oakland–Hayward, CA	11
12/18/2013	Terreno Realty Corporation	2.16	1160.25	San Francisco–Oakland–Hayward, CA	11
7/10/2006	Glenborough Realty Trust	-1.06	1725.31	San Francisco–Oakland–Hayward, CA	11
4/7/2005	Glenborough Realty Trust Inc.	2.7	1462.52	San Francisco–Oakland–Hayward, CA	11
9/3/2009	Ramco-Gershenson Properties Trust	1.71	663.38	Detroit-Warren-Dearborn, MI	12
9/19/2005	Ramco-Gershenson Properties Trust	2.67	1296.50	Detroit-Warren-Dearborn, MI	12
3/31/2003	Pan Pacific Retail Properties	1.82	634.63	San Diego-Carlsbad, CA	17
1/27/2003	Pan Pacific Retail Properties Inc.	-0.44	1242.18	San Diego-Carlsbad, CA	17
4/4/2012	Corporate Office Properties Trust	-2.26	236.52	Baltimore-Columbia-Towson, MD	20
2/2/2012	Corporate Office Properties Trust	-0.85	989.56	Baltimore-Columbia-Towson, MD	20
12/19/2011	Corporate Office Properties Trust	3.66	163.69	Baltimore-Columbia-Towson, MD	20
7/2/2012	Corporate Office Properties Trust	5.45	150.76	Baltimore-Columbia-Towson, MD	20
9/29/2006	Corporate Office Properties Trust	-1.69	108.58	Baltimore-Columbia-Towson, MD	20
7/28/2006	Corporate Office Properties Trust	2.36	1726.56	Baltimore-Columbia-Towson, MD	20
5/7/2012	Corporate Office Properties Trust	1.76	96.76	Baltimore-Columbia-Towson, MD	20
7/17/2012	UDR Inc.	1.41	1399.49	Denver-Aurora-Lakewood, CO	21
3/7/2003	Parkway Properties Inc.	2.35	1630.09	Orlando-Kissimmee-Sanford, FL	27
6/9/2006	Developers Diversified Realty Corp.	-1.57	2678.91	Cleveland-Elyria, OH	29
8/6/2004	Glimcher Realty Trust	-0.17	1837.45	Columbus, OH	32
1/6/2009	Glimcher Realty Trust	21.3	1149.32	Columbus, OH	32
7/25/2006	Duke Realty Corporation	2.99	2278.02	Indianapolis-Carmel-Anderson, IN	33
1/6/2009	Kite Realty Group Trust	7.26	1134.97	Indianapolis-Carmel-Anderson, IN	33
2/21/2012	Kite Realty Group Trust	-3.17	2704.51	Indianapolis-Carmel-Anderson, IN	33
9/30/2005	Duke Realty Corporation	1.33	1713.38	Indianapolis-Carmel-Anderson, IN	33
12/6/2007	Essex Property Trust Inc.	-0.83	2074.83	San Jose-Sunnyvale-Santa Clara, CA	34
9/11/2013	American Campus Communities, Inc.	1.09	1142.86	Austin-Round Rock, TX	35
8/14/2013	Regency Centers Corporation	1.03	2641.27	Jacksonville, FL	40
8/23/2012	Sovran Self Storage, Inc.	1.24	1090.67	Buffalo-Cheektowaga-Niagara Falls, NY	47
5/29/2009	Highwoods Properties, Inc.	-2.02	2859.93	Raleigh, NC	48
1/15/2009	Highwoods Properties, Inc.	28.42	389.97	Raleigh, NC	48
1/21/2003	Highwoods Properties, Inc.	5.14	1679.91	Raleigh, NC	48
6/7/2005	Highwoods Properties Inc.	0.45	1608.97	Raleigh, NC	48
12/17/2007	Highwoods Properties, Inc.	-2.45	2536.39	Raleigh, NC	48

4/10/2006	Colonial Properties Trust	-0.04	1722.31	Birmingham-Hoover, AL	49
10/25/2005	BNP Residential Properties, Inc.	2.67	2604.77	Birmingham-Hoover, AL	49
4/27/2006	CBL & Associates Properties Inc.	2.32	1437.70	Birmingham-Hoover, AL	49
7/8/2005	Colonial Properties Trust	4.64	1638.84	Birmingham-Hoover, AL	49
12/26/2007	Colonial Properties Trust	6.1	238.03	Birmingham-Hoover, AL	49
10/11/2005	Colonial Properties Trust	0.65	988.40	Birmingham-Hoover, AL	49
9/3/2013	CBL & Associates Properties, Inc.	-1.53	1646.31	Birmingham-Hoover, AL	49
7/3/2008	Colonial Properties Trust	0.33	1333.22	Birmingham-Hoover, AL	49
10/2/2006	Colonial Properties Trust	1.11	144.98	Birmingham-Hoover, AL	49
2/1/2006	Home Properties, Inc.	2.61	855.89	Rochester, NY	51
10/2/2006	Home Properties, Inc.	3.51	498.44	Rochester, NY	51
4/9/2013	Home Properties	-0.39	2050.46	Rochester, NY	51
4/1/2013	Starwood Hotels & Resorts World-wide, Inc.	5.37	1442.77	Bridgeport-Stamford-Norwalk, CT	58
7/29/2003	Starwood Hotels & Resorts World-wide,Inc.	3.43	1712.82	Bridgeport-Stamford-Norwalk, CT	58