What's Wrong with Pittsburgh?

Investor Composition and Trade Frequency in US Cities

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Abstract

Unlike many Over-the-Counter (OTC) markets, geography clearly demarcates Commercial Real Estate (CRE) markets making the interplay between investor composition and trade frequency easier to observe. I document differences in investor composition across US cities, show that delegated investors have shorter holding periods, and show that they are concentrated in cities with higher CRE turnover. I then calibrate the model of Vayanos and Wang (2007) to interpret these facts. The model shows that heterogeneity in liquidity preferences makes some markets more liquid even when assets have identical cash flows. The calibration generates an illiquidity premium of two percentage points annually.

JEL: G11, G12, R33.

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1 Introduction

As Table 1 shows, delegated investors don't find Pittsburgh commercial real estate (CRE) attractive. While the share of CRE purchases by delegated investors averages 23% across US cities, it is a mere 14% in Pittsburgh. Furthermore, as Figure 1 shows, CRE in Pittsburgh trades less frequently than in almost any other US city. On average, only 2.4% of the stock of CRE in Pittsburgh transacts in a given year while the average turnover across major US cities is 5.5%. More generally, why are delegated investors drawn to some cities and not others? Furthermore, what are the consequences of different investor bases for liquidity?

The goal of this paper is to document and explain key facts about the relationship between investor composition and trade frequency across markets. I start from the observation that some investors trade frequently while others are essentially buy-and-hold investors. Aragon (2007), Cherkes et al. (2009), Rehring (2012), Hanson et al. (2015), Chodorow-Reich et al. (2016), and Barth and Monin (2018) show how these different investment horizons affect portfolio allocation. I build on this insight to understand the implications of investor heterogeneity in liquidity preferences for investor composition, trade frequency, and asset prices across different markets. The key intuition is that investors that value liquidity the most, because they trade more frequently or cannot weather short-term fluctuations in asset prices, concentrate their investments in the most liquid markets. 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. In essence, liquidity begets liquidity.

I document several key empirical facts about CRE investor composition, dividend yields, and trade frequency consistent with this intuition. In the CRE market, investors that

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

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	38.4	44.4	33.0	32.5	13.3
2	DC Metro	DC	36.1	37.9	34.6	31.3	20.3
3	Seattle	STL	35.0	35.4	34.6	26.7	13.4
4	San Francisco	SFO	33.0	34.0	32.2	33.2	11.9
5	Memphis	MEM	30.4	27.7	32.8	24.6	19.4
6	Chicago	CHI	29.7	33.5	26.4	30.9	17.2
7	Dallas	DFW	28.8	32.7	25.4	28.2	17.2
8	Austin	AUS	28.4	26.2	30.3	26.1	16.1
9	Denver	DEN	28.0	26.9	28.9	27.8	16.4
10	San Jose	SJC	27.9	25.8	29.8	21.0	10.7
11	Atlanta	ATL	27.6	27.5	27.7	24.1	18.2
12	Houston	HOU	26.4	26.8	26.0	31.8	21.9
13	Indianapolis	IND	26.3	29.1	23.9	25.5	21.2
14	Baltimore	BWI	26.2	23.0	29.0	23.7	26.7
15	Minneapolis	MSP	26.1	24.8	27.2	21.8	24.2
16	Oakland	OAK	25.9	28.7	23.4	27.2	11.9
17	Columbus	CMH	25.5	21.2	29.2	20.5	19.0
18	San Diego	SAN	24.9	26.3	23.7	24.1	13.8
19	Portland	PDX	23.3	29.6	17.7	18.7	12.6
20	Los Angeles	LA	22.7	27.2	18.8	22.1	9.6
21	Orange County	OC	22.2	22.1	22.4	21.0	8.9
22	Cincinnati	CIN	21.6	21.7	21.4	19.4	30.0
23	Charlotte	CLT	21.4	20.3	22.3	19.8	19.1
24	Orlando	MCO	21.1	20.8	21.3	18.8	23.2
25	Nashville	BNA	20.9	20.8	21.0	18.9	20.8
26	Riverside	RIV	20.8	20.1	21.5	19.8	11.4
27	NYC Metro	NYC	19.7	22.1	17.6	23.2	16.1
28	Tampa	TPA	19.6	18.7	20.4	23.7	17.0
29	Kansas City	KC	19.5	21.7	17.6	18.4	22.7
30	Sacramento	SAC	19.0	26.0	12.8	15.3	10.8
31	Phoenix	PHX	17.1	19.8	14.8	19.4	18.0
32	Philadelphia	PHL	16.6	16.2	17.0	25.3	19.4
33	Salt Lake City	SLC	16.3	16.9	15.8	12.2	14.8
34	Jacksonville	JAX	16.2	10.4	21.3	20.4	21.3
35	Las Vegas	LAS	13.9	12.1	15.5	10.6	13.9
36	San Antonio	SAT	13.6	11.1	15.8	21.4	19.7
37	Pittsburgh	PIT	13.5	11.7	15.1	12.8	18.2
38	Cleveland	CLE	10.7	9.7	11.6	14.5	19.7
39	Detroit	DTW	9.3	6.8	11.5	16.8	12.9
Average			23.2	23.5	22.9	22.4	17.3
Median			22.7	23.0	22.3	21.8	17.2

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.

