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 their investments in cities with higher turnover. It then estimates a search model showing how heterogeneity in liquidity preferences makes some markets more liquid even when assets have identical cash flows. The paper provides evidence for clientele equilibria arising in frictional asset markets and suggests that a liquidity channel may explain divergent paths in city development.

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?

This paper argues that the low share of delegated investors in certain cities, such as Pittsburgh, is evidence for clientele equilibria in markets characterize by trading frictions. 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 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 liquidity needs than direct investors, an asset's attractiveness to delegated mangers depends on the existing concentration of delegated managers in an asset.

Unlike other asset markets characterized by search frictions, such as the corporate bond market, CRE transactions data from 39 cities over the 2001-2015 period allows me to identify investors by type and, in particular, to identify delegated investors. I am also able observe their holding periods. Furthermore, geography demarcates markets in CRE. 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 private equity funds but is also statistically significant for investment

[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

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.

Rank	msa	msalabel	(1) *delshare* Purchases 2001-2015	(2) *delshare* Purchases 2001-2007	(3) *delshare* Purchases 2008-2015	(4) *delshare* Sales 2001-2015	(5) *sharereit* Purchases 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

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. Within an MSA, increases in trade frequency over time are associated with a higher delegated investor share. 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 prefer 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. While I find that delegated investors prefer buildings whose main tenant is either the US Federal Government or a publicly listed firm, and that their share of transactions is thus higher in cities with high shares of publicly listed firms, the relationship between delegated investors and trade frequency persists after controlling for credit tenants. There is also strong MSA-level evidence that delegated investors prefer cities with higher shares of college-educated workers. Finally, although a delegated investor is more likely to purchase a property the more times the individual property has traded in the past, the relationship between delegated investors and market-level trade frequency persists

The paper then estimates the search 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.

The results suggest that a clientele channel may explain divergent paths of urban development across US 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. The clientele channel may intensify the persistent effects of early zoning codes (see Shertzer et al. (2018)) or transportation networks (see Bleakley and Lin (2012) and Brooks and Lutz (2019)) on urban development.

The findings are also important for understanding the implications of local policies that reduce liquidity. In particular, real estate transactions taxes directly reduce liquidity. While previous literature investigates how real estate transactions taxes affect trade volume and considered their efficiency, the results here show that reducing liquidity in a city may have the further unintended consequence of changing the potential investor base for a city.[2] Of course, reducing a city's investor base likely also affects the cost of capital for firms located in the city. On the other hand, 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.[3]

Finally, the results illustrate 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.[4]

[2]On the effects and efficiency of real estate transactions taxes see, for example, Benjamin et al. (1993), Besley et al. (2014), Best and Kleven (2017), Dachis et al. (2011), Slemrod et al. (2017), and Hilber and Lyytikäinen (2017).

[3]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)).

[4]See Andonov and Rauh (2018) regarding pension funds' allocations to real estate and non-real estate

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.[5] More recently, Chang (2018) presents a model where submarkets with different trade frequencies arise endogenously as a result of heterogeneity in traders' holding costs.

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 (see Han and Strange (2015) for a summary of early literature), 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 estimates the Vayanos and Wang (2007) model to explain the aforementioned facts. Section 5 concludes.

private equity. Koijen and Yogo (2019) 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.

[5] Plante (2017) nevertheless shows that there would be significant welfare gains to moving corporate bond trading to an exchange-traded platform.

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. 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.[6]

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 variables assisted with the classification but were not sufficiently detailed for this study since, for example, many private firms are delegated asset managers. I classify 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 Operat-

[6]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.

ing 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%.[7]

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 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

[7]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.

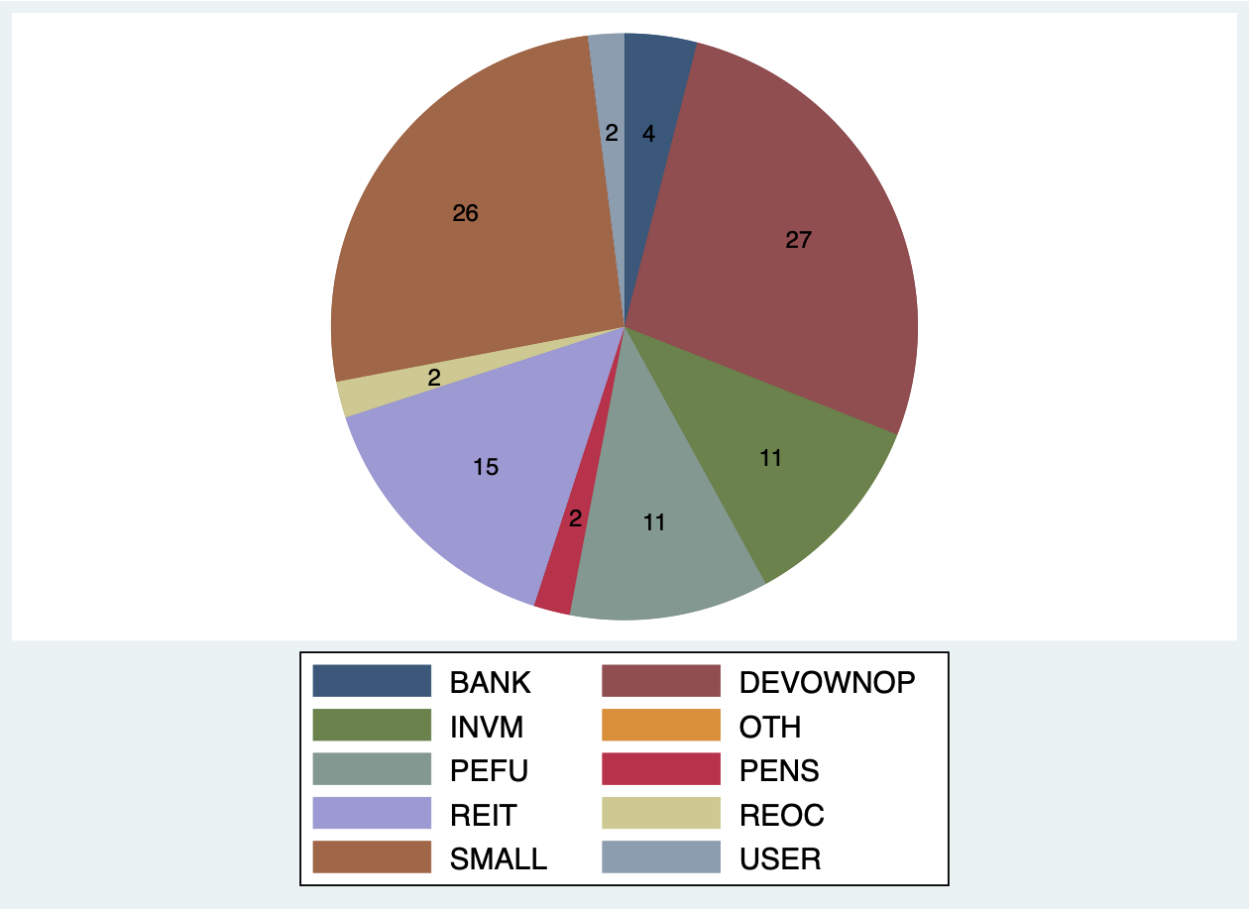

Fig. 1. Investor composition in US commercial real estate, 2001-2015

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.

fashion.[8] 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

[8]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.

by statute; see Mühlhofer (2019) 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 through 5 show the distributions of property size (square footage), property age, and quality across the three 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

Table 2: Transaction-level summary statistics

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.

	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

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*.

