What's Wrong with Pittsburgh?

Delegated Investors and Liquidity Concentration

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Abstract

What makes an asset institutional-quality? This paper proposes that one reason is the existing concentration of delegated investors in a market through a liquidity channel. Consistent with this intuition, it documents differences in investor composition across US cities and shows that delegated investors concentrate investments in cities with higher turnover. It then calibrates a search model showing how heterogeneity in liquidity preferences makes some markets more liquid even when assets have identical cash flows. The calibration indicates that commercial real estate commands an illiquidity premium of two percentage points annually relative to a perfectly liquid asset with similar credit risk.

JEL: G11, G12, R33.

Key words: Alternative asset classes, Delegated asset management, Liquidity.

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1 Introduction

As Table 1 shows, delegated investors don't find Pittsburgh attractive. While the share of commercial real estate (CRE) purchases by delegated investors averages 24% across US cities, it is a mere 14% in Pittsburgh. What makes Pittsburgh so much less attractive than other cities? More generally, what makes some assets appropriate for delegated managers and not others?

This paper argues that one reason delegated managers focus on some assets is the concentration of other institutions in that market. I start from the observation that some types of investors trade frequently while others are more likely to be buy-and-hold investors. The key intuition is that investors that value liquidity the most, because they trade more frequently or cannot weather short-term fluctuations in asset prices, concentrate their investments in the most liquid markets. In so doing, they give up an illiquidity premium. Thus, concern for liquidity segments markets by investor type. The market segmentation in turn makes the most liquid markets even more liquid because the main asset owners are those that trade relatively more frequently. To the extent that delegated managers are more likely to have higher illiquidity needs than direct investors, an asset's attractiveness to delegated mangers depends on the existing concentration of delegated managers in an asset.

This paper provides evidence on the relationship between investor composition and trade frequency in CRE consistent with this explanation. I use a dataset on all commercial property transactions in 39 cities over the 2001-2015 period that enables classification of purchasers by type and, in particular, identification of delegated investors. In the CRE market, investors managing their own money are more likely to play the role of buy-and-hold investors than are delegated investors.[1] Consistent with delegated investors having relatively more need for liquidity, they have shorter holding periods than non-delegated investors (i.e., direct investors) on average. Controlling for property characteristics, year of purchase, and the Metropolitan Statistical Area (MSA) of the property, delegated investors on average hold properties about one year less than direct investors. The difference is most pronounced for

[1] I treat Real Estate Investment Trusts (REITs) separately from other delegated investors because REITs must satisfy statutory minimum holding period requirements to be eligible for tax-exempt status.

Table 1: Average Share of Purchases by Delegated Investors and REITs by MSA

			(1)	(2)	(3)	(4)	(5)
			delshare	*delshare*	*delshare*	*delshare*	*sharereit*
			Purchases	Purchases	Purchases	Sales	Purchases
Rank	msa	msalabel	2001-2015	2001-2007	2008-2015	2001-2015	2001-2015
1	Boston	BOS	38.6	44.5	33.4	37.2	13.4
2	DC Metro	DC	36.3	38.0	34.9	34.1	20.2
3	Seattle	STL	35.1	35.3	34.9	29.5	13.3
4	San Francisco	SFO	33.2	34.0	32.5	37.7	11.9
5	Chicago	CHI	31.0	33.7	28.5	33.4	17.0
6	Memphis	MEM	30.7	27.7	33.3	25.0	19.4
7	Dallas	DFW	29.3	32.7	26.4	30.0	17.1
8	Austin	AUS	29.0	26.6	31.1	30.0	16.0
9	Atlanta	ATL	28.9	27.5	30.1	24.5	17.8
10	Denver	DEN	28.6	26.9	30.0	29.5	16.2
11	San Jose	SJC	27.9	26.0	29.6	25.7	10.9
12	Minneapolis	MSP	27.7	26.6	28.6	23.1	23.7
13	Indianapolis	IND	27.6	29.1	26.3	25.0	20.7
14	Columbus	CMH	27.3	21.1	32.7	20.5	19.0
15	Baltimore	BWI	26.6	23.0	29.7	23.6	26.7
16	Houston	HOU	26.5	26.7	26.3	31.8	21.9
17	Oakland	OAK	26.0	28.7	23.6	28.9	11.9
18	San Diego	SAN	25.4	26.3	24.6	26.8	13.8
19	Cincinnati	CIN	24.6	25.3	23.9	19.6	28.9
20	Portland	PDX	23.8	29.8	18.5	21.8	12.6
21	Orange County	OC	23.5	22.9	24.1	25.1	8.8
22	Los Angeles	LA	22.8	27.1	19.0	23.0	9.5
23	Orlando	MCO	22.6	20.8	24.2	18.8	22.8
24	Charlotte	CLT	22.0	20.3	23.5	20.5	19.0
25	Nashville	BNA	21.7	21.2	22.2	19.2	20.5
26	Tampa	TPA	21.2	18.7	23.4	23.9	16.5
27	Riverside	RIV	21.0	20.2	21.6	19.9	11.4
28	Kansas City	KC	20.6	21.6	19.7	19.1	22.5
29	NYC Metro	NYC	20.5	22.3	18.9	23.7	16.0
30	Sacramento	SAC	19.0	26.0	12.9	17.4	10.9
31	Phoenix	PHX	17.5	19.8	15.4	19.4	18.1
32	Philadelphia	PHL	16.7	16.2	17.1	26.6	19.4
33	Salt Lake City	SLC	16.4	16.9	16.0	14.2	14.8
34	Jacksonville	JAX	16.2	10.4	21.3	20.4	21.4
35	Las Vegas	LAS	15.9	12.1	19.2	11.5	13.6
36	San Antonio	SAT	14.3	11.0	17.3	21.6	19.6
37	Pittsburgh	PIT	14.3	12.5	15.9	13.7	17.9
38	Cleveland	CLE	12.0	9.8	13.9	15.5	19.3
39	Detroit	DTW	9.6	6.8	12.0	17.4	13.0
Average			23.9	23.8	24.0	23.8	17.1
Median			23.8	25.3	23.9	23.6	17.1

Notes: 1) *delshare* is the share of commercial real estate transactions made by delegated investors. 2) In columns (1)-(3) and (5), the shares are based on the identity of the buyer in the transaction; in column (4), the share is based on the identity of the seller in the transaction. 3) Delegated investors are entities that primarily manage money on behalf of others and include banks, pension funds, investment managers, and private equity funds. 4) *sharereit* is the share of purchases made by Real Estate Investment Trusts (REITs). 5) Shares are by $ volume not number of transactions. 6) Data for all cities except Pittsburgh and San Antonio covers 2001-2015. Data for Pittsburgh and San Antonio covers 2002-2015 and 2007-2015, respectively.

private equity funds but is also statistically significant for investment managers and banks.

Furthermore, a CRE purchase is more likely to be made by a delegated than a direct investor in markets with higher turnover even after controlling for property-level characteristics and the economic fundamentals of an MSA. A one standard deviation increase in the trade frequency in an MSA increases the likelihood the purchaser is a delegated investor by about 6%. Consistent with these transaction-level results, the share of delegated investors among all investors is higher in markets with more trade frequency. Finally, dividend yields are higher in markets with less trade frequency consistent with assets in such markets commanding illiquidity premia.

The paper considers several competing explanations for delegated investors' choice of cities. Most prominently, delegated investors have a preference for what are known as 'credit tenants'. That is, delegated investors want to own buildings where the tenants are publicly listed firms such that they are effectively exposed to cash flow risk similar to that of a corporate bond. To consider differences in the concentration of publicly listed firms across cities, I use detailed establishment-level employment data to compute the share of employment in a city of publicly listed firms. There is a relationship between the importance of publicly listed firms and the share of purchases made by delegated investors at the MSA-level. However, at the level of an individual transaction, there is no relationship between the share of employment by publicly listed firms and whether the transaction is made by a delegated investor. There is also strong MSA-level evidence that delegated investors prefer cities with higher shares of college-educated workers.

The paper then calibrates the model of Vayanos and Wang (2007), which features investors that are heterogeneous in the frequency with which they receive valuation shocks, to the US CRE market. The model illustrates how market segmentation by liquidity preference amplifies cross-market differences in liquidity. The model can replicate the large differences in trade frequency across cities and modest difference in cap rates. Quantitatively, the model generates an illiquidity premium for investing in US CRE of about two percentage points per year.

While I focus on the model of Vayanos and Wang (2007), the intuition that liquidity begets liquidity appears in other theories of OTC markets. For example, the models of Admati and Pfleiderer (1988) and Pagano (1989) generate such a prediction and Biais and Green (2007) discuss how endogenous liquidity has led to bonds usually trading OTC since the mid-20th century. More recently, Chang (2018) presents a model where submarkets with different trade frequencies arise endogenously as a result of heterogeneity in traders' holding costs.

The findings highlight path dependence in what different types of investors consider investible. Many delegated managers express a desire to increase their allocations to alternative asset classes but then assert that such product does not exist. One characteristic of the asset that makes it institutional quality is in fact the concentration of other institutions in that market due to the implications for liquidity of investor composition. As such, the findings in this paper suggest that it will be difficult for delegated investors to rapidly change their allocations to alternatives including real estate. This difficulty in increasing allocations to alternatives may lead to even further increases in the share of publicly traded equities held by institutional investors.[2]

The results also suggest that there may be path dependence in the development of cities to the extent that delegated investors have preferences over property characteristics other than liquidity. Delegated investors tend to purchase larger properties than direct investors, for example, and, within an MSA, buy higher-quality properties. Initial differences in a city's investor base may thus manifest in long-term differences in a city's urban design and, thus, the types of households and firms in a city. Stein (1989) highlights the inefficiency that may result from managers' short-termism. Recent work on publicly traded firms has also shown that investors with shorter holding periods invest in firms less committed to social and environmental responsibility (Starks et al. (2018)). It is thus plausible that the shorter expected holding periods of delegated investors in a city may lead them to shy away from long-term investments in a city's infrastructure and work force.

This paper builds on a literature exploring the implications of heterogeneity in in-

[2] See Andonov and Rauh (2018) regarding pension funds' allocations to real estate and non-real estate private equity. Koijen and Yogo (Forthcoming) show that the share of publicly traded equities held by institutions rose from 35% in the 1980-1984 period to 68% in the 2015-2017 period.

vestor liquidity needs for portfolio composition and asset prices. Aragon (2007) and Barth and Monin (2018) study how heterogeneity in redemption restrictions affects the portfolio composition of hedge funds. Cherkes et al. (2009) show that time variation in illiquidity premia can explain the closed-end fund puzzle. Hanson et al. (2015) and Chodorow-Reich et al. (2018) study the implications of differences in liquidity needs for the portfolio composition of banks and life insurers. The present paper instead studies how differences in liquidity needs affect the geography of investment. Cella et al. (2013) show how differences in trading prices affect how asset prices respond to shocks. Instead of asset price dynamics, this paper calibrates a model to average dividend yields to quantify illiquidity premia in steady state.

Finally, the paper adds to a body of work that explains facts about real estate markets using search and matching models. While a number of papers have used search and matching models to understand the housing market[3], the only other papers that study the CRE market using a search and matching model are Sagi (2017) and Badarinza et al. (2018). While Sagi (2017) explains the returns on individual properties with a search model, the current paper aims to explain heterogeneity across cities in CRE trade volumes and investor composition. Badarinza et al. (2018) uses a search model to quantify how search frictions arising from differences in investor nationality affect cross-border capital flows. Instead of studying the effects of heterogeneity in nationality, I study the effects of heterogeneity in the frequency of valuation shocks.