Figure 1: Delegated Investor Share and Trade Frequency are Positively Related

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

are not managing other people's money play the role of buy-and-hold investors. Consistent with delegated investors having relatively more need for liquidity, I show that they have shorter holding periods than non-delegated investors (i.e., direct investors) on average. 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. Furthermore, the share of delegated investors is higher in markets with more trade frequency. The relationship between the share of delegated investors and trade frequency is robust to the inclusion of several controls such as the share of the population with a college degree, the average transaction size, and the occupancy rate in the Metropolitan Statistical Area (MSA). Finally, dividend yields (cap rates) are lower in markets with more trade frequency.

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

In contrast to other Over-the-Counter (OTC) markets, where the line between certain markets must be drawn somewhat arbitrarily by criteria such as credit ratings, the definition of a market in CRE arises naturally due to the physical segregation of markets. 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 endogeneous liquidity has led to bonds usually trading OTC since the mid-20th century. More recently, Chang (2018) presents a model where submarkets with different trade frequencies arise endogenously as a result of heterogeneity in traders' holding costs. The heterogeneity I document in liquidity across CRE markets is also related to the concept of latent liquidity introduced by Mahanti et al. (2008). Latent liquidity describes the idea that some markets are naturally more liquid than others, regardless of measures of liquidity such as bid-ask spreads, because the investor base trades more frequently. In the CRE context, cities that have a higher share of delegated investors have more latent liquidity.

The findings suggest that there may be path dependence in the development of cities to the extent that delegated investors have preferences over property characteristics other than liquidity. Delegated investors tend to purchase larger properties than direct investors. 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.[1] Recent work on publicly traded firms has also shown that investors with shorter holding periods invest in firms less committed to social and environmental responsibility (Starks et al. (2018)). It is thus plausible that the shorter expected holding periods of delegated investors in a city may lead them to shy away from long-term investments in a city's infrastructure and work force.

More generally, this paper contributes to our understanding of how investor composition affects liquidity and asset prices. Using data from publicly traded equity markets, Gompers and Metrick (2001) show that the preference of institutional investors for large-cap stocks increased the price of those stocks. Several papers study the asset pricing implica-

[1]This is arguably the urban analog to the finding in corporate finance that a firm's investor base affects corporate decisions and control. See, for example, Ambrose and Megginson (1992), Becker et al. (2011), Bushee and Noe (2000), Bushee (2001), Gaspar et al. (2005), and Stulz et al. (1990).

tions of institutional or delegated investors being benchmarked against an index.[2] This paper instead studies how differences in the liquidity needs of delegated investors affect trade frequency and asset prices. In complementary work, Cella et al. (2013) show that stock market investors with shorter trading horizons are more likely to dispose of their assets during periods of market turmoil which creates larger price drops and subsequent reversals for stocks held by short-term investors. My focus here is not on institutional investors but rather delegated investors. While delegated investors in CRE make larger investments, I show that it is not their size that drives their shorter holding periods.

Finally, the paper adds to a body of work that explains facts about real estate markets using search and matching models. While a number of papers have used search and matching models to understand the housing market[3], to my knowledge the only other paper that studies the CRE market using a search and matching model is Sagi (2017). 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.

The next section of the paper describes my data in detail including differences in the types of properties that delegated investors, direct investors, and REITs purchase. Section 3 documents key facts about the relationship between CRE turnover and investor composition. Section 4 calibrates the Vayanos and Wang (2007) model to the US CRE market to explain the aforementioned facts. Section 5 concludes and discusses potential future research.

[2] See, for example, Cuoco and Kaniel (2011), Basak and Pavlova (2013), Basak and Pavlova (2016), and Breugen and Buss (2017).

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

2 Data and Investor Type Classification

The data covers 2001-2015 for 39 US MSAs. 2001 is the first year for which Real Capital Analytics (RCA) has transactions data. I use all cities for which I have data on transactions and the stock of CRE. RCA provided me with data on every transaction in these 39 cities in industrial, retail, and office property. I did not request data on multifamily property because city density greatly affects whether a city has a sizeable multifamily market and, if so, the number of large multifamily buildings. Including multifamily would likely lead to an overstatement of the difference in the size of delegated investors across cities given that delegated investors tend to buy larger properties.