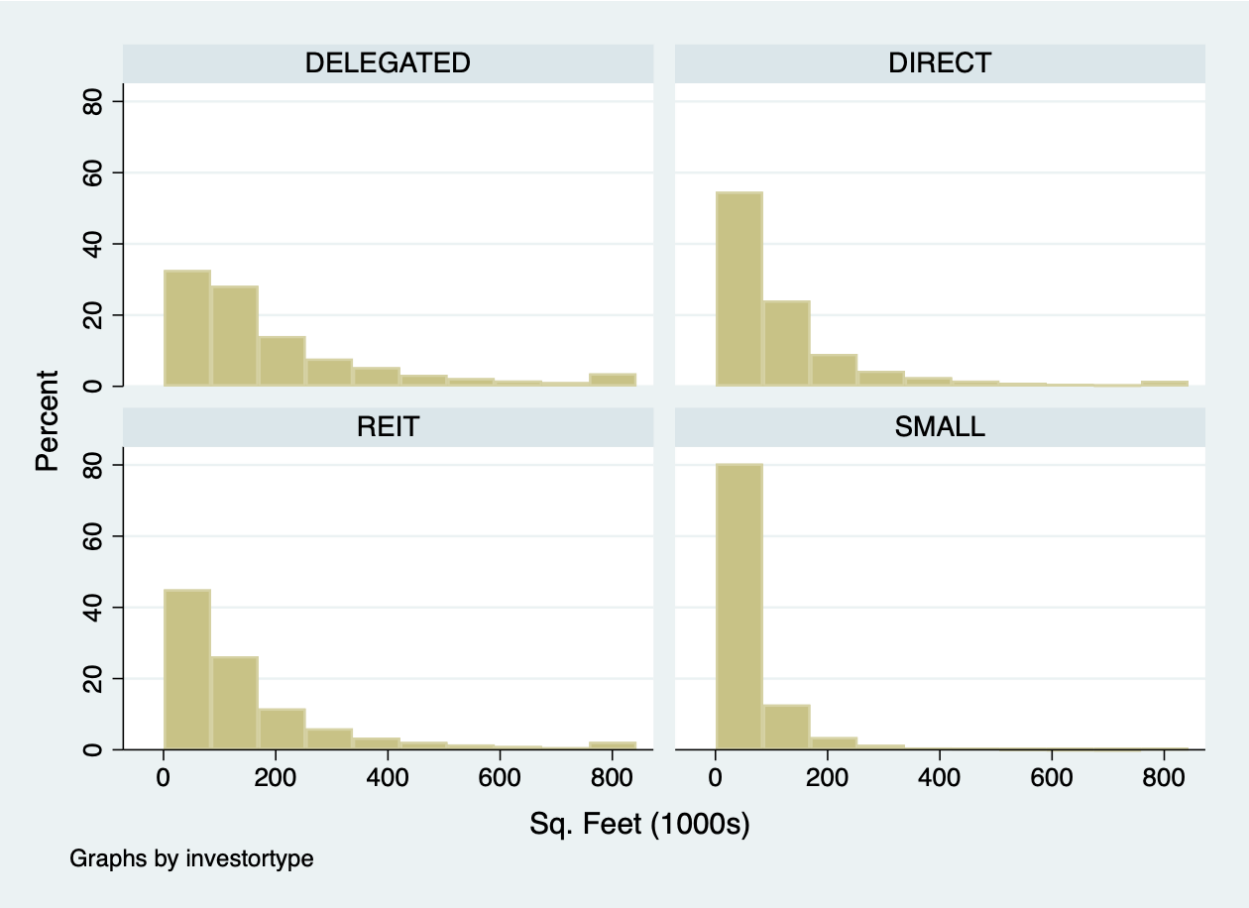

Fig. 2. Property size (square feet in 1000s) for 2001-2015 purchases by investor type

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.

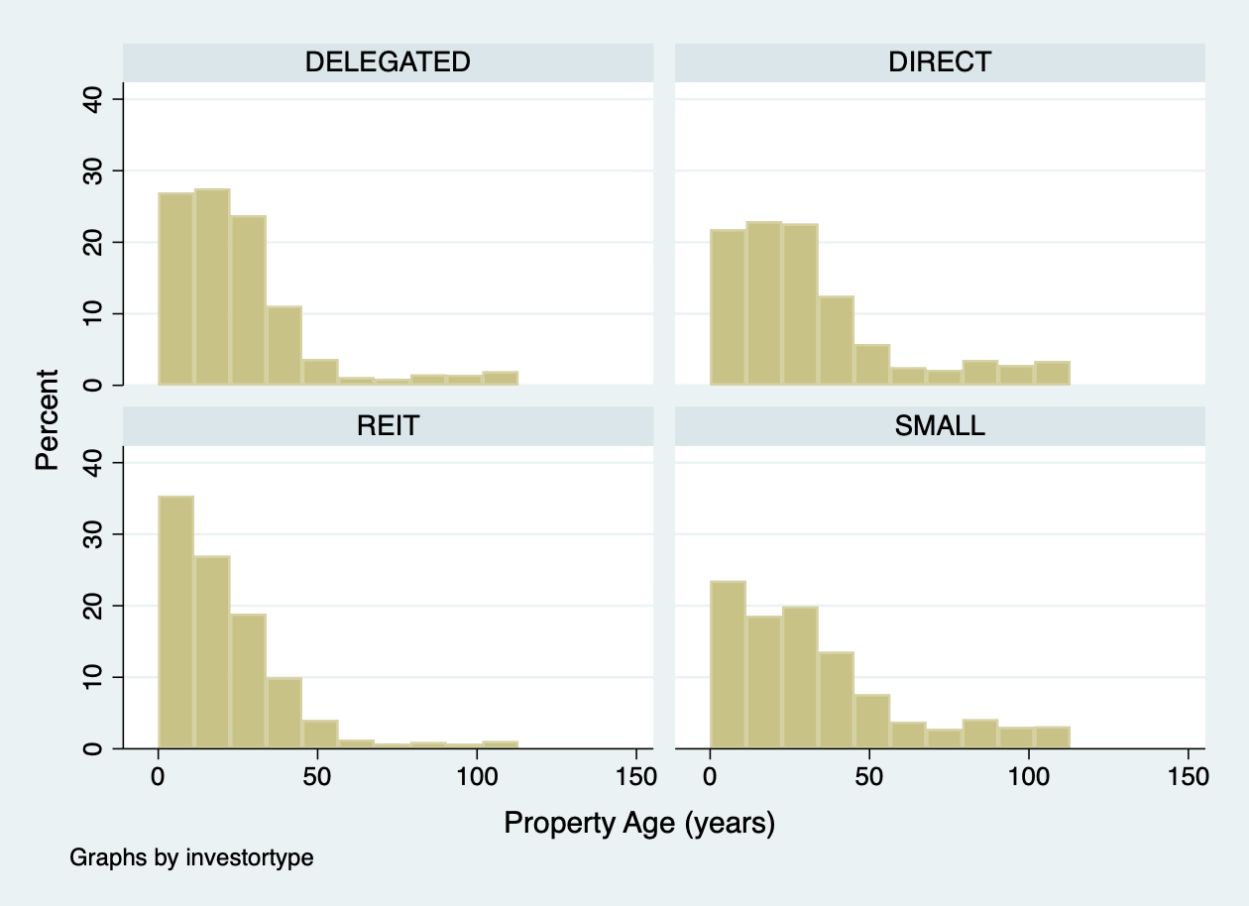

Fig. 3. Property age for 2001-2015 purchases by investor type

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.