The next section of the paper describes the data in detail including differences in the types of properties that delegated investors, direct investors, REITs, and small investors purchase. Section 3 shows that, relative to direct investors, delegated investors have shorter holding periods and purchase properties in higher turnover markets. Section 4 calibrates the Vayanos and Wang (2007) model to the US CRE market to explain the aforementioned facts. Section 5 concludes and discusses potential future research.

[3]See Han and Strange (2015) for a summary of early literature on housing search models. More recent work includes Han et al. (2017), Arefeva (2017), and Piazzesi et al. (2018).

2 Data and Investor Type Classification

2.1 CRE Transactions Data

The data covers 2001-2015 for 39 US MSAs. 2001 is the first year for which Real Capital Analytics (RCA) has transactions data. It includes all cities and years for which data on transactions and the stock of CRE are available that can also be merged to Census data using a standardized definition of an MSA. In some cases (e.g., South Florida), the data provider's definition of a market cannot be matched to a standard MSA definition making it difficult to merge the data with other data sources and I exclude such cities. RCA provided data on every purchase transaction in these 39 cities in industrial, retail, and office property. The sample of 115,734 observations covers more than 99% of CRE transactions in these cities over 2001-2015.[4]

A key advantage of the RCA data relative to, for example, deeds records, is RCA's ownership information. RCA standardizes buyer names and invests substantial resources in identifying the true buyer behind a transaction with a legal identity that is perhaps only an LLC that is not obviously linked to the actual owner. I classify purchases by buyers who made less than five purchases over the entire sample period simply as SMALL due to difficulties in accurately classifying such buyers. Buyers who make less than five purchases account for approximate 53% of all transactions by number but only 26% of transactions by dollar amount. Buyers with five or more transactions make a total of 54,600 transactions.

The data RCA provided contained the variables $BuyerCapGroup1$ and $SellerCapGroup1$ that classified buyers and sellers into groups such as "Institutional", "Private", and "Public". These variable assisted with the classification but were not sufficiently detailed for this study since, for example, many private firms are delegated asset managers. I clas-

[4]The sample RCA provided contained 116,307 observations which are all purchases of CRE in the 39 markets in industrial, retail, and office property over 2001-2015. This sample excludes entity-level purchases (i.e., property company mergers, approximately 3000 observations) and observations in which the interest conveyed was not 100% (approximately 4000 observations). 549 observations had missing data on the number of square feet. Excluding these observations reduced the sample size to 115,758. Of the remaining observations, 23 had a price per square foot of less than $1 suggesting the transactions were not arms-length and one observation had a property size of just 8 square feet suggesting a data entry error. Deleting these observations resulted in a dataset of 115,734 observations.

sify each buyer into one of the following nine types of investors: Banks (BANK), Developer/Owner/Operators (DEVOWNOP), Investment Managers (INVM), Private Equity Funds (PEFU), REITs (REIT), Pension Funds (PENS), Users (USER), Real Estate Operating Companies (REOC), and Other (OTH). I follow RCA in grouping Developer/Owner/Operators into a single category, DEVOWNOP, as firms often undertake one or more of these functions and it is difficult to clearly distinguish between the three categories.

In the case of BANK, REIT, PENS, and REOC, the classification is fairly unambiguous. The distinction between DEVOWNOP and INVM or PEFU is whether the entity is managing its own funds or those of other parties. The reason for this distinction is that the friction that gives delegated investors shorter holding periods is an agency friction between investors and managers. There is some ambiguity in whether to classify an entity as INVM or PEFU but, as both are delegated investors, the distinction does not matter for most of the analysis in this paper. I categorize entities that have multiple business lines and cannot be clearly categorized as either a DEVOWNOP or INVM/PEFU as OTH.

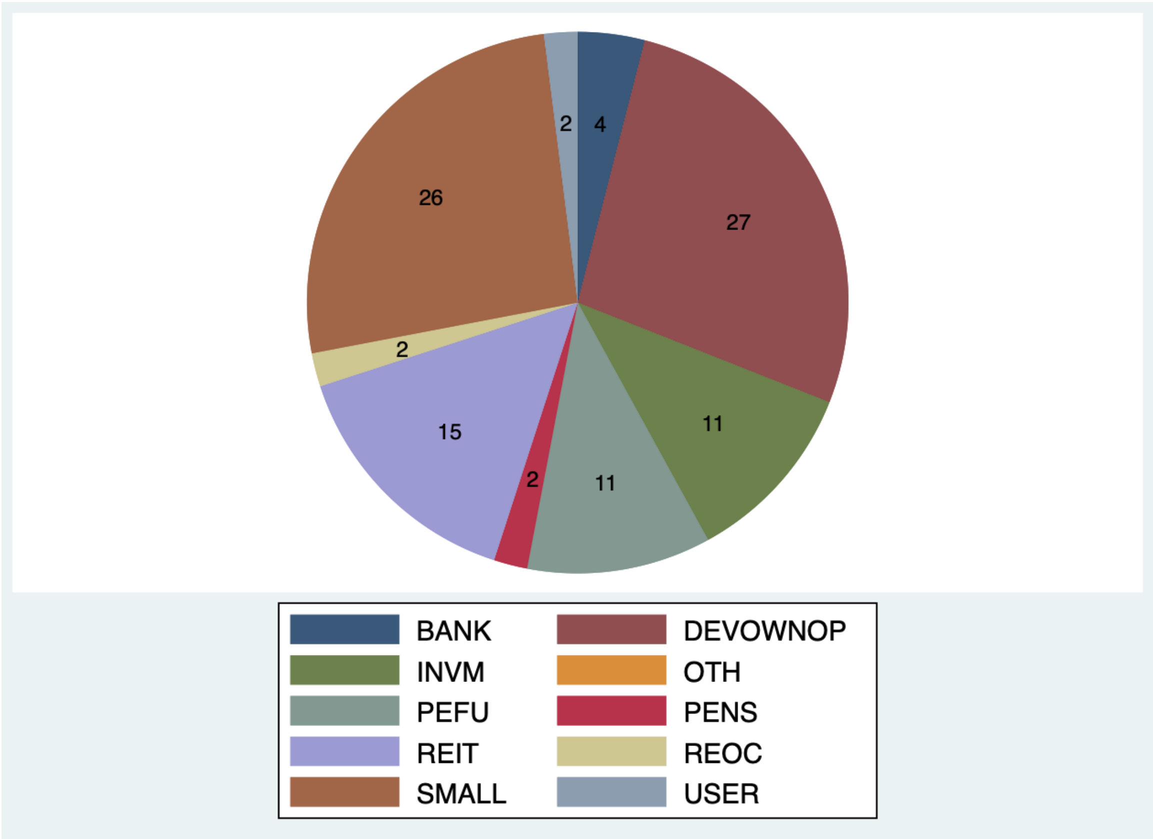
Figure 1 provides the shares of purchases made by each category of investors at the national level aggregated across all years, i.e., when I aggregate the data set across all 39 cities in the sample. The shares shown are based on the dollar volume of transactions, not the number of transactions. The single largest category is DEVOWNOP at 27% of all purchases. PEFU and INVM combined account for an additional 21% while REITs purchase 15% of property. Users account for an additional 2% of transactions while banks purchased 4%. Pension funds' direct purchases constitute only 2% of purchases each with the Other category accounting for less than 1%.[5]

Delegated Investors

I group investors into four categories: delegated investors, direct investors, REITs, and small investors. I hypothesize that delegated investors have shorter holding periods than

[5]The share of CRE purchases by pension funds may seem small. The share shown only captures investments in which the pension fund is the owner of record such that it excludes many joint ventures as well as any indirect CRE investment by pension funds. See Andonov et al. (2015) for additional discussion of the CRE investments of pension funds.

Figure 1: Investor Composition in US Commercial Real Estate, 2001-2015



Notes: 1) DEV denotes Developer/Owner/Operator, INVM denotes Investment Manager, PEFU denotes Private Equity Fund, PENS denotes Pension Fund, REOC denotes Real Estate Operating Company, OTH denotes Other, and SMALL denotes a buyer that makes less than five transactions over the full sample period. 2) Investor type shares are averaged over 2001-2015 and are value-weighted.

direct investors because of agency frictions. Because principals cannot observe the effort and skill level of managers, they require managers to dispose of the investments in a timely fashion.[6] The information asymmetry is especially acute in commercial real estate because of the heterogeneity in properties and the infrequency with which properties trade. Delegated investors may also have to dispose of a property before receiving all of their compensation from the principal. Given large discrepancies between appraisal and transaction prices (see Cannon and Cole (2011)), it's not feasible to compensate managers based on appraisal values. I separate REITs from other delegated investors because REITs have long holding periods by statute; see Mühlhofer (forthcoming) regarding REIT holding period constraints being binding. I consider BANK, PEFU, INVM, and PENS as delegated investors. The remaining non-REIT investor types I consider direct investors.

Property Characteristics

In addition to the buyer name, transaction price, and square footage, for most properties RCA provided the year the property was built, and the property's national and local Q-Scores. The RCA Q-Scores are proprietary measures of a property's relative quality varying from 1 to 100. They are more detailed alternatives to descriptors such as "Class A" or "Class C". The "scores incorporate not only physical attributes, but also market and locational factors". Costello (2017) provides additional discussion of the RCA Q-Scores. I present the relationship between investor composition and trade frequency both controlling and not controlling for them. To better understand what types of investors are most likely to undertake development, I create a variable called *development* that takes a value of 1 if the property is less than 1 year old. Finally, *office*, *industrial*, and *retail* are indicator variables for the property type.

Table 2 summarizes the property-level variables. Figures 2, 3, 4, and 5 show the distributions of property size (square footage), property age, and quality across the three

[6] Chakraborty and Ewens (2018) provide evidence from venture capital firms of agents delaying revealing negative information. Such agency conflicts necessitate contracts that incentivize delegated managers to dispose of investments in a timely fashion. Stein (1989) discusses several possible reasons delegated managers may have greater liquidity needs than principals.

different investor types. Consistent with the summary statistics in Panels B and C of Table 2, the biggest difference between the types of properties delegated and direct investors purchase is in size. Properties purchased by delegated investors are about 75,000 square feet larger on average than properties purchased by direct investors, a difference that is highly statistically significant in a univariate t-test for the difference in means. Not surprisingly, small investors overwhelmingly own physically small properties.

Delegated investors also invest in slightly younger properties on average. On average, properties purchased by delegated investors are about seven years younger and the difference is highly statistically significant in a univariate t-test for the difference in means. A fatter right tail primarily drives the difference in the mean property age between delegated and direct investors. The difference between the medians is only three years while the difference rises to 30 years at the 90th percentile. As Table 2 shows, there is no substantial difference between delegated and direct investors in the share of development properties.

$QScoreLocal$ is about six percentage points higher for delegated than for direct investors indicating that delegated investors buy higher quality properties than direct investors within an MSA. However, there is not a substantial difference between $QScoreNat$.

2.2 MSA Characteristics

Potential Credit Tenants

A key potential driver of delegated investors' decisions regarding which cities to invest in is the availability of credit tenants. Credit tenants are generally nationally known publicly traded firms and delegated investors may have a preference for such tenants because they can readily show measures of credit-worthiness to their investment boards. The argument is similar to the 'prudent-man' laws Del Guercio (1996) shows affect the choice of equity holdings of institutional investors. I compute the assets of publicly traded firms headquartered in an MSA in each year from Compustat. I take the natural log of these to get $logfirmassets$.