2.1 Transaction-Level Data

The sample RCA provided contained 145,228 observations. I drop 3,176 observations for which there was no buyer name, 5,637 entity-level purchases (i.e., property company mergers), and 3,793 observations in which the interest conveyed was not 100%. Applying these filters results in a dataset of 132,622 observations. 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 54% of all transactions by number but only 27% of transactions by dollar amount.

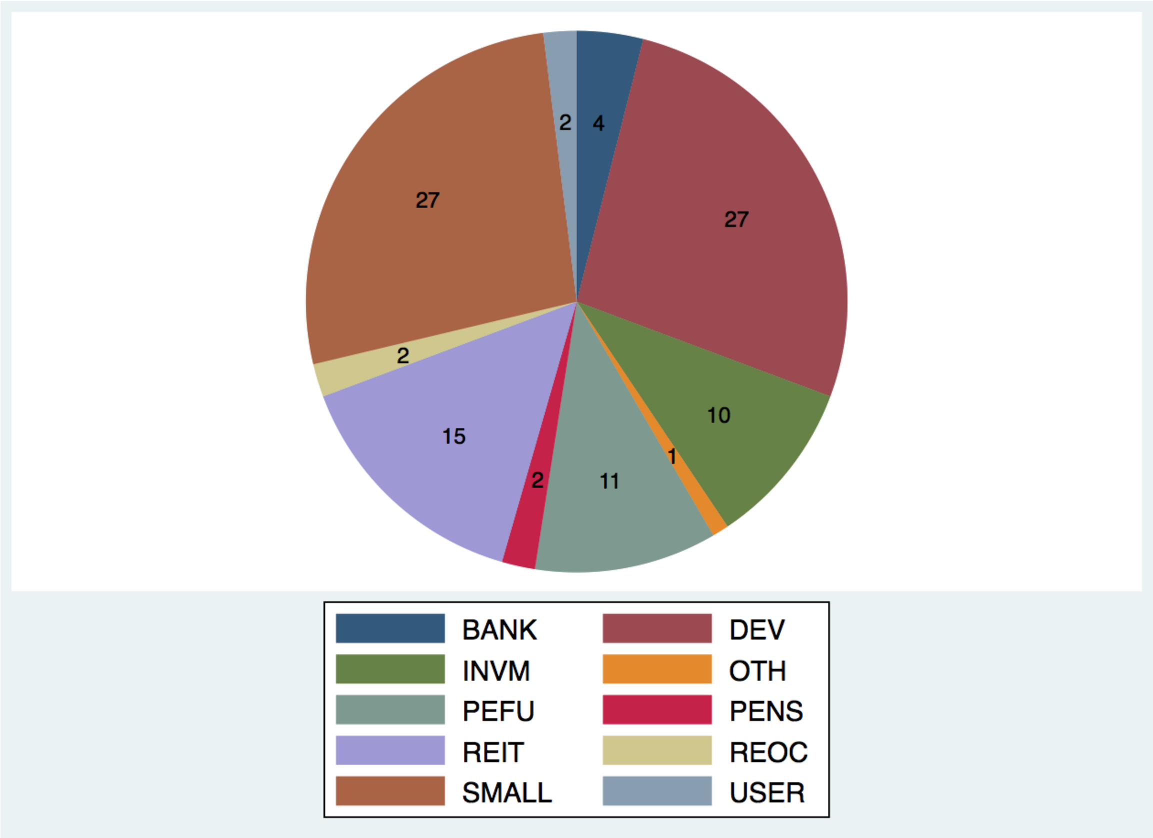
Buyers with five or more transactions make a total of 60,801 transactions. Through an internet search of the buyer name, I classify each buyer into one of the following nine types of investors: Banks (BANK), Developer/Owner/Operators (DEV), Investment Managers (INVM), Private Equity Funds (PEFU), REITs (REIT), Pension Funds (PENS), Users

(USER), Real Estate Operating Companies (REOC), and Other (OTH). I follow RCA in grouping Developer/Owner/Operators into a single category 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. To distinguish between DEV and INVM or PEFU, I focus on whether the entity is managing its own funds or those of other parties. My reason for focusing on 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 I consider them both delegated investors, the distinction does not matter for the analysis in this paper. I categorize entities that have multiple business lines and cannot be clearly categorized as either a DEV or INVM/PEFU as OTH.