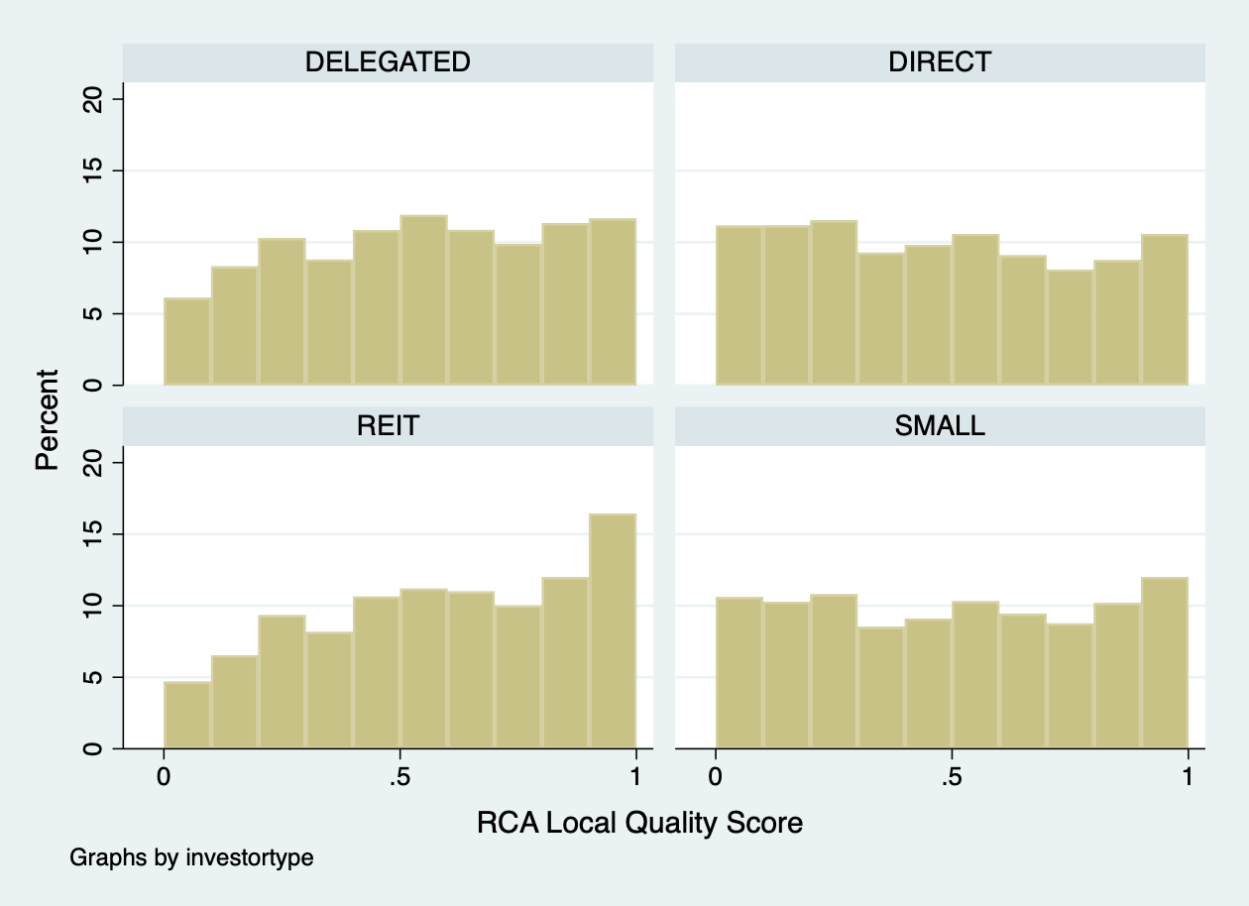

Fig. 4. Within MSA property quality for 2001-2015 purchases by investor type

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.

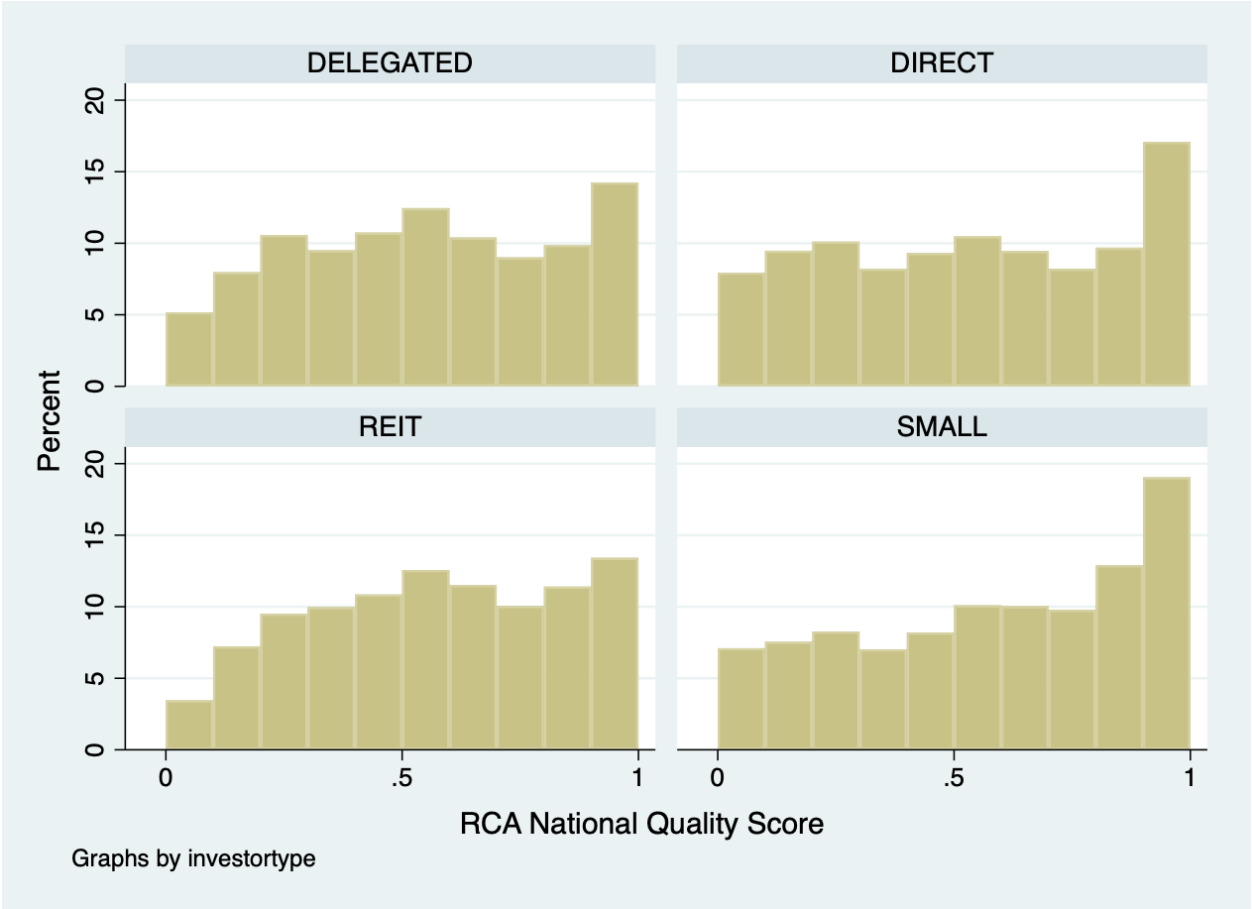

Fig. 5. National property quality for 2001-2015 purchases by investor type

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.

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 prefer 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 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 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

Table 4 provides univariate statistics on holding periods of delegated and direct investors. In Table 4, I code transactions that have not sold by the end of the property as having a holding period of 15, one year longer than the maximum actual holding period in the data of 14 years (2015-2001). 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 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. The table presents Tobit regressions of the holding period on whether the purchaser is a delegated investor. The Tobit specification accounts for censoring from the left at 0 and censoring from the right at the maximum holding period (2015-year purchased). I also control for the total dollar volume of transactions by the purchaser. 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 -0.91 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 -0.92, 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 -1.5 while those on *invm* and *bank* are about -0.3 and -0.7. 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.

In columns 4 and 5, I use data on the second buyer name to better identify whether it is delegation in particular that leads to shorter holding periods. In column 4, I include only the set of transactions in which a direct investor is one of the first two buyers. *delegated* then represents that a direct buyer is acting on behalf of a direct investor in a Joint Venture (JV). Because JVs likely differ from other transactions along other dimensions, I include a fixed effect for whether the purchase is part of a JV according to RCA in this specification. In this specification, the coefficient on *delegated* is similar to the benchmark specification and statistically significant at the 1% level.

I column 5, I restrict the sample to the set of transactions where I see a direct buyer playing different roles in at least two transactions. In particular, I keep only transactions where the same party acts as a sole direct buyer in one transaction and in a JV with a delegated investor in other transactions. This allows me to include fixed effects for the direct buyer which I term "true buyer fixed effects" and isolate the effect on the holding period when the buyer acts as a delegated agent instead of on her own behalf. The coefficient on *delegated* continues to be negative and statistically significant at the 1% level.

Column 6 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 appendix presents 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 3: US cities' economic fundamentals

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.