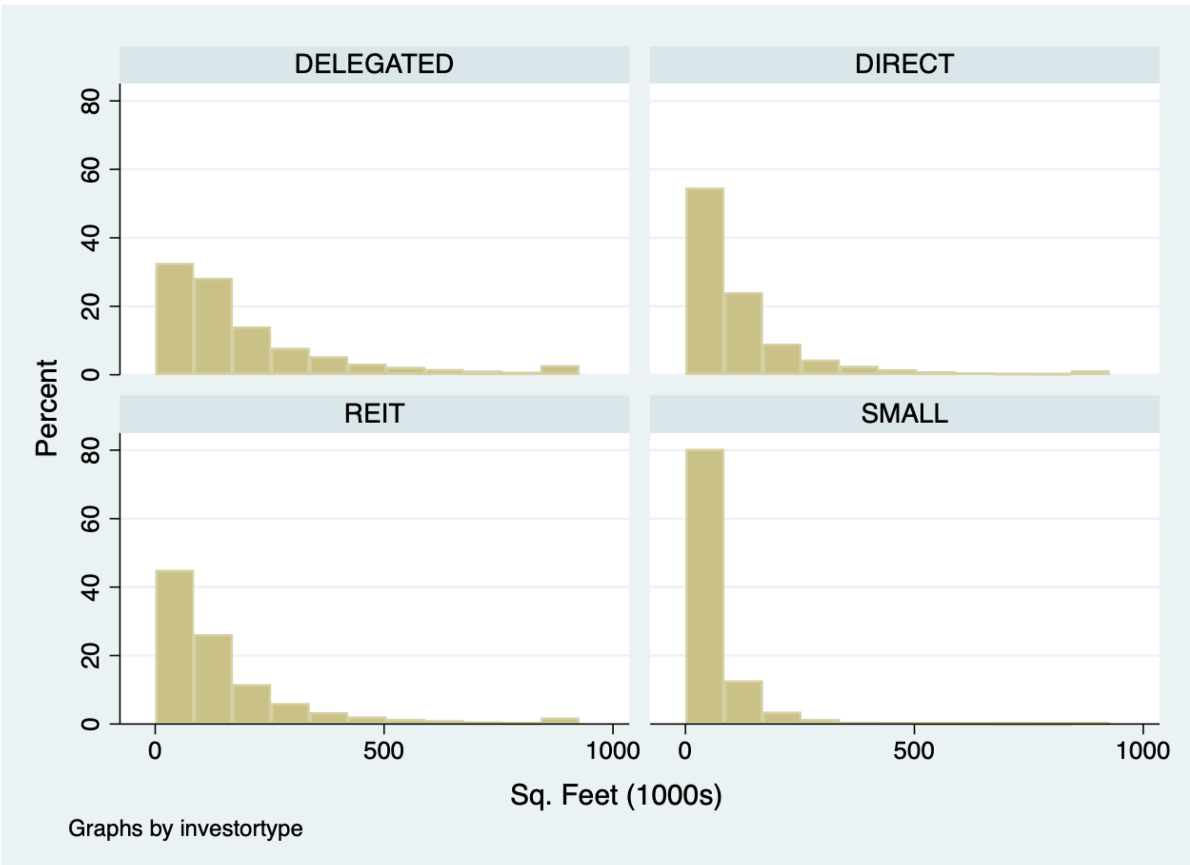
However, the headquarters of a firm is not where all their economic activity takes place; see García and Norli (2012). I therefore also use establishment-level employment data

Table 2: Transaction-Level Summary Statistics

	Obs.	Mean	Median	Std. Dev.	Min.	Max
Panel A: All Transactions						
YearBlt	109,082	1978.3	1985.0	26.7	1111.0	2020.0
Price	115,734	$ 15,000,000	$ 5,695,875	$ 42,800,000	$ 23,484	$ 2,950,000,000
Units	115,734	106.8	53.0	172.5	0.6	5500.0
QScoreLocal	97,593	0.51	0.51	0.29	0	1
QScoreNat	97,593	0.57	0.59	0.29	0	1
development	115,734	0.02	0	0.15	0	1
office	115,734	0.33	0	0.47	0	1
industrial	115,734	0.35	0	0.48	0	1
retail	115,734	0.31	0	0.46	0	1
Panel B: Delegated Investor Purchases						
YearBlt	14,116	1984.2	1987.0	21.9	1803.0	2020.0
Price	14,872	$ 33,000,000	$ 14,000,000	$ 68,400,000	$ 196,237	$ 2,200,000,000
Units	14,872	205.7	128.8	235.5	1.3	3787.2
QScoreLocal	11,126	0.54	0.55	0.28	0	1
QScoreNat	11,126	0.55	0.55	0.28	0	1
development	14,872	0.02	0	0.14	0	1
office	14,872	0.43	0	0.49	0	1
industrial	14,872	0.41	0	0.49	0	1
retail	14,872	0.16	0	0.37	0	1
Panel C: Direct Investor Purchases						
YearBlt	27,972	1977.2	1984.0	26.9	1708.0	2018.0
Price	29,372	$ 18,500,000	$ 8,150,000	$ 47,200,000	$ 44,472	$ 2,950,000,000
Units	29,372	129.2	75.3	188.3	0.7	5500.0
QScoreLocal	24,395	0.48	0.46	0.29	0	1
QScoreNat	24,395	0.54	0.55	0.30	0	1
development	29,372	0.02	0	0.13	0	1
office	29,372	0.36	0	0.48	0	1
industrial	29,372	0.30	0	0.46	0	1
retail	29,372	0.34	0	0.47	0	1
Panel D: REIT Purchases						
YearBlt	9,584	1987.5	1990.0	20.2	1635.0	2016.0
Price	10,356	$ 25,200,000	$ 11,200,000	$ 66,500,000	$ 112,548	$ 2,800,000,000
Units	10,356	158.6	98.1	214.0	1.2	4348.1
QScoreLocal	7,982	0.58	0.60	0.28	0	1
QScoreNat	7,982	0.56	0.57	0.27	0	1
development	10,356	0.03	0	0.17	0	1
office	10,356	0.27	0	0.44	0	1
industrial	10,356	0.33	0	0.47	0	1
retail	10,356	0.40	0	0.49	0	1
Panel E: Small Investor Purchases						
YearBlt	57,410	1975.8	1983.0	28.1	1111.0	2018.0
Price	61,134	$ 7,266,014	$ 4,010,000	$ 18,600,000	$ 23,484	$ 1,250,000,000
Units	61,134	63.1	32.8	114.2	0.6	5400.0
QScoreLocal	54,090	0.50	0.50	0.30	0	1
QScoreNat	54,090	0.58	0.62	0.30	0	1
development	61,134	0.02	0	0.15	0	1
office	61,134	0.30	0	0.46	0	1
industrial	61,134	0.37	0	0.48	0	1
retail	61,134	0.33	0	0.47	0	1

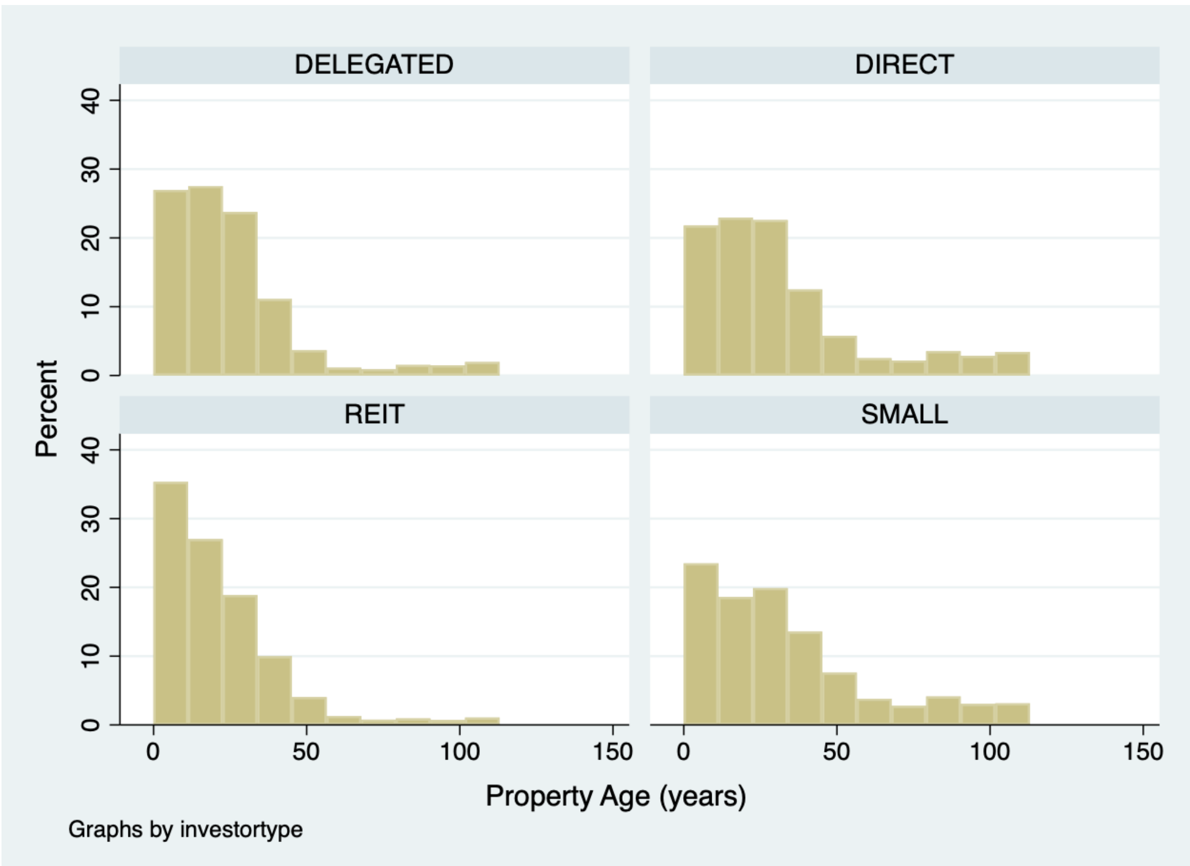
Notes: 1) YearBlt is the year the property was built or is anticipated to be completed in the case or properties still under development. 2) Units is the number of square feet in 1000s. 3) *QScoreLocal* and *QScoreNat* are proprietary RCA measures of the quality of the property relative to other properties in that MSA and in the Nation, respectively. 4) *development* takes a value of 1 if the property is under one year of age at the time of purchase.