I measure the purchases made by each category of investors as the dollar volume of transactions in an MSA and year made by those categories of investors. Figure 2 provides the shares at the national level aggregated across all years, i.e., when I aggregate the data set across all 39 cities in my sample. The single largest category is DEV 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 1%.

In addition to the buyer name, RCA provides me with the square footage of the property, the year the property was built, and the property's national Q-Score. The RCA Q-Score is a proprietary measure of a property's relative quality varying from 1 to 100. The "scores incorporate not only physical attributes, but also market and locational factors". Costello (2017) provides additional discussion of the RCA Q-Score. To better understand

Figure 2: 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.

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, I know the type of property (office, industrial, or retail) and encode this information in indicator variables.

Table 2 summarizes these variables. Given the outliers in property size and the Year Built, I winsorize the right tail of property size and the age of the property (current year - Year Built) at the 1% level for the analyses in Section 2.2.

2.2 Delegated Investors

I group investors into three categories: delegated investors, REITs, and direct investors. I hypothesize that delegated investors have shorter holding periods than direct investors because of agency frictions. Because of the inability of principals to observe the effort and skill level of managers, they require managers to dispose of the investments in a timely fashion. 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. I separate REITs from other delegated investors because REITs have long holding periods by statute; see Mühlhofer (forthcoming) regarding REIT holding period constraints being binding. I consider BANK, PEFU, INVM, and PENS as delegated investors. The remaining four non-REIT investor types I consider direct investors.

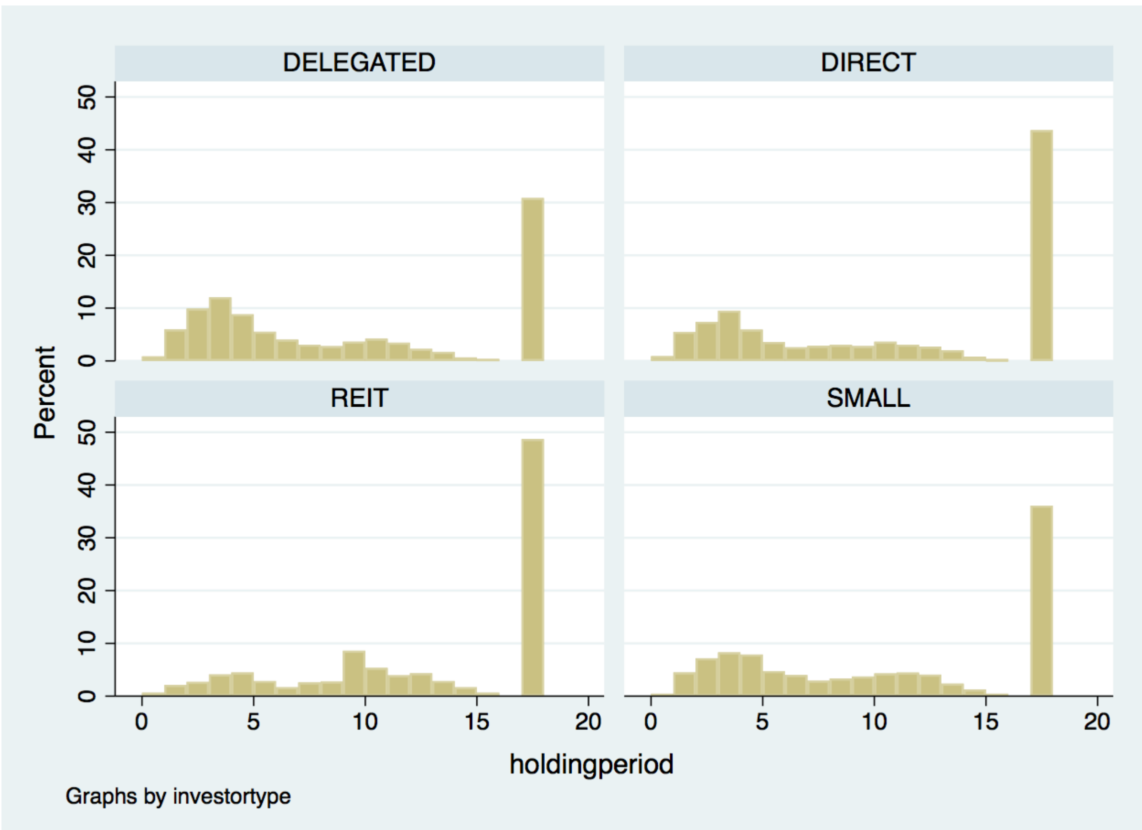
Figure 3 shows that there are significant differences in the distribution of holding periods across investor types. Direct investors have longer holding periods and are less likely to have sold the property by the end of the sample than delegated or, to a lesser extent, small investors. REITs have the longest holding periods.