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

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: Tobit regressions of holding period on investor type

Notes: 1) Dependent variable is the number of years the property was held for or years since the property was purchased for properties not yet sold. 2) The table presents coefficients from Tobit regression to account for both left and, for all columns except (6), 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 purchases where at least one buyer is a direct investor. 5) The sample in column (5) includes only purchases where the same buyer acts as a direct investor in some transactions and a delegated investor in others and includes fixed effects for the buyer. 6) The sample in column (6) includes only 2001-2003 purchases sold by the end of 2015. 7) Standard errors in parentheses. 6) ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
delegated	-0.91***	-0.92***		-1.25***	-0.71***	-0.50***
	(0.081)	(0.097)		(0.26)	(0.21)	(0.18)
invm			-0.31**			
			(0.14)			
pefu			-1.53***			
			(0.13)			
bank			-0.68***			
			(0.22)			
pens			-0.20			
			(0.37)			
office		-1.54***	-1.55***	-1.57***	-0.56*	-0.57**
		(0.12)	(0.12)	(0.14)	(0.33)	(0.23)
industrial		-1.13***	-1.14***	-1.60***	-0.45	-0.50**
		(0.13)	(0.13)	(0.16)	(0.36)	(0.25)
JV				-1.36***		
				(0.19)		
Observations	44,097	35,435	35,435	24,863	7,263	2,016
Purchase Years Included	2001-2015	2001-2015	2001-2015	2001-2015	2001-2015	2001-2003
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
MSA FEs	No	Yes	Yes	Yes	Yes	Yes
Prop. Size Quintiles	No	Yes	Yes	Yes	Yes	Yes
Prop. Age Quintiles	No	Yes	Yes	Yes	Yes	Yes
Buyer Size Quintiles	No	Yes	Yes	Yes	No	No
Prop. Quality Quintiles	No	Yes	Yes	Yes	Yes	Yes
True Buyer FEs	No	No	No	No	Yes	No
PseudoR^2	1.0%	1.9%	1.9%	2.3%	8.9%	1.6%

3.2. Trade frequency and investor composition

3.2.1. MSA-level relationships

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

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.

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

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 explanations for the empirical relationship between the share of purchases by delegated investors and trade frequency other than the one this paper proposes. I consider several alternative explanations for the relationship in Figure 6.

Fig. 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.[9] 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 economic fundamentals included in columns (1)-(5) control for some MSA-level characteristics. However, there are many MSA characteristics that may matter to investors that the regressions do not include. To control for omitted variables specific to a city, I include MSA fixed effects in the final specification in Table 7. In this specification, I include a binary variable that takes a value of one if the observation comes from the years 2001-2007 to control for heterogeneity over time. I do not control for year fixed effects since variation from year-to-year in trade frequency is often idiosyncratic, especially for smaller cities, rather than indicating persistent differences. Thus, in column 6 the relationship between delegated

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

investor share and trade frequency is identified off variation between the first and second half of the sample within an MSA. The coefficient on trade frequency is of similar magnitude to the benchmark specification in column 2 and 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 educated cities.

3.2.2. Transaction-level evidence that delegated investors choose higher trade frequency cities

I next explore the relation between trade frequency and delegated investors using transactions-level data. The advantage of this approach is that I can control for property-level characteristics. I therefore run 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

Table 7: Delegated investor share and trade frequency

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; $half1$ takes a value of one if the observation is from 2001-2007, zero otherwise. 5) See Table 3 for remaining variable definitions. 6) Standard errors clustered by MSA are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	delshare	*delshare*	*delshare*	*delshare*	*delshare_sell*	*delshare*
tf	1.74***	1.52***	1.56***	1.60***	0.91***	1.65***
	(0.36)	(0.22)	(0.22)	(0.21)	(0.15)	(0.22)
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)		
half1						-1.27
						(0.96)
Observations	578	578	578	541	578	578
R^2	23.4%	26.9%	27.1%	29.1%	22.6%	37.5%
Year FEs	Yes	Yes	Yes	Yes	Yes	No
Pop Quintiles	No	Yes	Yes	Yes	Yes	No
MSA FEs	No	No	No	No	No	Yes

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 in a single transaction.

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 OLS. 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. 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. Delegated investors also prefer industrial and office properties relative to retail (the omitted category).

Table 8: OLS regressions of investor type on trade frequency

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) Prop. Quality Quintiles are quintiles for national and local property quality. 7) Standard errors clustered by MSA in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
tf	0.0072*			0.0068*		
	(0.0036)			(0.0040)		
tfavg_bytype		0.0064***			0.0054**	
		(0.0022)			(0.0024)	
tfavg_firsthalf			0.0054			0.012**
			(0.0043)			(0.0057)
pubempshare	-0.0026	-0.0032	0.0022	-0.0026	-0.0027	0.0035
	(0.0022)	(0.0027)	(0.0025)	(0.0028)	(0.0030)	(0.0031)
emp_HHI	-1.61	-1.31	1.17	-0.71	-0.32	2.94**
	(1.14)	(1.09)	(1.42)	(1.32)	(1.26)	(1.44)
estsperemp	-0.96	-1.00	0.40	-2.01*	-1.96	-0.96
	(1.05)	(1.02)	(0.79)	(1.19)	(1.20)	(0.83)
college	0.0019	0.0024**	0.0010	0.0016	0.0022*	-0.000079
	(0.0012)	(0.0011)	(0.0011)	(0.0013)	(0.0013)	(0.0013)
occrate_bytype	0.0042**	0.0051**	0.0044**	0.0042**	0.0051**	0.0076***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0021)	(0.0027)
rentgr_bytype	-0.00026	-0.00015	0.00065	-0.00063	-0.00052	-0.00014
	(0.00044)	(0.00048)	(0.00099)	(0.00050)	(0.00053)	(0.00099)
office	0.15***	0.13***	0.12***	0.11***	0.096***	0.11***
	(0.023)	(0.026)	(0.024)	(0.025)	(0.029)	(0.030)
industrial	0.14***	0.17***	0.13***	0.080***	0.10***	0.048*
	(0.023)	(0.023)	(0.025)	(0.023)	(0.024)	(0.026)
Observations	43,300	43,313	24,544	34,897	34,906	19,353
R^2	9.2%	9.2%	9.1%	11.0%	11.0%	10.4%
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Size Pop Age Quintiles	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Quality Quintiles	No	No	No	Yes	Yes	Yes

3.2.3. Robustness

Probit estimation Column 2 of Table 9 presents the results from estimating equation (1) by Probit rather than OLS. The statistical significance of the coefficients on the trade

frequency measures in column 2 are very similar to those in the benchmark specification in column 1.

Property-level liquidity One possible explanation of the results in Table 8 is that there are simply more buildings of the sort that turn over frequently in high trade frequency cities than in lower turnover cities. The concern is that there are unobservable building qualities that make a property more liquid that delegated investors prefer. For example, certain buildings have prestige that may generate press coverage reducing information asymmetry and thus increasing turnover. While a finding that delegated investors prefer buildings that turn over more frequently, or that have transacted in the past, is interesting, it is a somewhat different explanation for the differences across cities than the market segmentation by liquidity that this paper proposes to explain the relationship in Figure 6.

In column 3 of Table 9, I exploit repeat transactions to understand whether property-level liquidity drives the relationship in Figure 6 and Table 8. In particular, I include dummies for the number of times the property has transacted prior to the transaction as controls. The top category is "2 or more times" since fewer than 1000 transactions involve properties that have transacted more than twice prior to the transaction. The coefficient on the MSA-level trade frequency measure continues to be positive and very similar in magnitude to the benchmark specification indicating that property-level trade frequency is not driving the relationship between investor type and MSA-level trade frequency.

The probability that a purchaser is a delegated investor is monotonically increasing in the number of times the property has transacted in the past. One possible reason is that individual properties are known by investors to be more or less liquid independent of observable characteristics like size, age, etc... This is consistent with delegated investors preferring to invest in more liquid properties independently of market segmentation across geographies. Rather, it could be because of less asymmetric information about the building because of the number of past transactions. Certainly, any large property that has recently transacted will have more news coverage and investors are likely more familiar with it.