Figure 2: Property Size (Square Feet in 1000s) for 2001-2015 Purchases by Investor Type



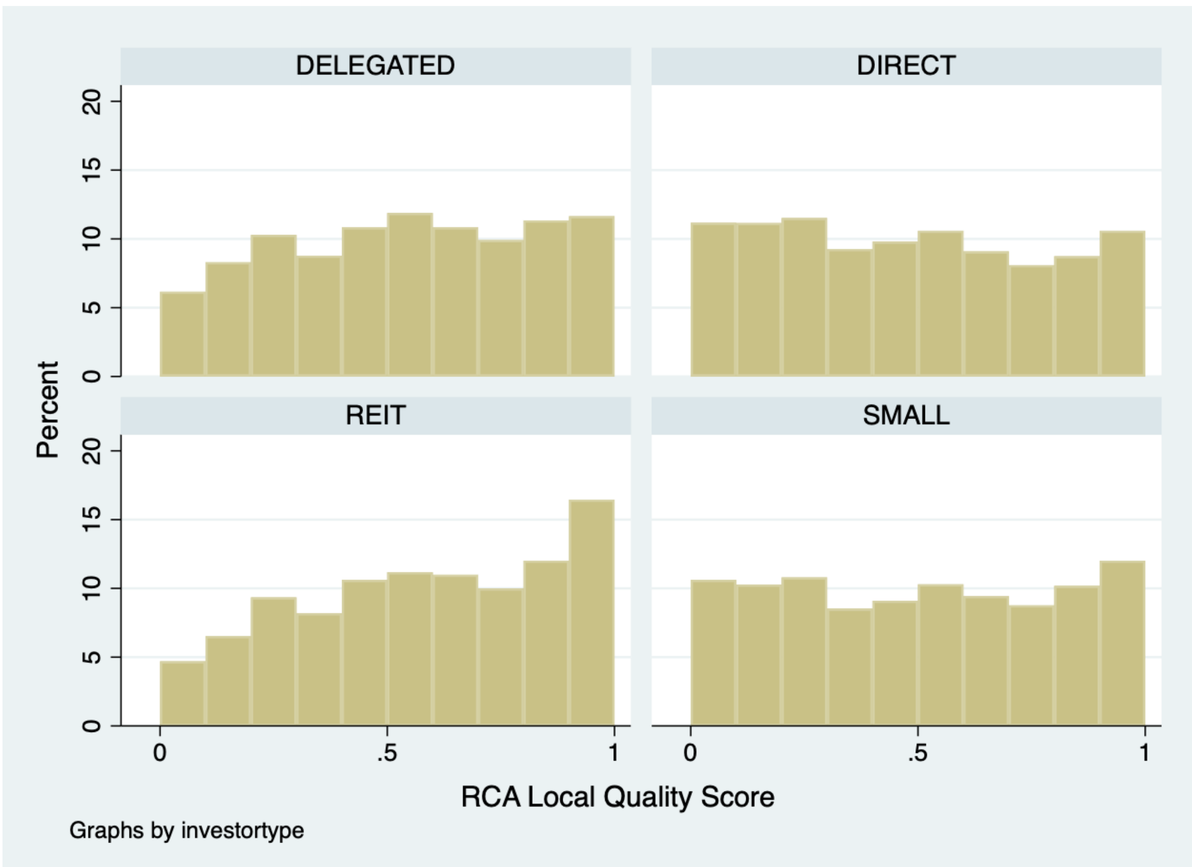
Notes: 1) DELEGATED includes banks, investment managers, private equity funds, and pension funds. 2) SMALL investors are investors with less than five transactions over the sample period. 3) I winsorize the right tail at the 1% level due to a handful of outliers.

Figure 3: Property Age for 2001-2015 Purchases by Investor Type



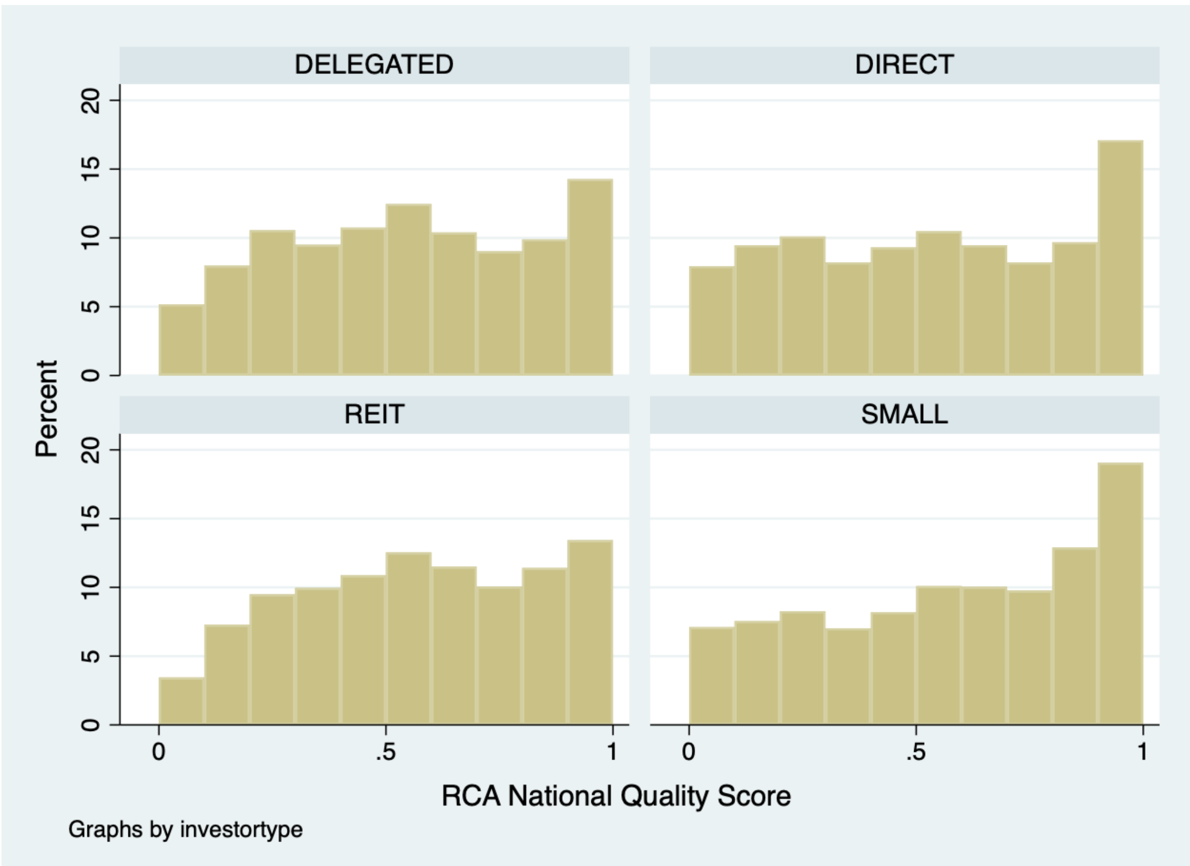
Notes: 1) DELEGATED includes banks, investment managers, private equity funds, and pension funds. 2) SMALL investors are investors with less than five transactions over the sample period. 3) Property age measured in years. 4) I winsorize the right tail at the 1% level due to a handful of outliers.

Figure 4: Within MSA Property Quality for 2001-2015 Purchases by Investor Type



Notes: 1) DELEGATED includes banks, investment managers, private equity funds, and pension funds. 2) SMALL investors are investors with less than five transactions over the sample period. 3) Property quality is a proprietary metric constructed by RCA; see Costello (2017) for details.

Figure 5: National Property Quality for 2001-2015 Purchases by Investor Type



Notes: 1) DELEGATED includes banks, investment managers, private equity funds, and pension funds. 2) SMALL investors are investors with less than five transactions over the sample period. 3) Property quality is a proprietary metric constructed by RCA; see Costello (2017) for details.

from Your-economy Time Series (YTS) to identify the share of employment in an MSA that is from publicly traded firms. The underlying data for YTS is the Infogroup Historic Datafiles. The data is an annual establishment-level time series database that follows companies at their unique locations across the US. YTS focuses on establishments that are "in-business" in the sense that it filters out firms that are created for tax purposes or merely holding companies. Additional details on the YTS data, and how it compares with other establishment-level employment data, are available at http://bdrc.uwex.edu/downloads/YTSdatadescription.pdf and http://bdrc.uwex.edu/insights/YTSreview.pdf.

The YTS data provide linking codes that link establishments to the headquarters firm. I identify publicly traded firms by whether they have a stock ticker symbol in the YTS data. Averaging across 2001-2015, the YTS data reveal that about 72% of the average publicly traded firm's employment is in the same Core-Based Statistical Area (CBSA) as the firm's headquarters. However, the share is much smaller for large firms such that weighting by total firm employment rather than equally-weighting firms results in a much larger share of employment outside of a firm's headquarters CBSA. Of all employment in publicly traded firms, only about 17% is in the same CBSA as the firm's headquarters.

To get a measure of the availability of credit tenants in an MSA, I aggregate all the employment in establishments linked to publicly traded firms and divide it by the total employment in the MSA. I denote this variable *pubempshare*. Table 3 ranks the cities in the sample according to the share of employment by publicly traded firms.

Other MSA-Level Economic Fundamentals

I also use the YTS data to measure industry concentration in each city and the overall level of competitiveness of firms. I measure the industry concentration in each city by constructing the Herfendahl-Hirschman Index (HHI) using establishment-level employment in 2-digit NAICS code industries. I term this variable emp_HHI. I construct the overall degree of competition between firms in a city by dividing the total employment in a city by the number of establishments (*estsperemp*).

The Bureau of Economic Analysis (BEA) provides real GDP at the MSA-level from

Table 3: US Cities' Economic Fundamentals
MSAs Ranked by Share of MSA Employment in Publicly Traded Firms

Rank	msa	msalabel	*pubempshare*	*estsperemp*	*emp_HHI*	*college*
1	Las Vegas	LAS	24.4	0.067	0.091	19.9
2	San Jose	SJC	22.6	0.077	0.075	43.7
3	Memphis	MEM	20.6	0.078	0.068	23.8
4	Cincinnati	CIN	19.9	0.071	0.067	26.4
5	Indianapolis	IND	19.4	0.071	0.070	29.2
6	Atlanta	ATL	19.2	0.085	0.064	34.3
7	Dallas	DFW	18.9	0.081	0.064	30.0
8	Orlando	MCO	18.9	0.082	0.073	26.6
9	Denver	DEN	18.6	0.083	0.062	36.8
10	Phoenix	PHX	18.5	0.078	0.065	26.7
11	Houston	HOU	18.4	0.082	0.063	27.9
12	Nashville	BNA	17.9	0.081	0.074	28.3
13	Kansas City	KC	17.7	0.073	0.068	32.0
14	Minneapolis	MSP	17.3	0.066	0.068	37.0
15	Jacksonville	JAX	17.0	0.086	0.068	26.3
16	Charlotte	CLT	16.9	0.084	0.062	30.3
17	Tampa	TPA	16.7	0.088	0.073	24.6
18	Columbus	CMH	16.5	0.066	0.077	32.0
19	Salt Lake City	SLC	16.3	0.071	0.065	28.5
20	Chicago	CHI	16.2	0.077	0.065	32.1
21	Seattle	STL	16.0	0.086	0.069	35.8
22	San Francisco	SFO	15.5	0.091	0.067	43.1
23	Oakland	OAK	15.5	0.091	0.067	43.1
24	San Antonio	SAT	15.5	0.084	0.072	24.2
25	Detroit	DTW	15.1	0.080	0.074	26.3
26	Portland	PDX	14.9	0.089	0.067	31.9
27	Cleveland	CLE	14.7	0.074	0.073	26.7
28	Pittsburgh	PIT	14.7	0.084	0.076	27.1
29	Riverside	RIV	14.4	0.093	0.069	18.9
30	San Diego	SAN	14.3	0.084	0.069	33.9
31	Austin	AUS	14.2	0.084	0.068	39.1
32	DC Metro	DC	14.0	0.076	0.073	46.0
33	Orange County	OC	13.8	0.093	0.065	29.3
34	Los Angeles	LA	13.8	0.093	0.065	29.3
35	Philadelphia	PHL	13.8	0.082	0.072	31.6
36	Baltimore	BWI	13.5	0.082	0.075	33.1
37	Sacramento	SAC	13.2	0.091	0.072	29.9
38	Boston	BOS	13.1	0.081	0.073	40.5
39	NYC Metro	NYC	11.7	0.090	0.069	34.9

Notes: 1) *pubempshare* is the fraction of employees in an MSA employed by a publicly traded firm. 2) Calculations of *pubempshare*, *emp_HHI*, and *estsperemp* based on establishment-level data provided by YTS. 3) *pubempshare*, *emp_HHI*, and *estsperemp* are averaged over 2001-2015 period. 4) *college* is the share of the population with a college degree from the 2005 American Community Survey.