Table 2: Transaction-Level Summary Statistics

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
Panel A: All Transactions						
YearBlt	124,059	1978.5	1985.0	26.7	1111.0	2020.0
Units	131,082	104	51	169	0	5500
QScoreNat	110,665	0.56	0.58	0.29	0	1
development	131,739	0.02	0.00	0.15	0	1
office	131,739	0.33	0.00	0.47	0	1
industrial	131,739	0.35	0.00	0.48	0	1
retail	131,739	0.32	0.00	0.47	0	1
Panel B: Delegated Investor Purchases						
YearBlt	15,097	1984.2	1987.0	22.5	1803.0	2020.0
Units	15,883	203	127	233	1	3787
QScoreNat	12,007	0.55	0.55	0.28	0	1
development	15,938	0.02	0.00	0.14	0	1
office	15,938	0.43	0.00	0.49	0	1
industrial	15,938	0.40	0.00	0.49	0	1
retail	15,938	0.17	0.00	0.38	0	1
Panel C: Direct Investor Purchases						
YearBlt	31,814	1977.5	1984.0	26.9	1708.0	2018.0
Units	33,286	128	74	186	1	5500
QScoreNat	27,523	0.54	0.54	0.30	0	1
development	33,431	0.02	0.00	0.13	0	1
office	33,431	0.36	0.00	0.48	0	1
industrial	33,431	0.31	0.00	0.46	0	1
retail	33,431	0.34	0.00	0.47	0	1
Panel D: REIT Purchases						
YearBlt	10,586	1987.8	1991.0	20.2	1635.0	2016.0
Units	11,393	158	98	211	1	4348
QScoreNat	8,792	0.56	0.57	0.27	0	1
development	11,432	0.03	0.00	0.17	0	1
office	11,432	0.27	0.00	0.44	0	1
industrial	11,432	0.33	0.00	0.47	0	1
retail	11,432	0.39	0.00	0.49	0	1
Panel E: Small Investor Purchases						
YearBlt	66,562	1976.3	1983.0	27.9	1111.0	2019.0
Units	70,520	63	33	112	0	5400
QScoreNat	62,343	0.58	0.61	0.30	0	1
development	70,938	0.02	0.00	0.15	0	1
office	70,938	0.30	0.00	0.46	0	1
industrial	70,938	0.36	0.00	0.48	0	1
retail	70,938	0.33	0.00	0.47	0	1

Notes: 1) YearBlt is the year the property was built or is anticipated to be completed in the case or properties still under development. 2) Units is the number of square feet in 1000s. 3) QScoreNat is the proprietary RCA measure of the quality of the property. 4) *development* takes a value of 1 if the property is under one year of age at the time of purchase. 5) $office$ takes a value of 1 if the property is an office property; *industrial* and *retail* are similarly defined.

Figure 3: Holding Periods by Investor Type



Notes: 1) DELEGATED includes banks, investment managers, private equity funds, and pension funds. 2) Holding period measured in years. 3) A holding period equal to 18 indicates the property has not been sold by the end of the sample. 4) SMALL investors are investors with less than five transactions over the full sample period of 2001-2015.

Table 3 shows that delegated investors have shorter holding periods even after controlling for which city they invest in, the year of purchase, and various property characteristics. I also control for the total dollar volume of transactions by the purchaser. The table presents Tobit regressions of the holding period on whether the purchaser is a delegated investor for 2001-2015 purchases by non-REIT investors that are large enough for me to classify. The first two columns present results for all years. The last four columns present results for purchases made in 2001, 2004, 2007, and 2010 separately. In all specifications, the coefficient on *delegated* is negative and statistically significant at the 1% level. Adding control variables reduces the coefficient but it remains highly statistically significant. The point estimate indicates that delegated investors hold their investments an average of one year less than direct investors. The coefficient on the log of the total dollar volume of transactions by the purchaser is negative indicating that larger buyers have longer holding periods but the relationship is not robust across subsamples. Investors also hold higher quality properties longer.