Table 9: Robustness of regressions of investor type on trade frequency

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) Columns (1) and (3)-(8) present OLS coefficients; column (2) presents coefficients from a Probit regression. 4) Sample is 2001-2015 purchases by delegated and direct investors. 5) *tfavg_bytype* is the average trade frequency in that MSA and property type. 6) Size Pop Age Qs are quintiles for property age, property size, and MSA population. 7) *pasttrans_1* = 1 if the property sold exactly once before and *pasttrans_2plus* = 1 if the property has sold two or more times before. 8) *credittenant* = 1 if the tenant is a publicly-traded firm and *govtenant* = 1 if the tenant is is a Federal government agency. 9) Standard errors clustered by MSA in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tfavg_bytype	0.0064***	0.016***	0.0062***	0.011	0.0059***	0.0064***	0.0060**	0.0074***
	(0.0022)	(0.0058)	(0.0022)	(0.013)	(0.0017)	(0.0022)	(0.0023)	(0.0023)
pasttrans_1			0.018**					
			(0.0079)					
pasttrans_2plus			0.032*					
			(0.017)					
pubempshare	-0.0032	-0.0080	-0.0032		-0.0025	-0.0032	-0.0036	-0.0032
	(0.0027)	(0.0076)	(0.0027)		(0.0021)	(0.0026)	(0.0026)	(0.0028)
emp_HHI	-1.31	-4.15	-1.33		-1.07	-1.11	-0.79	
	(1.09)	(3.28)	(1.09)		(0.90)	(1.22)	(1.24)	
estsperemp	-1.00	-2.81	-0.99		-0.13	-0.96	-0.83	
	(1.02)	(2.95)	(1.02)		(0.65)	(1.03)	(1.02)	
college	0.0024**	0.0066**	0.0023**		0.0039***	0.0026**	0.0027**	0.0027**
	(0.0011)	(0.0032)	(0.0011)		(0.00085)	(0.0013)	(0.0013)	(0.0012)
occrate_bytype	0.0051**	0.015***	0.0050**	0.0025	0.0076***	0.0051**	0.0050**	0.0048**
	(0.0020)	(0.0058)	(0.0020)	(0.0056)	(0.0018)	(0.0020)	(0.0021)	(0.0020)
rentgr_bytype	-0.00015	-0.00055	-0.00015	0.00050	-0.00085	-0.00013	-0.00013	-0.00011
	(0.00048)	(0.0013)	(0.00048)	(0.0011)	(0.00057)	(0.00048)	(0.00047)	(0.00048)
credittenant					0.025***			
					(0.0061)			
govtenant					0.087**			
					(0.033)			
HHIbuyer						-0.050		
						(0.15)		
transfertaxrate							-0.0058	
							(0.0090)	
pricegrowth_bytype								0.00012
								(0.00022)
capgrowth								-0.00066**
								(0.00030)
Observations	43,313	43,313	43,313	24,039	26,379	43,313	43,313	36,382
R^2	9.2%		9.2%	68.7%	9.7%	9.2%	9.2%	9.6%
Pseudo-R^2		7.6%						
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size Pop Age Qs	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Prop. Quality Qs	No	No	No	No	No	No	No	No
Property FEs	No	No	No	Yes	No	No	No	No

Unobservable property characteristics Column 4 restricts the sample to properties that transact at least twice and includes property fixed effects. Although the standard errors increase substantially in this specification due to the large number of fixed effects estimated, the coefficient remains positive and of a similar magnitude to the benchmark specification.

Tenant quality The MSA-level regressions in Table 7 uncovered a relationship between credit tenant's in an MSA and the share of delegated investors. Does the same pattern hold at the individual property-level, i.e., are buildings with credit tenants more likely to be purchased by a delegated than a direct investor? While tenant information is only available for a subset of the RCA transactions, the tenant names can be matched to the universe of Compustat firms via a fuzzy matching algorithm to determine whether the largest tenant in a building (*Tenant 1*) is a publicly-listed firms. I create a variable called *credittenant* for each transaction that takes a value of one if *Tenant 1* is a publicly-traded firm and 0 if it is not. I also classify names of tenants that are likely U.S. Federal Government agencies since the U.S. Federal Government is unlikely to default on its lease obligations. The variable *govtenant* takes a value of 1 if *Tenant 1* is a U.S. Federal Government agency and 0 if it is not. [10]

Column 5 of Table 9 presents the results when I include *credittenant* and *govtenant*. Indeed, the relationship between tenant quality and whether the investor is delegated is much stronger at the property-level than at the MSA-level. The coefficients on both *credittenant* and *govtenant* are positive and statistically significant at the 5% level. A publicly traded tenant is associated with a three percentage point higher probability that the purchaser is a delegated investor while a Federal Government tenant is associated with a nine percentage point higher chance that the purchaser is a delegated investor. The coefficient on trade frequency is very similar to the benchmark specification after I include these variables, however.

[10] I search *Tenant 1* for terms such as "United States Post", "GSA", "Veteran", "United States of America", "US Post", "US Government", etc... and variants of these terms. I code these as Federal Government tenants and then manually check and correct misclassifications based on this coding.

Market power Delegated investors, who may be less likely to be local, may 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. Column 6 of Table 9 presents the results when I include this variable. The coefficient on the HHI index is negative but statistically insignificant. More importantly for the present paper, the coefficient on the trade frequency measure is little changed from the benchmark specification in Column 1.

Transfer tax rates Pittsburgh in particular has unusually high real estate transfer tax rates. During the 2001-2015 sample period, Pittsburgh and Philadelphia had the highest real estate transfer tax rates in the sample at 4.0%. In contrast, nine cities had no real estate transfer taxes and 30 cities had a transfer tax rate of less than 1.0%. While a finding that delegated investors do not like Pittsburgh because of the high transfer taxes is consistent with them having a higher preference for liquidity, finding that this is the sole reason investors avoid Pittsburgh is slightly different from the market segmentation story the model of the next section proposes. Column 7 of Table 9 therefore presents the results of the probit regression of *delegated* on the trade frequency measures and the transfer tax rate in that MSA. The coefficients on the trade frequency variables are quite similar to that in Column 1 while the coefficient on the transfer tax rate is far from statistically significant.[11]

Capital appreciation and cap rate growth The analysis above considers several city characteristics that delegated investors may prefer that could be correlated with trade frequency. A further possibility is that delegated investors are simply better at predicting CRE returns and cities with higher turnover have higher returns. In column 8 of Table 9, I include actual price appreciation and the growth in cap rates in that year in that property type.

[11] The tax rates used in this analysis combine state-level and any municipal-level taxes and were obtained by internet search. An appealing idea is to use the transfer tax rates as an instrument for trade frequency. Unfortunately, the correlation between trade frequency and transfer tax rates is quite low, likely because there is little variation in transfer tax rates across most cities.

The coefficient on the MSA-level trade frequency measure is unchanged.

Outlier cities Figure 7 explores the robustness of the results to the MSAs included in the sample. It shows the coefficient on $tfavg\_bytype$ of the 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 0.0068 from the regression with all thirty-nine MSAs.

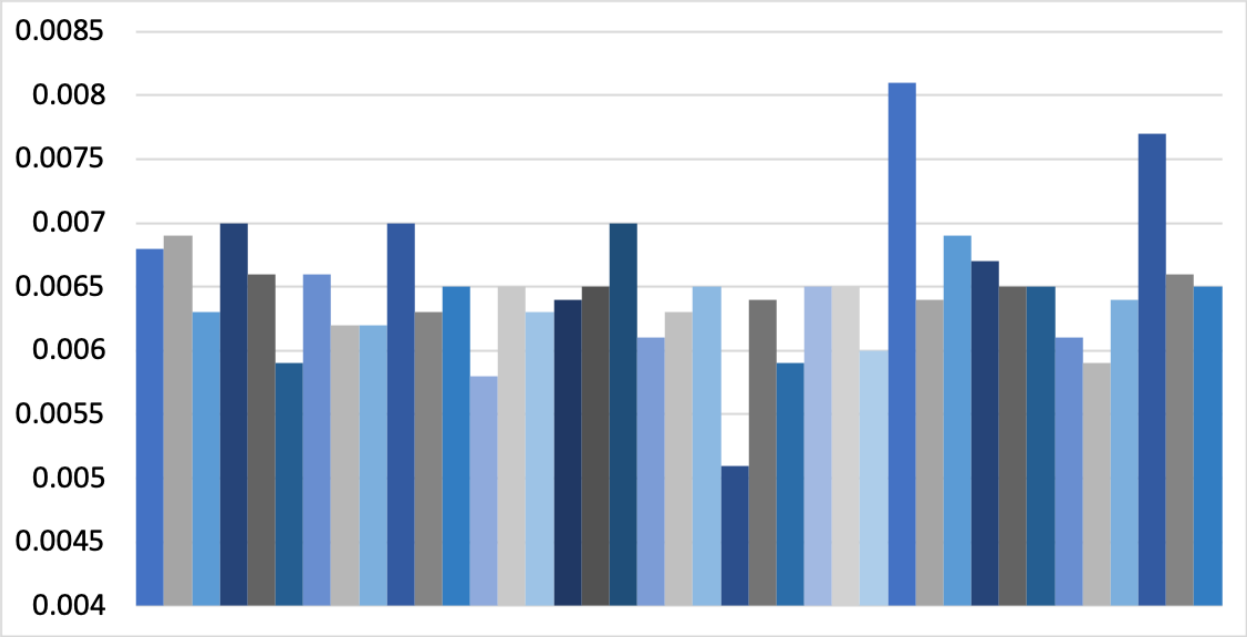

Fig. 7. Coefficients on trade frequency dropping one MSA at a time

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. The finding that cap rates are higher in cities with lower trade frequency is consistent with the model below.