2001 onwards from which I calculate GDP growth for 2002 onwards. I take the share of the population with a four-year college degree or more education (*college*) from the 2005 American Community Survey (ACS). I take the population of the MSA from the 2010 US Census.

Property Market Variables

RCA also provides data on capitalization (cap) rates. CRE investors use the term cap rate to refer to the dividend yield of a property. I use these data to calibrate the model of Section 4. CBRE, a major CRE brokerage firm, provides the data on the stock of commercial real estate by MSA. Information on the stock in Pittsburgh and San Antonio starts only in 2002 and 2007 such that the samples are shorter for these cities. CBRE also provides data on occupancy rates and rent growth by property type and MSA.

3 Empirical Facts

3.1 Delegated Investors Have Shorter Holding Periods than Direct Investors

Table 4 provides univariate statistics on holding periods of delegated and direct investors. For Table 4 only, I code transactions that have not sold by the end of the property as having a holding period of 15; I recode this as 14 for the Tobit regressions in Table 5. The first panel shows all transactions and illustrates a modest difference in the overall holding periods. On average, delegated investors hold their properties 0.6 years less. The small difference in the full sample is largely because most properties have still not sold by the end of the sample. However, the 25th percentile of the holding period for delegated investors is 6 years which is two years less than the 25th percentile for direct investors. The second panel includes only purchases made in 2001-2003, such that there is time for the investor to have sold the property before the end of the sample. For the 2001-2003 transactions, the median holding period for delegated investors in 6 years while it is 12 for direct investors.

Table 4: Holding Periods of Direct and Delegated Investors

	mean	p25	p50	sd	min	max	n
2001-2015 Purchases							
Direct	11.7	8	15	5.2	0	15	29,372
Delegated	11.1	6	15	5.4	0	15	14,872
All	11.5	7	15	5.3	0	15	44,244
2001-2003 Purchases Only							
Direct	9.9	4	12	5.4	0	15	2,933
Delegated	8.0	3	6	5.3	0	15	1,289
Total	9.3	4	10	5.4	0	15	4,222

Table 5 shows that delegated investors have shorter holding periods even after controlling for which city they invest in, the year of purchase, and various property characteristics. I also control for the total dollar volume of transactions by the purchaser. The table presents Tobit regressions of the holding period on whether the purchaser is a delegated investor. The regression includes all transactions by delegated and direct investors; it excludes transactions by REITs and SMALL investors.

The first three columns of Table 5 present results for all years. In column 1, the only controls are year fixed effects. The coefficient on *delegated* is -0.64 and statistically significant at the 1% level. The specification in column 2 adds MSA fixed effects, a full set of property-level controls, and controls for buyer size. The coefficient is -0.66, very close to the specification without any controls, and is statistically significant at the 1% level. Column 3 disaggregates *delegated* into the delegated subcategories *invm*, *pefu*, *bank*, and *pens*. The coefficient on *pefu* is highest at -1.09 while those on *invm* and *bank* are about -0.3. All three of these coefficients are statistically significant at the 5% level. The coefficient on *pens* is, however, small and statistically insignificant suggesting that pension funds may be less susceptible to liquidity shocks than other types of delegated managers.

Column 4 presents the coefficient estimates from the regression when I include only properties that are sold by the end of the sample. In this specification, I include only purchases from 2001-2003. The coefficient on *delegated* falls slightly but remains statistically significant at the 1% level. As such, the overall effect found in columns 1 - 3 is driven both by direct investors being less likely to have sold a property by the end of the sample and by them having held on longer to properties they bought at the beginning of the sample and have since disposed of.

The last four columns present results for purchases made in 2001-2003, 2004-2006, 2007-2009, and 2010-2015 separately. In all specifications, the coefficient on *delegated* is negative and statistically significant at the 1% level.

Table 5: Tobit Regressions of Holding Period on Investor Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
delegated	-0.64***	-0.66***		-0.48***	-1.55***	-0.93***	-0.92***	-1.38***
	(0.047)	(0.055)		(0.17)	(0.20)	(0.19)	(0.19)	(0.18)
invm			-0.32***					
			(0.076)					
pefu			-1.09***					
			(0.072)					
bank			-0.30**					
			(0.14)					
pens			0.11					
			(0.22)					
office		-0.82***	-0.82***	-0.55**	-1.95***	-2.24***	-0.75***	-0.90***
		(0.067)	(0.067)	(0.22)	(0.23)	(0.23)	(0.24)	(0.23)
industrial		-0.62***	-0.63***	-0.46*	-0.82***	-1.63***	0.092	-1.65***
		(0.069)	(0.069)	(0.24)	(0.25)	(0.24)	(0.25)	(0.23)
QScoreLocal		1.29***	1.28***	0.99	0.65	0.67	1.06	4.32***
		(0.18)	(0.18)	(0.69)	(0.71)	(0.69)	(0.66)	(0.60)
QScoreNat		0.25	0.19	0.047	0.49	2.42***	0.30	-0.061
		(0.23)	(0.23)	(0.87)	(0.88)	(0.87)	(0.85)	(0.75)
Observations	44,244	35,521	35,521	2,018	3,330	9,047	6,015	17,129
Purchase Yrs Included	2001-2015	2001-2015	2001-2015	2001-2003	2001-2003	2004-2006	2007-2009	2010-2015
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Size Quintiles	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Age Quintiles	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer Size Quintiles	No	Yes	Yes	No	No	No	No	No
Pseudo-R^2	1.9%	2.4%	2.4%	1.6%	1.6%	1.5%	1.0%	8.3%

Notes: 1) Dependent variable is the number of years the property was held for. 2) The table presents coefficients from Tobit regression to account for both left and, for all columns except (4), right censoring. 3) Sample is purchases 2001-2015 by delegated and direct investors; sample does not include purchases by REITs or SMALL investors. 4) The sample in column (4) includes only 2001-2003 purchases sold by the end of 2015. 5) Standard errors in parentheses. 6) ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$.

3.2 MSA-Level Trade Frequency and Investor Composition

Table 1 aggregates the data across years to show how investor type shares range across MSAs. The table presents the average shares of purchases by delegated investors and REITs in each MSA over the 2001-2015 period. Delegated investors comprised 39% of purchases in the Boston metro area but only 10% of purchases in Detroit. Perhaps surprisingly, delegated investors accounted for less than the median share in the NYC Metro area. While delegated investors concentrate their purchases in coastal cities, Chicago and Dallas also have high shares of purchases by delegated investors.

The second and third columns of Table 1 show the shares of purchases by delegated investors over the first half and second half of the sample. While the shares change somewhat over time, there is substantial persistence. Table 6 illustrates this more formally. The table presents the regression coefficients from a regression of the share in the second half of the sample on the first half of the sample. The coefficient is 0.58. Perhaps even more striking, the R^2 of 53% shows that a city' historical investor composition explains more than half of its recent composition.

Table 6: Persistence of Delegated Investor Share Over Time

	delsh 2008-2015
delsh 2001-2007	0.58***
	(0.091)
Constant	10.3***
	(2.27)
Observations	39
R^2	52.5%

Notes: 1) Standard errors in parentheses. 2) *** indicates $p < 0.01$. 3) Dependent variable is share of purchases by delegated investors in MSA averaged 2008-2015.

Figure 6 illustrates that there is a positive relationship between ownership by delegated investors and trade frequency but does not control for any covariates. As the model of the next section shows, the causality between investor composition and trade frequency runs both ways rather than the positive relationship being solely because delegated investors choose markets with higher trade frequency. That is, trade frequency and investor composition are jointly determined such that a positive relationship between a market's delegated investor share and trade frequency is an equilibrium outcome. Nevertheless, it is worth considering a few explanations for the empirical relationship between the share of purchases by delegated investors and trade frequency other than the one this paper proposes. While an exhaustive empirical analysis of the determinants of ownership of CRE is beyond the scope of this paper, I consider several alternative explanations for the relationship in Figure 6.

Figure 6: Delegated Investor Share and Trade Frequency are Positively Related

Notes: 1) Delegated Investor shares for each MSA are averaged over 2001-2015. 2) Turnover is annual.

I first explore whether the bivariate relationship in Figure 6 persists at the MSA-level after controlling for MSA-level characteristics. In addition to preferring credit tenants, delegated investors may concentrate their investments in cities that grow faster. I include

MSA-level GDP growth as well as controls for factors that the urban economics literature empirically shows predict faster growth in a city over the long run. To the extent that delegated investors are more sophisticated than direct investors, they may be able to such long-term winners. Glaeser (2012) argues that the share of the population with a college degree increases MSA-level growth.[7] Glaeser et al. (1992) show empirically that cities with more variety across industries and cities with more firm-level competition grow more rapidly. I therefore include *college*, emp_HHI, and *estsperemp* as control variables.

The first column of Table 7 controls only for year fixed effects. The coefficient on the share of property transacting in an MSA, tf, is 1.74 indicating that a one standard deviation increase in trade frequency is associated with a 6-percentage point increase in the delegated investor share. The second column controls for year fixed effects, city population, and economic fundamentals. The coefficient on tf falls slightly to 1.52 but is still statistically at the 1% level. Instead of proxying for the availability of credit tenants using establishment-level employment data, column 3 includes the total assets of publicly-traded firms headquartered in the MSA ($logfirmassets$). Column 4 adds MSA-level GDP growth as a control which reduces the sample size by one year since MSA-level GDP is not available until 2001. The coefficient on GDP growth is negative but far from statistically significant. The coefficient on tf remains similar to that in columns 1 - 3. The dependent variable in column 5 is the share of sales by delegated investors instead of the share of purchases. The coefficient falls to 0.91 but remains statistically significant at the 1% level.

The results in Table 7 provide some support for the credit tenant hypothesis. The coefficient on *pubempshare* is positive and statistically significant at the 10% level. The magnitude is such that a one percentage point increase in the share of employment in publicly traded firms increases the delegated investor share by about 0.35 percentage points. Thus, a one standard deviation increase in *pubempshare* raises the share of delegated investors by about 1.2 percentage points. In column 3, the coefficient on $logfirmassets$ is also positive and statistically significant. The coefficient on *college* is highly statistically significant in all specifications indicating that delegated investors concentrate their investments in more

[7]See also Glaeser and Maré (2001), Moretti (2004), and Shapiro (2006).

educated cities.

Table 7: Delegated Investor Share and Trade Frequency

	(1)	(2)	(3)	(4)	(5)
	delshare	*delshare*	*delshare*	*delshare*	*delshare_sell*
tf	1.74***	1.52***	1.56***	1.60***	0.91***
	(0.36)	(0.22)	(0.22)	(0.21)	(0.15)
pubempshare		0.36*		0.34*	-0.11
		(0.19)		(0.20)	(0.13)
logfirmassets			1.35*		
			(0.69)		
emp_HHI		-178	-152	-130	-225**
		(123)	(111)	(154)	(89.4)
estsperemp		-34.1	28.5	3.11	114
		(68.9)	(73.1)	(71.4)	(72.8)
college		0.50***	0.34**	0.51***	0.49***
		(0.13)	(0.13)	(0.14)	(0.092)
gdpgrowth				-0.10	
				(0.17)	
Observations	578	578	578	541	578
R^2	23.4%	26.9%	27.1%	29.1%	22.6%
Year FEs	Yes	Yes	Yes	Yes	Yes
Pop Quintiles	No	Yes	Yes	Yes	Yes
Std. Errors Clustered by MSA	Yes	Yes	Yes	Yes	Yes

Notes: 1) ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$. 2) Dependent variable in columns (1) through (4) is the share of purchases by delegated investors in an MSA in that year. 3) Dependent variable in column (5) is the share of sales by delegated investors in an MSA in that year. 4) tf is percent of property stock transacting in that MSA-year; $logfirmassets$ is the log of the sum of the assets of all publicly-listed firms headquartered in that MSA; *gdpgrowth* is MSA-level annual GDP growth available 2002-2015. 5) See Table 3 for remaining variable definitions. 6) Standard errors clustered by MSA are in parentheses.