Table 3: Tobit Regressions of Holding Period on Investor Type

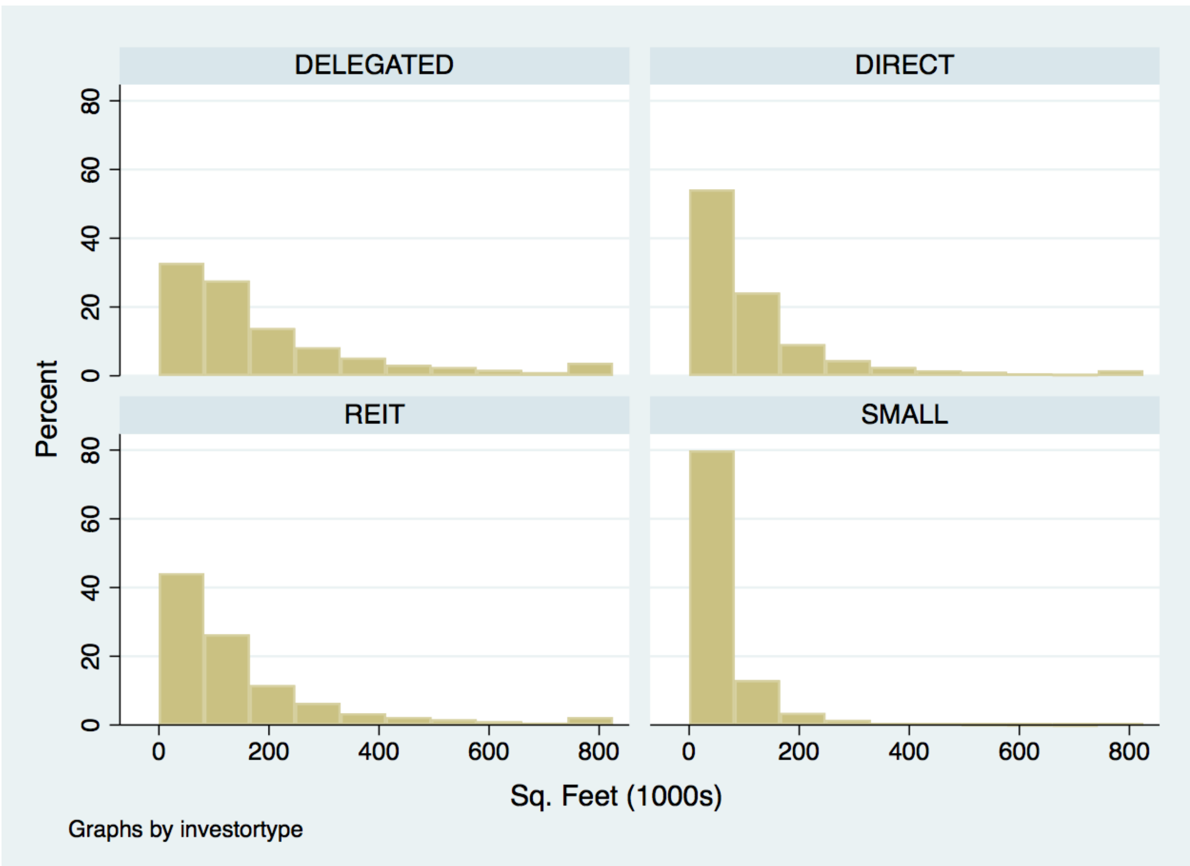
delegated	-1.03***	-1.07***	-1.84***	-1.56***	-0.90***	-2.31***
	(0.060)	(0.080)	(0.58)	(0.38)	(0.27)	(0.56)
Tot Purch.		0.000029***	-0.000035	0.000080**	0.000071**	0.000051
by Buyer ($M)		(0.000010)	(0.000057)	(0.000039)	(0.000034)	(0.000078)
RCA Quality		1.82***	4.26***	5.02***	1.19**	4.02***
Score		(0.14)	(1.09)	(0.68)	(0.53)	(0.87)
Prop. Age (yrs)		0.0027*	0.0034	0.012	0.00094	0.014
		(0.0014)	(0.011)	(0.0077)	(0.0050)	(0.0096)
Sq. Feet (1000s)		0.00095***	0.0041***	0.0036***	-0.00027	-0.00059
		(0.00021)	(0.0013)	(0.00095)	(0.00070)	(0.0014)
office		-0.85***	-1.83***	-2.12***	-1.36***	0.42
		(0.081)	(0.59)	(0.37)	(0.29)	(0.56)
industrial		-0.63***	0.21	-1.16***	0.30	0.064
		(0.085)	(0.67)	(0.41)	(0.30)	(0.59)
Observations	49,369	38,175	835	2,154	3,722	1,115
Purchase Yrs Inc.	2001-2015	2001-2015	2001	2004	2007	2010
Year Fixed Effects	Yes	Yes	No	No	No	No
MSA Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	2.2%	2.6%	1.9%	1.4%	0.7%	1.4%

Notes: 1) Dependent variable is the number of years the property was held for. 2) The table presents coefficients from Tobit regression to account for both left and right censoring. 3) Sample is purchases 2001-2015 by delegated and direct investors. 4) The right tails of property age and size are winsorized at the 1% level. 5) Properties still under development at the time of purchase are coded as property age=0. 6) Standard errors in parentheses. 7) ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$.