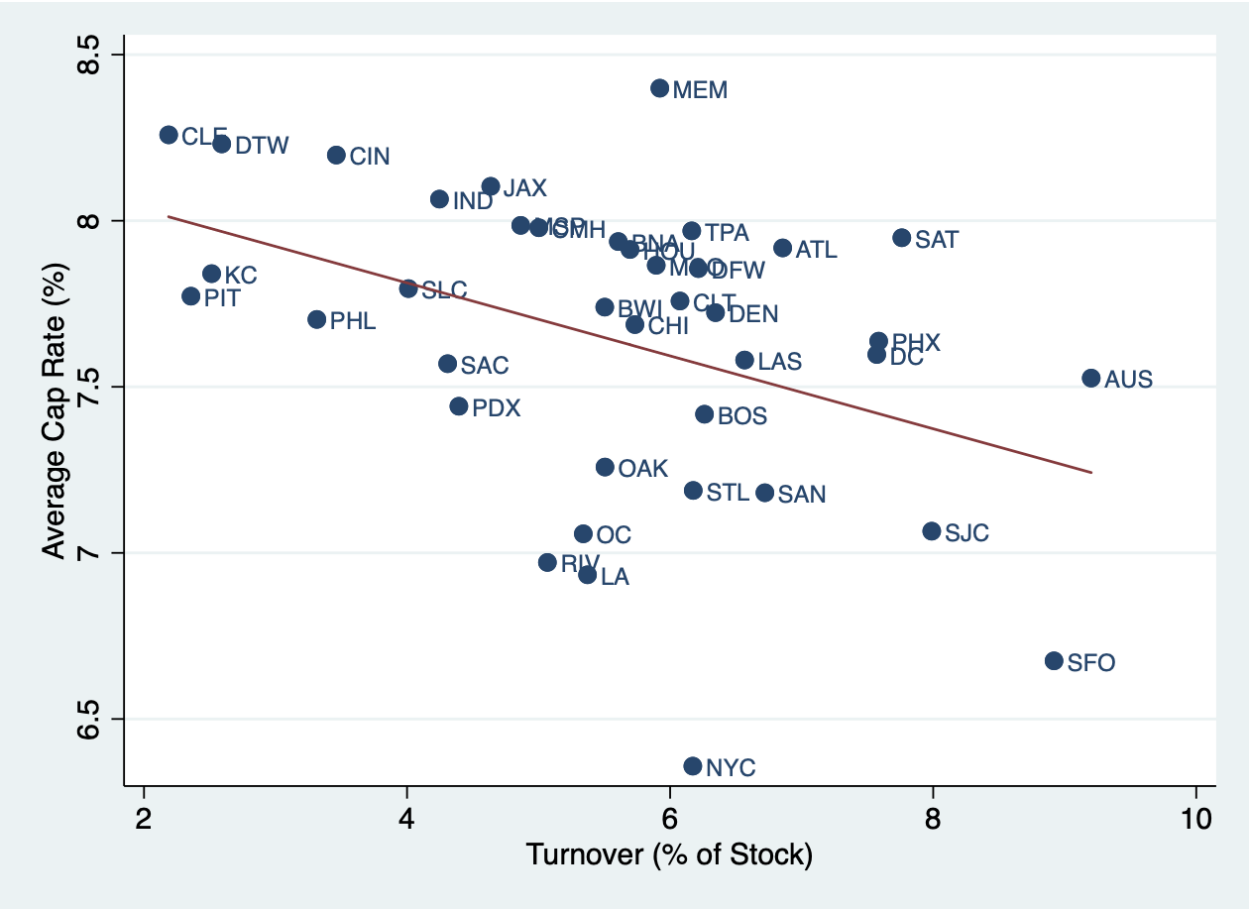

Fig. 8. Cap rates and trade frequency are inversely related

Note: 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. As Table 1 illustrates, all cities have a mix of delegated and other investors such that the correct interpretation of the model is not that it predicts *all* delegated investors go to one market and all direct investors go to another.

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.

When investors are born into the economy, some are direct and some are delegated. Both delegated and direct agents differ in the likelihood that they will receive a valuation shock. Valuation shocks arrive at Poisson rate κ. The unconditional distribution of valuation

shocks is uniform over the interval $[\underline{\kappa}, \overline{\kappa}]$. While the unconditional distribution is uniform, direct type investors are more likely to draw low κs and delegated investors are more likely to draw high κs.

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 $\frac{1}{2}$.

Buyers and sellers meet randomly within each market. Given total masses of buyers and sellers in market i, μ_B^i and μ_S^i, the matching function

$$M(\mu_B^i, \mu_S^i) = \lambda \mu_B^i \mu_S^i \tag{4}$$

characterizes the search technology. It features increasing returns to scale (IRS) 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.

I follow Vayanos and Wang (2007) in assuming IRS in the matching function. However, IRS in the matching function is somewhat non-standard in the real estate search literature. For example, Han and Strange (2015), Piazzesi and Schneider (2009), Piazzesi

et al. (2020) all assume constant returns to scale (CRS) in the matching function. Labor economists often assume the matching function exhibits CRS although many empirical studies in fact find evidence of IRS.[12] There are no empirical estimates of the matching function in real estate. In their review of the literature on matching functions, Petrongolo and Pissarides (2001) suggest that a key effect of the matching function being IRS is that it can give rise to multiple equilibria if search effort is endogenous. In the Vayanos and Wang (2007) model, agents have no decision on the amount of effort to exert in search, only which of the two markets to search in although even with IRS there are multiple equilibria in the Vayanos and Wang (2007) model. As I discuss below, the IRS assumption is not critical for getting an equilibrium with different liquidity across the two markets.

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.[13] Let $\mu_B^i(\kappa)$, $\mu_O^i(\kappa)$, and $\mu_S^i(\kappa)$ 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 such agents in the economy are then

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

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

$$\int_{\underline{\kappa}}^{\overline{\kappa}} \mu_S^i(\kappa) d\kappa = \mu_S^i \tag{7}$$

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

[12] The CRS assumption on the matching function has been extensively debated in the labor search literature; see, for example, Burdett et al. (2001) and Petrongolo and Pissarides (2001).

[13] 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.

market 2. The IRS property of the matching function is not critical to the existence of a clientele equilibrium. Even if the matching function were, for example, Cobb-Douglas, the clientele equilibrium would continue to exist. The intuition behind this result is that buyers with more frequent valuation shocks would still go to the market with more sellers because it increases the chance of a match. To see this, suppose that the matching function were instead $M(\mu_B, \mu_S) = \lambda \mu_B^{\alpha} \mu_S^{1-\alpha}$ where I have dropped the i superscript to simplify notation. The probability that a buyer will meet a seller is $\lambda \mu_S^{1-\alpha}$ which is still increasing in μ^S. This means that buyers with higher κ will still choose to be in the market with a larger mass of sellers. There continues to be a unique value of κ, κ^* such that a buyer gets the same utility from market 1 as from market 2.[14]

Given the existence of the clientele equilibrium, 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^*:

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

$$\frac{1}{\overline{\kappa}-\underline{\kappa}} \int_{\underline{\kappa}}^{\kappa^*} \frac{\lambda \mu_S^2}{k(k+\lambda \mu_S^2)} dk + \mu_S^2 = S \tag{9}$$

$$\begin{aligned} \mu_S^1 - \mu_S^2 + \mu_S^1 \frac{1}{2(r+\kappa^*)(\overline{\kappa}-\underline{\kappa})} \int_{\underline{\kappa}}^{\kappa^*} \frac{\lambda(r+\kappa^*+0.5\lambda\mu_S^2)}{(k+\lambda\mu_S^2)(r+k+0.5\lambda\mu_S^2)} dk \\ + \mu_S^2 \frac{1}{2(r+\kappa^*)(\overline{\kappa}-\underline{\kappa})} \int_{\kappa^*}^{\overline{\kappa}} \frac{\lambda(r+\kappa^*+0.5\lambda\mu_S^1)}{(k+\lambda\mu_S^1)(r+k+0.5\lambda\mu_S^1)} dk = 0 \end{aligned} \tag{10}$$

Trading volume in the model is determined entirely by the parameters $\underline{\kappa}$, $\overline{\kappa}$, and λ.