Transaction-Level Evidence that Delegated Investors Choose Higher Trade Frequency Cities

I next explore the robustness of the relationship between the trade frequency and delegated investors using the transactions-level data. The advantage of this approach is that I can control for property-level characteristics. I therefore run probit and OLS regressions where the dependent variable takes a value of one if the transaction is made by a delegated investor and zero if the purchase is that of a direct investor. In particular I estimate,

$$delegated = \alpha_0 + \beta tfmeasure + \Gamma X + \epsilon \tag{1}$$

where $tfmeasure$ is one of three measures of what an individual investor might expect the trade frequency in a market to be.

I first consider tf, which is the overall turnover in that year and MSA. Second, I consider a property-type specific measure, $tfavg\_bytype$. The reason for considering a property-type specific measure is that many investors specialize not just in particular types of cities but also in particular property types. An investor that focuses on industrial property likely does not care about the trade frequency of retail in a city. Because there are often only a few or sometimes no transactions in a particular property type in any particular MSA in a given year, I average this measure over all years in an MSA-property type. Finally, I consider a measure of trade frequency that is predetermined, $tfavg\_firsthalf$, and look only at transactions from the second half of the sample.

The control variables in X include MSA-level economic fundamentals, MSA-level property market characteristics, individual property characteristics, quintiles for city size, quintiles for property size, and quintiles for property age. I include property size controls because delegated investors, who often need to deploy large amounts of capital and have limited resources to carefully examine many properties, may focus their investments on properties where they can deploy a large amount of capital on a single property.

As is known from the bond market (see, for example, Edwards et al. (2007) and Green et al. (2007)), higher quality assets usually trade more frequently. It is thus possible that the relationship in Figure 6 merely reflects delegated owners preferring higher quality assets and those assets also being more liquid. In all specifications, I include controls for the general state of that MSA's property market using property type-specific measures of rent growth and occupancy, $rentgr\_bytype$ and $occrate\_bytype$ and property age quintiles. In some specifications, I also include the RCA property-quality controls.

Table 8 presents the results from estimating equation (1) using a Probit model. The first three columns present the results without the RCA property-quality measures. Each column uses a different measure of the trade frequency an investor could expect in an MSA. In all three specifications, the coefficient on the trade frequency measure is positive and of a similar magnitude. It is statistically significant for tf and $tfavg\_bytype$.

In Table 8, the coefficients on the MSA-level economic fundamentals are mostly insignificant in contrast to the MSA-level results in Table 7. The coefficient on *college* is usually positive and is statistically significant in columns 2 and 5 consistent with it having a robust relationship with delegated investor share in Table 7. Rather than credit tenants not mattering at the individual transaction level, the insignificance of *pubempshare* is likely simply due to an MSA's credit tenant base being a weak measure of the share of an individual building occupied by credit tenants. Unfortunately, detailed tenant data is not readily available for the universe of commercial properties in the United States.

In the last three specifications, I include both the local and national property-quality controls. The sample size shrinks as the property-quality measures are only available for a subset of transactions. However, the coefficients on the trade frequency measures in columns 4 and 5 are similar to those in columns 1 and 2. The coefficient in column 6 is about twice the size of the one in column 3. The coefficient on $QScoreLocal$ is positive and statistically significant at the 1% level indicating that delegated investors choose higher quality properties within an MSA. They also prefer industrial and office properties relative to retail (the omitted category).

Table 9 presents the results from estimating equation (1) by OLS rather than Probit to both test the robustness of the results and to facilitate interpretation of the coefficients. The coefficients indicate that a one percentage point increase in trade frequency increases the likelihood that the transaction is made by a delegated investor by about 0.6 percentage points. The mean of *delegated* is 0.34 and, across the 578 MSA-years in the sample, the standard deviation of trade frequency is 3.2 percentage points. Thus, we can conclude that a one standard deviation increase in trade frequency in an MSA increases the likelihood that a delegated investor purchases a property by about 6%. The statistical significance of the coefficients on the trade frequency measures in Table 9 are very similar to those in Table 8.

Table 8: Probit Regressions of Investor Type on Trade Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
tf	0.019*			0.019		
	(0.010)			(0.012)		
tfavg_bytype		0.017***			0.016**	
		(0.0058)			(0.0068)	
tfavg_firsthalf			0.015			0.041**
			(0.012)			(0.017)
pubempshare	-0.0057	-0.0075	0.0076	-0.0050	-0.0053	0.012
	(0.0061)	(0.0074)	(0.0070)	(0.0080)	(0.0088)	(0.0089)
emp_HHI	-4.65	-3.81	3.60	-1.53	-0.33	9.17**
	(3.47)	(3.31)	(4.11)	(4.07)	(3.94)	(4.09)
estsperemp	-2.69	-2.69	0.97	-5.16	-4.90	-2.80
	(3.07)	(2.98)	(2.28)	(3.64)	(3.65)	(2.48)
college	0.0056	0.0067**	0.0026	0.0055	0.0072*	-0.00033
	(0.0036)	(0.0032)	(0.0033)	(0.0040)	(0.0038)	(0.0036)
occrate_bytype	0.012**	0.015**	0.014**	0.014**	0.017***	0.027***
	(0.0056)	(0.0058)	(0.0056)	(0.0059)	(0.0062)	(0.0075)
rentgr_bytype	-0.00073	-0.00049	0.0020	-0.0018	-0.0015	-0.00034
	(0.0012)	(0.0013)	(0.0027)	(0.0015)	(0.0015)	(0.0028)
office	0.45***	0.40***	0.37***	0.36***	0.32***	0.35***
	(0.059)	(0.068)	(0.061)	(0.069)	(0.080)	(0.081)
industrial	0.42***	0.50***	0.38***	0.26***	0.32***	0.14*
	(0.061)	(0.062)	(0.066)	(0.064)	(0.064)	(0.073)
QScoreLocal				0.71***	0.73***	0.83***
				(0.080)	(0.087)	(0.11)
QScoreNat				-0.10	-0.14	-0.30**
				(0.099)	(0.11)	(0.13)
Observations	43,444	43,415	24,636	34,983	34,966	19,404
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Size Pop Age Quintiles	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	7.5%	7.6%	7.4%	9.2%	9.2%	8.8%

Notes: 1) ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$. 2) Dependent variable = 1 if purchase by delegated investor, 0 if purchase by direct. 3) Sample is 2001-2015 purchases by delegated and direct investors. 4) *tf* is the trade frequency in that MSA-year; *tfavg_bytype* is the average trade frequency in that MSA and property type; *tfavg_firsthalf* is the average trade frequency in that MSA over the 2001-2007 period. 5) Size Pop Age Quintiles are quintiles for property age, property size, and MSA population. 6) Standard errors clustered by MSA in parentheses.

Table 9: OLS Regressions of Investor Type on Trade Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
tf	0.0071*			0.0069*		
	(0.0036)			(0.0040)		
tfavg_bytype		0.0065***			0.0057**	
		(0.0021)			(0.0024)	
tfavg_firsthalf			0.0053			0.013**
			(0.0044)			(0.0059)
pubempshare	-0.0023	-0.0030	0.0025	-0.0024	-0.0025	0.0034
	(0.0021)	(0.0026)	(0.0025)	(0.0026)	(0.0030)	(0.0030)
emp_HHI	-1.53	-1.20	1.29	-0.51	-0.076	3.15**
	(1.16)	(1.10)	(1.43)	(1.32)	(1.26)	(1.39)
estsperemp	-0.93	-0.95	0.41	-1.85	-1.79	-0.87
	(1.06)	(1.03)	(0.80)	(1.18)	(1.19)	(0.79)
college	0.0020	0.0024**	0.0011	0.0018	0.0024*	7.6e-06
	(0.0012)	(0.0011)	(0.0011)	(0.0013)	(0.0013)	(0.0013)
occrate_bytype	0.0042**	0.0050**	0.0043**	0.0043**	0.0052**	0.0079***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0021)	(0.0027)
rentgr_bytype	-0.00022	-0.00013	0.00071	-0.00059	-0.00049	-0.00010
	(0.00044)	(0.00048)	(0.00097)	(0.00050)	(0.00053)	(0.00098)
office	0.15***	0.13***	0.12***	0.11***	0.094***	0.11***
	(0.023)	(0.026)	(0.024)	(0.024)	(0.029)	(0.030)
industrial	0.14***	0.17***	0.13***	0.079***	0.10***	0.047*
	(0.023)	(0.023)	(0.025)	(0.023)	(0.023)	(0.025)
QScoreLocal				0.22***	0.23***	0.25***
				(0.030)	(0.030)	(0.051)
QScoreNat				-0.020	-0.032	-0.073
				(0.034)	(0.037)	(0.055)
Observations	43,444	43,415	24,636	34,983	34,966	19,404
R^2	9.2%	9.2%	9.1%	10.9%	11.0%	10.4%
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Size Pop Age Quintiles	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$. 2) Dependent variable = 1 if purchase by delegated investor, 0 if purchase by direct. 3) Sample is 2001-2015 purchases by delegated and direct investors. 4) *tf* is the trade frequency in that MSA-year; *tfavg_bytype* is the average trade frequency in that MSA and property type; *tfavg_firsthalf* is the average trade frequency in that MSA over the 2001-2007 period. 5) Size Pop Age Quintiles are quintiles for property age, property size, and MSA population. 6) Standard errors clustered by MSA in parentheses.

Delegated investors, who may be less likely to be local, may also shy away from markets where certain investors have market power due to their size relative to the market. To the extent that buyer concentration is correlated with trade frequency in a market, perhaps because delegated investors are more diversified across markets than direct investors, buyer concentration belongs in X in estimating equation 1. To consider this possibility, I construct the HHI index of buyers in each city. Table 10 presents the results when I include this variable. The coefficient on the HHI index is negative but never statistically significant. More importantly for the present paper, the coefficient on the trade frequency measures are little changed from the benchmark specifications in Table 8.