Figures 4, 5, and 6 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 through D 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 73,674 square feet larger on average than properties purchased by direct investors, a difference that is highly statistically significant in univariate t-tests. Not surprisingly, small investors overwhelmingly own physically small properties.

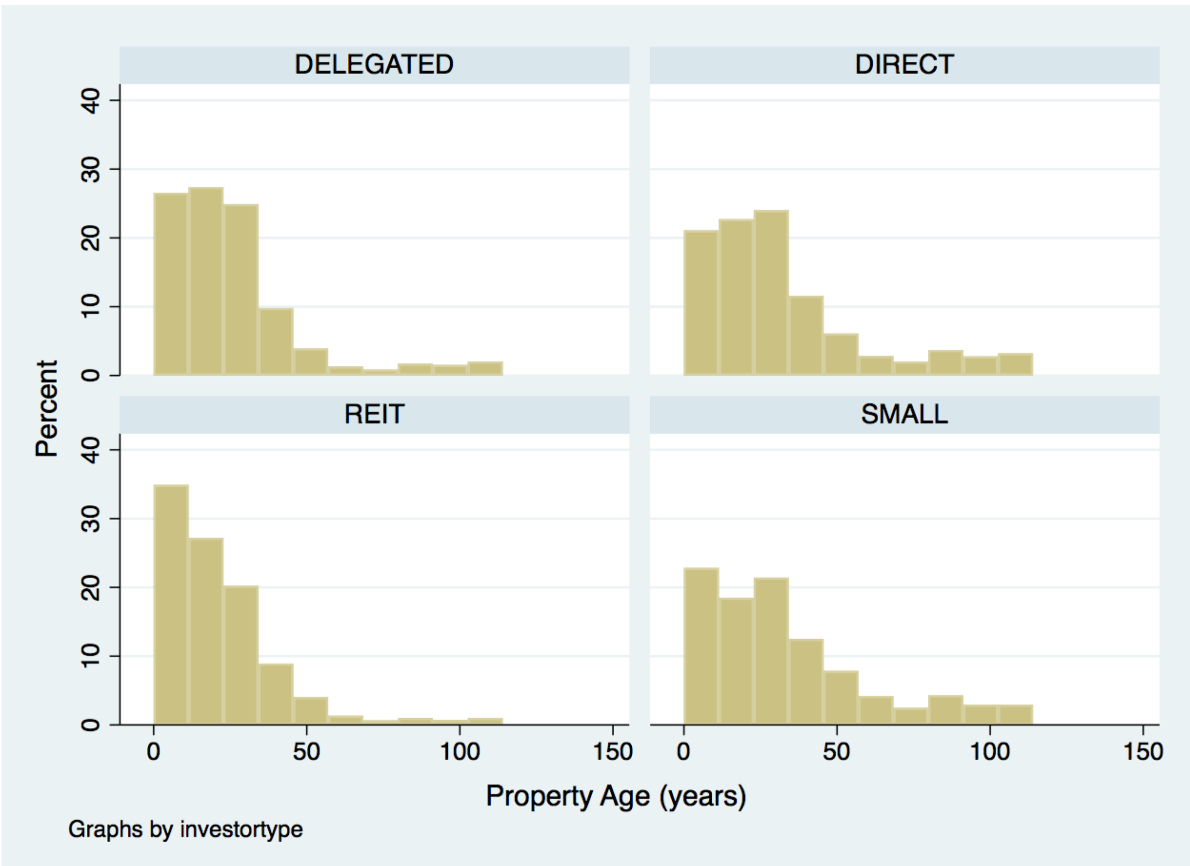
Delegated investors also invest in slightly younger properties on average. On average, properties purchased by delegated investors are about 6.6 years younger and the difference is highly statistically significant in a univariate t-tests for the difference in means. A fatter right tail primarily drives the difference in the mean property age between delegated and direct investors. The difference between the medians is only 4 years while the difference rises to 30 years at the 90th percentile. As Table 2 shows, there is no substantial difference between delegated and direct investors in the share of development properties. While the difference in the quality of buildings bought by the two different investor types is statistically significant given the large sample size, it is less than 1% such that it is not economically significant; the mean of property quality is 53.5% for direct investors while it is 54.7% for delegated investors.