[14] A similar intuition gives rise to clientele equilibria in models of competitive search where the matching function is not IRS. For example, in Guerrieri et al. (2010) potential asset buyers post contracts that consist of a probability of purchase and the price. Sellers then sort into one of two markets depending on the quality of their asset. Similarly, in Lester et al. (2015), dealers post prices and execution speeds and buyers sort into asset markets depending on their asset positions and private payoffs.

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. Estimation

I split the sample of cities into two sets of cities, very high and very low turnover. Very high turnover cities are the top four cities by turnover. Very low turnover cities are the bottom four cities by turnover. I use the extremes of the distribution of cities because the model has no role for other types of heterogeneity in investor preferences such as certain investors' preferences for credit tenants and for more educated cities uncovered in Section 3.

I orthogonalize the cap rates to key variables that are outside the model that determine cap rates across cities before using them as moments to estimate the model. I first regress MSA-level cap rates on these variables on *college*, the average price growth, and average occupancy rates in the MSA. I do this for all property types combined as well as within property type to reduce the heterogeneity in MSAs that is outside the model further. Panel A of Table 10 shows the result of these regressions. Cap rates are lower in cities with rapid price growth, cities with higher occupancy rates, and cities with higher shares of college educated workers.

I estimate the model using Generalized Method of Moments (GMM). Table 11 provides the data I use to estimate the model. I take the average trade frequency and cap rate in each of the four highest and lowest trade frequency cities so that I can treat them each as being one market consistent with the data. For the years in which TOM is not available (2001-2006), I set the TOM equal to the average for 2007-2015. The empirical covariance matrix uses the time series dimension of the data to calculate a clustered weighting matrix;

Table 10: Cap rate moments

Notes: 1) The dependent variable in Panel A is the average cap rate from the RCA-MSA level data. 2) An observation is an MSA. 3) Standard errors in parentheses in Panel A. 4) Panel B presents cap rates orthogonalized to the variables in the regression presented in Panel A.

	(1)	(2)	(3)	(4)
Property Type	Combined	Office	Industrial	Retail
Panel A: Cap rate regression coefficients				
occrate_CBRE	-0.084***	-0.058*	-0.13	-0.082**
	(0.030)	(0.034)	(0.087)	(0.031)
pricegrowth	-0.057***	-0.070**	-0.061	-0.0012
	(0.020)	(0.030)	(0.073)	(0.014)
college	-0.025***	-0.030***	0.039	-0.034***
	(0.0092)	(0.010)	(0.027)	(0.0092)
Constant	16.1***	13.7***	19.0**	15.8***
	(2.66)	(2.70)	(7.94)	(2.79)
Observations	39	39	39	39
R^2	44.0%	52.5%	16.8%	36.7%
Panel B: Orthogonalized cap rates				
Very High TF ($\geqslant$ 89th percentile)	7.30	7.41	7.72	7.05
Very Low TF ($\leqslant$11th percentile)	8.03	8.06	8.62	7.80
Very Low - Very High (bp)	73	65	90	75

see Bazdresch et al. (2018) for the optimality of clustered weight matrices relative to identity matrices in GMM estimation.

The five empirical moments I match to are 1) the average time on the market of 11.6 months consistent with CoStar (2018)'s estimates for 2007-2015, the only years with an estimate of time-on-the-market (TOM) for the CRE market, 2) average annual turnover in the four highest trade frequency cities (8.4%), 3) average annual turnover in the four lowest trade frequency cities (2.4%), 4) average cap rates in the four highest trade frequency cities (7.36%), 5) average cap rates in the four lowest trade frequency cities (8.13%). These five moments are the averages over the time series dimension of the data. The data then allow me to estimate the five parameters of the model, r, $\underline{\kappa}$, $\overline{\kappa}$, λ, and x. Because the model is exactly identified, the estimated model moments match the data moments as the last two rows of Table 11 shows.

Figure 9 plots trade frequency over time in very high and very low turnover cities. Although liquidity is lower in both sets of cities during 2001-2002 and especially during 2009 – times it is reasonable to treat as having experienced aggregate shocks to investors' valuation – trade frequency is higher in the very high turnover cities than in the very low turnover cities in every single year. This is important because the model abstracts from aggregate risks to liquidity. However, if delegated investors are more concerned with liquidity when there are aggregate shocks than other types of investors, the model would no longer necessarily deliver the segmentation by liquidity preferences. In particular, the clientele equilibrium might not be a rational expectations equilibrium if the ordinarily high trade frequency markets become especially low trade frequency markets during times when liquidity is scarce. Thus, the finding that high turnover cities still have more trade frequency during recessions suggests that a clientele equilibrium would still exist in a world in which delegated investors cared about aggregate liquidity shocks.

Table 12 presents the GMM estimates. For these parameter estimates, the value of κ that separates the two sets of agents is $\kappa^* = 0.10$. 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 0.61 and 0.29 such that the equilibrium times on

Table 11: Data used in GMM estimation

Notes: 1) TOM = Time-on-the-market in months from CoStar (2018) (US Average - extrapolated for 2001-2006). 2) Columns (2) and (4) average trade frequency (in %) and orthogonalized cap rates (in %) from the four highest trade frequency cities; columns (3) and (5) average trade frequency and orthogonalized cap rates from the four lowest trade frequency cities. 3) Cap rates are orthogonalized according to Table 10.

	(1)	(2)	(3)	(4)	(5)
Year	TOM	TF_VHighTF	TF_VLowTF	Cap_VHighTF	Cap_VLowTF
2001	11.6	3.7	0.8	8.41	9.03
2002	11.6	2.7	1.5	9.05	8.95
2003	11.6	3.4	1.5	8.76	8.91
2004	11.6	8.6	2.4	7.93	8.12
2005	11.6	11.8	3.6	7.36	7.70
2006	11.6	12.8	3.3	6.93	7.48
2007	8.2	15.3	4.0	6.31	7.52
2008	9.0	4.1	1.8	6.26	8.14
2009	9.9	1.4	0.9	8.22	8.67
2010	11.5	5.4	1.3	7.88	8.34
2011	13.2	9.8	2.5	7.31	8.21
2012	14.0	11.0	2.9	6.88	7.90
2013	13.6	9.1	3.1	6.58	7.90
2014	13.2	13.3	3.0	6.38	7.69
2015	11.5	13.6	3.3	6.23	7.42
Average (data moment)	11.6	8.4	2.4	7.36	8.13
Estimated model moment	11.6	8.4	2.4	7.36	8.13