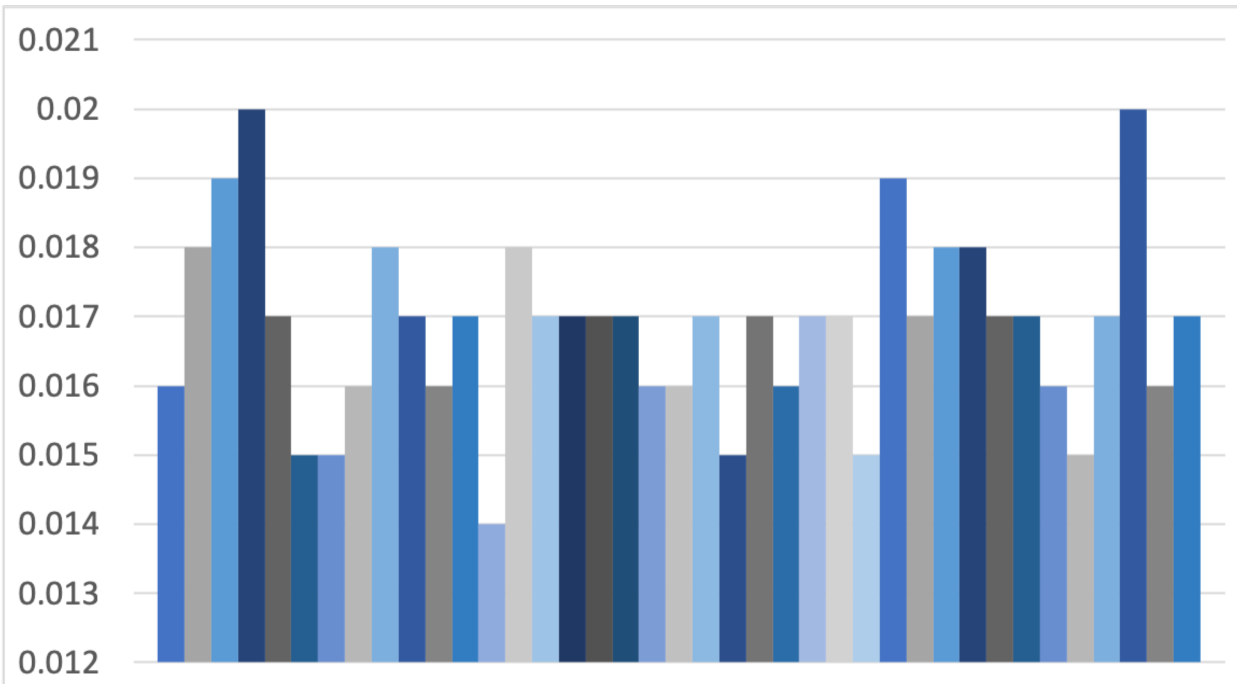
Figure 7 explores the robustness of the results to the MSAs included in the sample. It shows the coefficient on $tfavg\_bytype$ of the probit regression estimated in column (2) of Table 8 dropping one MSA at a time. The figure illustrates that the results are not heavily influenced by any single MSA. All of the coefficients are statistically significant at the 5% level and are close to the point estimate of 0.017 from the regression with all thirty-nine MSAs.

Table 10: Probit Regressions of Investor Type on Trade Frequency Controlling for Buyer Concentration

	(1)	(2)	(3)	(4)	(5)	(6)
tf	0.019*			0.019		
	(0.010)			(0.012)		
tfavg_bytype		0.017***			0.016**	
		(0.0059)			(0.0070)	
tfavg_firsthalf			0.015			0.040**
			(0.013)			(0.017)
pubempshare	-0.0057	-0.0075	0.0076	-0.0051	-0.0055	0.011
	(0.0060)	(0.0071)	(0.0060)	(0.0079)	(0.0087)	(0.0082)
emp_HHI	-4.24	-3.00	5.92	-1.02	0.44	10.8***
	(3.98)	(3.78)	(4.33)	(4.48)	(4.41)	(4.10)
estsperemp	-2.61	-2.55	1.35	-5.11	-4.83	-2.62
	(3.15)	(3.03)	(2.41)	(3.70)	(3.72)	(2.55)
college	0.0061	0.0078**	0.0058	0.0062	0.0082*	0.0019
	(0.0045)	(0.0038)	(0.0040)	(0.0046)	(0.0044)	(0.0039)
occrate_bytype	0.012**	0.015**	0.013**	0.014**	0.016***	0.026***
	(0.0057)	(0.0059)	(0.0060)	(0.0060)	(0.0062)	(0.0077)
rentgr_bytype	-0.00069	-0.00042	0.0022	-0.0018	-0.0015	-0.00011
	(0.0012)	(0.0013)	(0.0027)	(0.0015)	(0.0015)	(0.0028)
office	0.45***	0.40***	0.37***	0.36***	0.31***	0.35***
	(0.060)	(0.069)	(0.063)	(0.069)	(0.081)	(0.082)
industrial	0.42***	0.50***	0.39***	0.26***	0.32***	0.15**
	(0.061)	(0.062)	(0.066)	(0.063)	(0.064)	(0.071)
HHIbuyer	-0.10	-0.20	-0.61	-0.15	-0.22	-0.47
	(0.40)	(0.43)	(0.40)	(0.44)	(0.49)	(0.42)
QScoreLocal				0.70***	0.72***	0.81***
				(0.075)	(0.081)	(0.10)
QScoreNat				-0.093	-0.12	-0.26**
				(0.094)	(0.11)	(0.12)
Observations	43,444	43,415	24,636	34,983	34,966	19,404
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Size Pop Age Quintiles	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	7.5%	7.6%	7.4%	9.2%	9.2%	8.8%

Notes: 1) ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$. 2) Dependent variable = 1 if purchase by delegated investor, 0 if purchase by direct. 3) Sample is 2001-2015 purchases by delegated and direct investors. 4) *tf* is the trade frequency in that MSA-year; *tfavg_bytype* is the average trade frequency in that MSA and property type; *tfavg_firsthalf* is the average trade frequency in that MSA over the 2001-2007 period. 5) Size Pop Age Quintiles are quintiles for property age, property size, and MSA population. 6) $HHIbuyer$ is the HHI index of buyer concentration for the MSA calculated over the full sample. 7) Standard errors clustered by MSA in parentheses.

Figure 7: Coefficients on Trade Frequency in Regressions Dropping one MSA at a Time

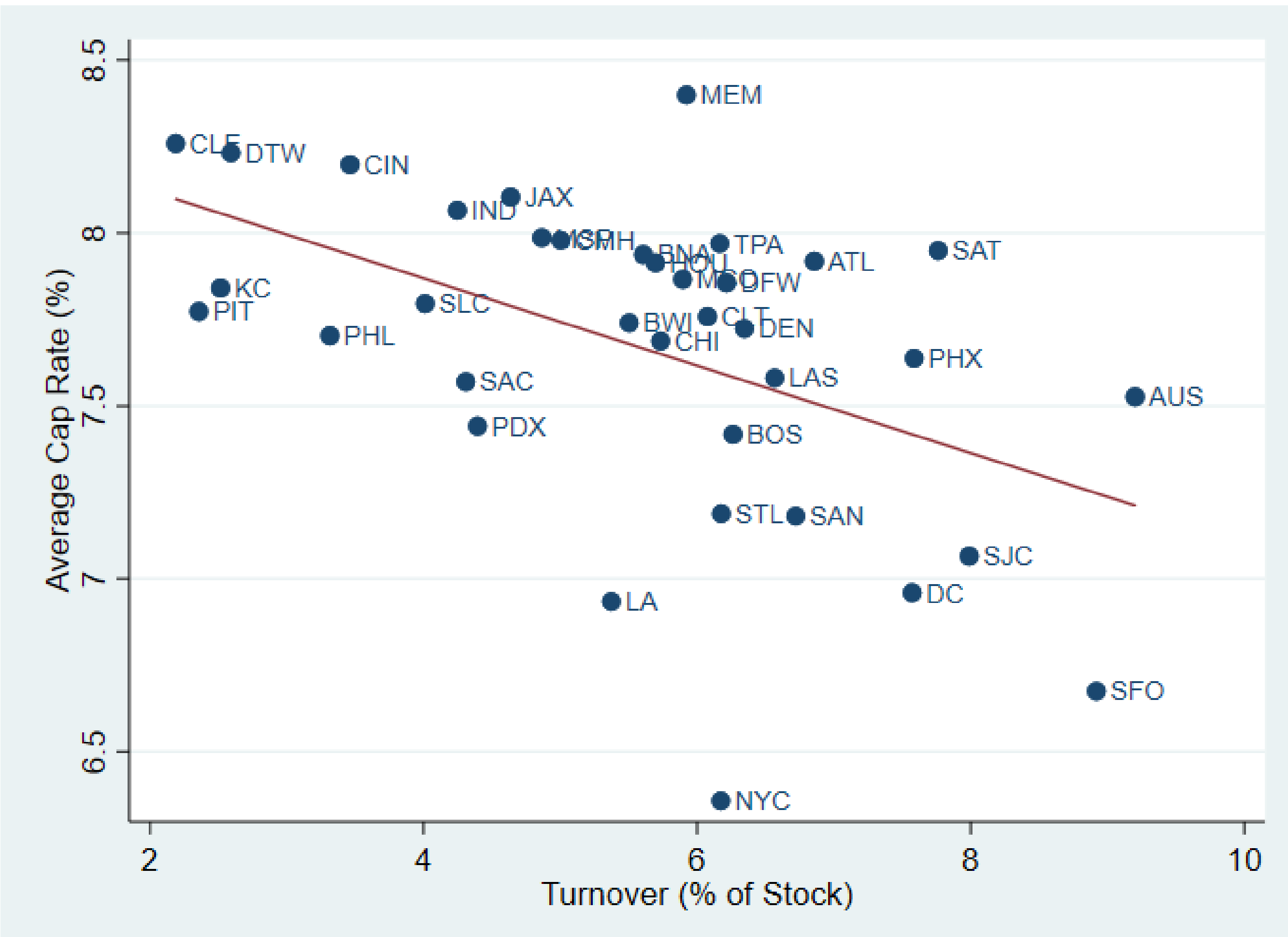


Notes: 1) Each bar represents the coefficient from a regression dropping a single MSA in the regression in column (2) of Table 8. 2) All coefficients are statistically significant at the 5% level.

3.3 Trade Frequency and Cap Rates

Figure 8 shows that, in general, cap rates are lower in MSAs in which trade is more frequent. This is consistent with there being an illiquidity premium for CRE. However, cap rates do not vary as much across MSAs as turnover does. The range of average cap rates across cities is only two percentage points. In contrast, average annual turnover across MSAs ranges from two to nine percent of the stock. While a full analysis of the differences in cap rates across MSAs is beyond the scope of this paper, the finding that cap rates are higher in cities with lower trade frequency is consistent with the model below.

Figure 8: Cap Rates and Trade Frequency are Inversely Related



Notes: 1) Cap rates for each MSA are averaged over 2001-2015.

4 Explaining the Facts

I explain the facts above by calibrating a version of Vayanos and Wang (2007) to the US CRE Market. I model delegated investors in CRE as more likely to have liquidity shocks than direct investors. For the model to have relevant empirical predictions, delegated investors need only have a higher average concentration of investors with frequent liquidity shocks; both delegated and direct investors can be individuals who frequently get valuation shocks and thus have high liquidity needs.

4.1 Model

There are two assets, 1 and 2, traded in markets 1 and 2. Both assets pay a dividend of 1 per period and are in supply S. The two markets are *ex ante* identical. Investors must commit to searching in only one market at any given time. In the context of CRE, one may interpret such a restriction as a high cost of acquiring information about a particular city's property market that prevents an investor from searching simultaneously in all possible markets.

Investors are risk-neutral and have a rate of time preference of r. Each period, there is an inflow of new agents into the economy. Investors are born into the market without the asset and enjoying a high valuation of the asset, i.e., their per period benefit is the full dividend of 1. Their valuation of the asset can switch to a low valuation in which case their per period benefit of owning the asset is $1 - x$. In contrast to Duffie et al. (2005) and Duffie et al. (2007), once an agent becomes a low valuation agent, it remains a low valuation agent until it sells the property. Once it has sold the property, it exits the economy. Agents that become low valuation agents without having bought a property also exit the economy.

Agents differ in the likelihood that they will receive a valuation shock. Valuation shocks arrive at Poisson rate κ. The density of investors that enter the economy is $f(\kappa)$, which I take as the uniform distribution over the interval $[\underline{\kappa}, \overline{\kappa}]$.