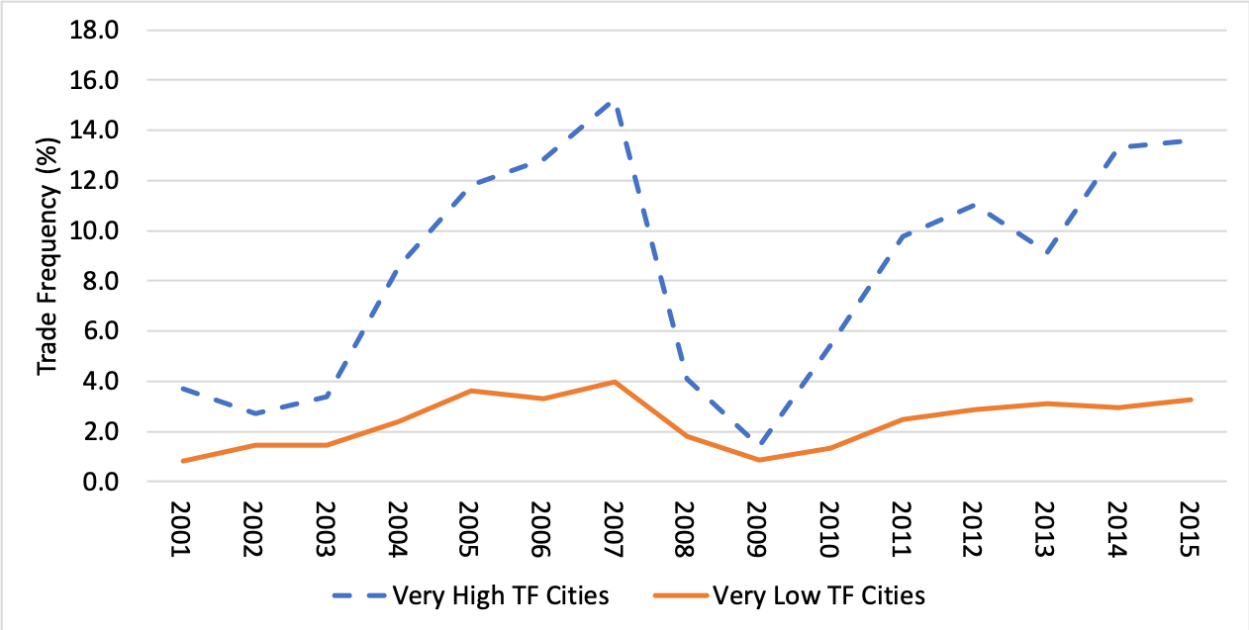

Fig. 9. Time series patterns in trade frequency

Note: Average trade frequency in the four highest average and four lowest average trade frequency US MSAs.

the market ($\frac{1}{\lambda\mu_B^i}$) are approximately 9.3 and 19.7 months.[15]

The trade technology parameter, λ, is fairly precisely estimated. The return on the perfectly liquid asset, r, is 5.26% with a standard error of 1.65%. While the point estimate of 5.26% implies that the average illiquidity premium in the liquid and illiquid markets are 2.1% and 2.9%, the high standard error on r makes the estimated illiquidity premia imprecisely estimated. The imprecision on the illiquidity premium is likely because the cap rates used are aggregated and only from the subset of properties for which RCA has income data. There is unfortunately no comprehensive data set with property income. Furthermore, there are many differences across cities not captured by the model that likely generate differences in cap rates. It is possible that disaggregated data on TOM would improve the accuracy of the illiquidity premium.

The small *relative* illiquidity premia because of the heterogeneity in how investors value liquidity. Although the illiquidity premium across markets is positive, those investors

[15]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 12: Parameter estimates from search model with investor heterogeneity

Notes: 1) Model estimated via GMM using data in Table 11. 2) λ is the matching technology parameter; r is the annual return on a perfectly liquid asset with comparable credit risk to US CRE; $\underline{\kappa}$ and $\overline{\kappa}$ are the lower and upper bounds on the probabilities an agent receives a downward valuation shock; x is the discount on the dividend when an agent becomes a low-valuation agent.

	Point Estimate	Std. Error
λ	2.10	0.54
r	5.26%	1.65%
$\underline{\kappa}$	0.012	0.005
$\overline{\kappa}$	0.162	0.104
x	0.450	0.218

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.

The point estimates imply that CRE sells at a 29-35% discount relative to a perfectly liquid asset of comparable credit risk or offers two percentage points compensation in yield for its inherent illiquidity. While the model is highly stylized and abstracts from other frictions, such as information asymmetries across investors in different markets, this is the first estimate of the illiquidity premium of CRE in the literature.[16] In the housing market, Piazzesi et al. (2020) report "frictional" price discounts of between 10-40% of the price of a property.[17] Consistent with real estate being much less liquid than financial securities, this is a substantially higher illiquidity return 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

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

[17] In part because they allow for heterogeneity in search over other dimensions of the property (e.g., number of bathrooms), and because potential buyers do not sort solely along the liquidity of the segment as they do here, Piazzesi et al. (2020) find much larger differences in illiquidity discounts across segments than what I find in the CRE market.

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 properties occupied by publicly traded firms, and in highly educated cities.

The findings provide evidence of market segmentation by liquidity preferences in frictional asset markets. In particular, 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. The results indicate that policies that reduce trade frequency in a market, such as real estate transactions taxes, also change the investor base of that market and thus the cost of capital. 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 and deliberate policy actions that change the investor base.

Finally, 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.

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Appendix A. Not-for-Publication Appendix

Table A.1: Tobit Regressions of Holding Periods: Subperiod Analysis

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

	(1)	(2)	(3)	(4)
delegated	-2.30***	-0.76***	-0.72***	-0.34***
	(0.30)	(0.17)	(0.17)	(0.11)
office	-3.14***	-1.83***	-0.63***	-0.41***
	(0.36)	(0.21)	(0.22)	(0.14)
industrial	-1.45***	-1.54***	-0.012	-0.89***
	(0.39)	(0.22)	(0.22)	(0.14)
Observations	3,324	9,022	6,004	17,085
Purchase Years Included	2001-2003	2004-2006	2007-2009	2010-2015
Year FEs	Yes	Yes	Yes	Yes
MSA FEs	Yes	Yes	Yes	Yes
Prop. Size Quintiles	Yes	Yes	Yes	Yes
Prop. Age Quintiles	Yes	Yes	Yes	Yes
Prop. Quality Quintiles	Yes	Yes	Yes	Yes
Pseudo-R^2	2.3%	1.5%	1.1%	3.9%

Table A.2: Robustness of Regressions of Investor Type on Trade Frequency with Property Quality Controls

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. 3) *tfavg_bytype* is the average trade frequency in that MSA and property type. 4) Size Pop Age Qs are quintiles for property age, property size, and MSA population. 5) Prop. Quality Qs are quintiles for RCAs property quality measures. 6) Standard errors clustered by MSA in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
tfavg_bytype	0.0054**	0.014**	0.0052**	0.0053**	0.0054**	0.0056**	0.0061**
	(0.0024)	(0.0067)	(0.0024)	(0.0022)	(0.0025)	(0.0025)	(0.0028)
pubempshare	-0.0027	-0.0058	-0.0027	-0.0027	-0.0027	-0.0024	-0.0015
	(0.0030)	(0.0091)	(0.0030)	(0.0030)	(0.0031)	(0.0029)	(0.0032)
emp_HHI	-0.32	-1.15	-0.34	-0.74	-0.12	-0.68	
	(1.26)	(3.98)	(1.27)	(1.21)	(1.42)	(1.47)	
estsperemp	-1.96	-5.57	-1.98	-1.48	-1.93	-2.10*	
	(1.20)	(3.68)	(1.20)	(1.00)	(1.23)	(1.20)	
college	0.0022*	0.0064*	0.0022*	0.0031**	0.0025*	0.0020	0.0029**
	(0.0013)	(0.0039)	(0.0013)	(0.0014)	(0.0014)	(0.0015)	(0.0012)
occrate_bytype	0.0051**	0.016***	0.0050**	0.0069***	0.0050**	0.0052**	0.0054**
	(0.0021)	(0.0061)	(0.0021)	(0.0020)	(0.0021)	(0.0020)	(0.0022)
rentgr_bytype	-0.00052	-0.0016	-0.00051	-0.0012**	-0.00050	-0.00053	-0.00060
	(0.00053)	(0.0015)	(0.00053)	(0.00058)	(0.00053)	(0.00052)	(0.00053)
pasttrans_1			0.0086				
			(0.0076)				
pasttrans_2plus			0.035**				
			(0.016)				
credittenant				0.025***			
				(0.0075)			
govtenant				0.087**			
				(0.034)			
HHIbuyer					-0.055		
					(0.17)		
transfertaxrate						0.0041	
						(0.010)	
pricegrowth_bytype							0.00021
							(0.00018)
capgrowth							-0.00046*
							(0.00025)
Observations	34,906	34,906	34,906	22,582	34,906	34,906	29,603
R^2	11.0%		11.0%	11.4%	11.0%	11.0%	11.4%
Pseudo-R^2		9.3%					
Prop. Type FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size Pop Age Qs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Quality Qs	Yes	Yes	Yes	Yes	Yes	Yes	Yes