These assumptions in turn imply that the density of all high valuation agents in the economy (rather than that of new entrants to the economy) is

$$g(\kappa) = \frac{1}{\kappa} \tag{2}$$

such that D_h, the measure of high-valuation ages is $\frac{log(\overline{\kappa})-log(\underline{\kappa})}{\overline{\kappa}-\underline{\kappa}}$. I focus on the case where there is neither excess demand nor excess supply such that

$$S = \frac{D_h}{2} = 0.5 * \frac{log(\overline{\kappa}) - log(\underline{\kappa})}{\overline{\kappa} - \underline{\kappa}} \tag{3}$$

When a buyer (a newly born agent) meets a seller (an agent that had bought the asset as a high valuation agent but who now only gets $1 - x$ from owning the asset), they use bilateral bargaining to split the gains from trade. In particular, one party is randomly selected to make a take-it-or-leave-it offer. The probability that the buyer is selected to make the offer is $\frac{z}{1+z}$, $z \in (0, \infty)$.

Buyers and sellers meet randomly within each market. Given total masses of buyers and sellers in market i, μ^i_B and μ^i_S, the matching function $M(\mu^i_B, \mu^i_S) = \lambda\mu^i_B\mu^i_S$ characterizes the search technology. It features increasing returns to scale consistent with the intuition that matching is easier in markets with large masses of both buyers and sellers. The parameter λ can be thought of as capturing the efficiency of the search technology.

4.2 Equilibrium

I focus on the clientele equilibrium in which high κ agents choose to enter the high liquidity market, which I take as market 1 without loss of generality.[8] Let $\mu^i_B(\kappa)$, $\mu^i_O(\kappa)$, and $\mu^i_S(\kappa)$ denote the density of agents with valuation shock frequency κ in market i who are looking to buy the asset, who own the asset and remain high valuation, and who own the asset but have become low valuation such that they are looking to sell the asset. The total masses of

[8]Vayanos and Wang (2007) show that there also exists a continuum of symmetric equilibria in which the measure of sellers is the same across both markets. In addition to being indeterminate, these equilibria are inconsistent with the empirical facts in Section 3.

such agents in the economy are then

$$\int_{\underline{\kappa}}^{\overline{\kappa}} \mu_B^i(\kappa)d\kappa = \mu_B^i \tag{4}$$

$$\int_{\underline{\kappa}}^{\overline{\kappa}} \mu_O^i(\kappa)d\kappa = \mu_O^i \tag{5}$$

$$\int_{\underline{\kappa}}^{\overline{\kappa}} \mu_S^i(\kappa)d\kappa = \mu_S^i \tag{6}$$

By Lemma 1 of Vayanos and Wang (2007), there is a unique value of κ, κ^*, such that all investors with $\kappa > \kappa^*$ choose to enter market 1 and all investors with $\kappa < \kappa^*$ go to market 2. Given this fact, to determine μ_B^1 (for example), I use the fact that the inflow of buyers into market 1 is $\frac{1}{\overline{\kappa}-\underline{\kappa}}d\kappa$ for $\kappa > \kappa^*$ and 0 for $\kappa < \kappa^*$ while the outflow is $\lambda\mu_B^1(\kappa)\mu_S^i d\kappa$. This gives an equation for $\mu_B^i(\kappa)$ in terms of μ_S^i and the parameters. I similarly set the inflow into owners equal to the outflow for a given κ to solve for μ_O^i in terms of μ_S^i and the underlying parameters. Finally, I impose that the mass of owners and sellers must equal total supply in each market (i.e., $\mu_O^i + \mu_S^i = S$).

The equilibrium of the model then requires the following three equations to be solved for the three unknowns μ_S^1, μ_S^2, and κ^*:

$$\frac{1}{\overline{\kappa}-\underline{\kappa}}\int_{\kappa^*}^{\overline{\kappa}} \frac{\lambda\mu_S^1}{k(k+\lambda\mu_S^1)}dk + \mu_S^1 = S \tag{7}$$

$$\frac{1}{\overline{\kappa}-\underline{\kappa}}\int_{\underline{\kappa}}^{\kappa^*} \frac{\lambda\mu_S^2}{k(k+\lambda\mu_S^2)}dk + \mu_S^2 = S \tag{8}$$

$$\begin{aligned}\mu_S^1 - \mu_S^2 + \mu_S^1\frac{1}{2(r+\kappa^*)(\overline{\kappa}-\underline{\kappa})}\int_{\underline{\kappa}}^{\kappa^*} \frac{\lambda(r+\kappa^*+0.5\lambda\mu_S^2)}{(k+\lambda\mu_S^2)(r+k+0.5\lambda\mu_S^2)}dk \\ +\mu_S^2\frac{1}{2(r+\kappa^*)(\overline{\kappa}-\underline{\kappa})}\int_{\kappa^*}^{\overline{\kappa}} \frac{\lambda(r+\kappa^*+0.5\lambda\mu_S^1)}{(k+\lambda\mu_S^1)(r+k+0.5\lambda\mu_S^1)}dk = 0\end{aligned} \tag{9}$$

Trading volume in the model is determined entirely by the parameters $\underline{\kappa}$, $\overline{\kappa}$, and λ. Trading volume does not depend on the discount from a liquidity shock, x. x matters only for price determination.

Transaction prices are heterogeneous in each market. While transaction prices have closed form solutions, in the interests of space, I do not reproduce the expressions for them from Vayanos and Wang (2007). Section 4.3 presents the average cap rates in markets 1 and 2 as these are the analogues to the empirical MSA averages. See Vayanos and Wang (2007) for additional details on the model solution.

4.3 Calibration

Given that the model has no role for heterogeneity in liquidity needs or technologies over time, I collapse the data to the means for each of the 39 MSAs. I then split the sample of cities into two sets of cities, high and low turnover. High turnover cities are the top half of cities by turnover. Table 11 shows that the most liquid cities have turnover of 6.85% while the least liquid cities have turnover of just 4.30%. The difference in turnover between the two sets of cities is more than 45% of the mean level of turnover. By comparison, the difference in the average cap rates across the two sets of cities is a mere 13 basis points or less than 2% of the average cap rate.

I fix z to 1 such that buyers and sellers have equal bargaining weight. I set r at 5.45% which is considerably higher than the average yield on the 10-year US Treasury over 2001-2015. The risk-free rate in the model must be higher to match the data because, in the model, there is no credit risk. Given the moments in the data, the model fits the data relatively well by setting $\underline{\kappa}$, $\overline{\kappa}$, λ, and x to 0.035, 0.09, 3.0, and 0.39. The midpoint of the range of κ is such that each high valuation agent faces a 6.25% chance of getting a liquidity shock in any given year and thus becoming a low valuation agent.

For these parameter values, the value of κ that separates the two sets of agents is $\kappa^* = 0.056$. As Vayanos and Wang (2007) point out, there are both more buyers and more sellers in the more liquid market. The equilibrium masses of buyers in markets 1 and 2 are 0.44 and 0.33 such that the equilibrium times on the market ($\frac{1}{\lambda \mu_B^i}$) are approximately 9 and 12 months. Publicly available compilations of the time required to sell in the CRE market do not exist but these timelines seem within the plausible range for CRE.[9]

The differences in cap rates between the high and low turnover markets is very small,

[9]See Carrillo (2013) and Carrillo and Pope (2012) for discussions of time on the market as a measure of liquidity in the residential market.

Table 11: Search Model with Investor Heterogeneity

	Data: US Cities			Model	
	All	High Turnover	Low Turnover	High Turnover Market ($\kappa > \kappa^*$)	Low Turnover Market ($\kappa \leqslant \kappa^*$)
Avg. Cap Rate	7.63%	7.51%	7.74%	7.51%	7.73%
Turnover	5.54%	6.85%	4.30%	6.80%	4.28%
Del. Share	23.9%	21.2%	26.7%		
N	39	19	20		
μ_B				0.45	0.34
μ_O				8.15	8.23
μ_S				0.43	0.36
Mos. to Sell				8.92	11.65
κ^*				0.056	
Illiquidity Premium (bp)				206	228

Notes: 1) κ^* is the unique value in the distribution of κ such that investors with values of κ above that choose to search in market 1 (high turnover) and investors with values of κ below that choose to search in market 2 (low turnover). 2) Mos. to sell is the expected number of months a seller expects to wait before finding a buyer. 3) The data from US cities covers 2001-2015. 4) The illiquidity premium is the spread above Treasuries for investing in illiquid CRE with the same credit risk as Treasuries.

a mere 22 basis points. In practice, the cash flows of CRE may differ across cities, which would generate additional heterogeneity in cap rates. The lack of credit risk in the model is also why I calibrate the model with a higher risk-free rate than that in the data. The model generates small *relative* illiquidity premia because of the heterogeneity in how investors value liquidity. Although the illiquidity premium across markets is positive, those investors that don't place a high value on liquidity choose the illiquid market and do not have to be paid a lot to do so. In contrast, if investors were homogeneous in their liquidity preferences, the illiquidity premium would have to be higher to get to an equilibrium in which there is no excess supply of the asset in the less liquid market.

Overall, however, the model implies a full two percentage point compensation for the illiquidity inherent in CRE, about 40% more yield than that of the perfectly liquid, risk-free asset. While the model is highly stylized, this is the first estimate of the illiquidity premium of CRE in the literature.[10] Consistent with CRE being much less liquid than financial

[10] Fisher et al. (2003) adjust CRE returns for differences in the ability to quickly sell a property at different points in the CRE cycle.

securities, this is a substantially higher illiquidity premium than what the literature finds for funds that hold financial securities. Aragon (2007) reports a 4-7% percent higher return on hedge funds with lockup restrictions relative to unrestricted funds. Barth and Monin (2018) construct a measure of illiquidity based on the average number of days it would take to liquidate a portfolio. Using this measure and data from hedge funds' security holdings, they find an illiquidity premium of 82 basis points per year per additional log-day of illiquidity. Khandani and Lo (2011) estimate illiquidity premia of 2.74% to 9.91% in hedge funds and mutual funds.

5 Conclusions

This paper has shown that the composition of the investor base in CRE differs markedly across cities. Delegated investors, who are more likely to have shorter holding periods, are more prevalent in markets with higher turnover. The shorter average holding period of delegated investors is not just due to their larger size. Rather, the greater need for liquidity arises from the agency issues associated with managing outside money. From the perspective of a delegated investor, the problem with Pittsburgh and similar cities is that they lack liquidity. The low share of delegated investors in markets like Pittsburgh is itself a reason that CRE in Pittsburgh trades infrequently. Finally, delegated investors prefer to invest in larger assets, in cities where a larger fraction of the work force is employed by a publicly traded firm, and in highly educated cities.

A search model with heterogeneity in the frequency with which investors get liquidity shocks can explain the relationship between trade frequency and investor composition. In the model, CRE markets are *ex ante* homogeneous and yet one market emerges as having more liquidity and lower returns than the other. In practice, there are likely some initial differences across CRE markets that give one set of cities an edge in attracting investors that have a greater need for liquidity. The model highlights that there is path dependency in liquidity and thus the ability of a city to attract certain types of capital. There are likely consequences of being unable to attract delegated investors, who prefer larger buildings, for urban design and thus the ability to attract certain types of workers. I leave to future research the question of the consequences for cities of being unable to attract delegated investors due to path dependency in investor composition.

The findings illustrate how path dependence arises in the definition of institutional-quality assets. Part of what makes an asset institutional-quality is the existing concentration of institutions in its investor base. Given how investor preferences for liquidity and the liquidity of a market reinforce one another, a market needs to have a critical mass of investors with similar liquidity preferences for it to attract investors that will in turn generate higher trade frequency.

One limitation of the model is that it assumes that liquidity shocks are idiosyncratic. In practice, shocks to liquidity may be correlated across investors. Furthermore, different types of investors may have different correlations among their liquidity shocks. It seems plausible, for example, that herding behavior among delegated investors increases the correlation of their liquidity shocks. I leave the modeling and measurement of correlation in liquidity shocks within markets and investor types to future work.

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