Figure 4: Property Size (Square Feet in 1000s) for 2001-2015 Purchases by Investor Type



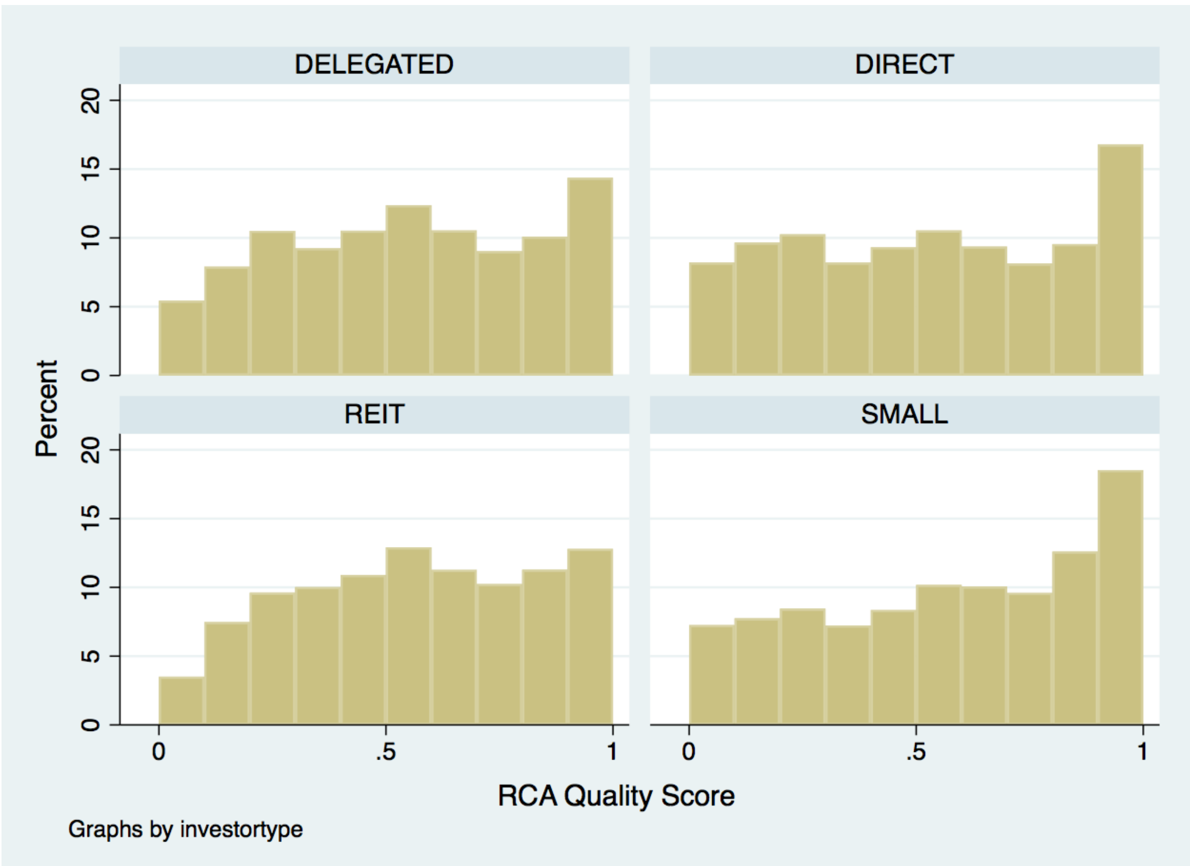
Notes: 1) DELEGATED includes banks, investment managers, private equity funds, and pension funds. 2) SMALL investors are investors with less than five transactions over the sample period. 3) I winsorize the right tail at the 1% level due to a handful of outliers.

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



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

Figure 6: 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.

2.3 MSA-Level Data

RCA also provides data on capitalization rates. CBRE provided the data on the stock of commercial real estate by MSA. I proxy for the average property size in an MSA using the transactions-level RCA data. In particular, I construct *avgsize* by dividing the total square footage transacted by the number of transactions and average across all years. I average across all years to mitigate the influence of any cyclical trends in which size properties transact in an MSA.

In some specifications, I control for the MSA-level occupancy rate. I construct MSA-level occupancy rates from TREPP property-level data. I exclude data from multifamily housing, manufactured housing, lodging, securities, and coop housing in constructing MSA-level occupancy rates from the TREPP data. The resulting average occupancy rates are value-weighted by property type. While the property-level data in TREPP skews towards properties that are financed by Commercial Mortgage-Backed Security (CMBS) loans, comprehensive property-level data are not available for the universe of commercial properties. See Downs and Xu (2015), Ghent and Valkanov (2016), and Black et al. (2017) for a comparison of the properties financed by CMBS with those financed with portfolio loans. I also measure lagged revenue growth using the property-level data in TREPP. I winsorize property-level revenue growth at the 1% level. I consider MSA-level occupancy and rent growth rates from CBRE for robustness.

I take the number of publicly traded firms headquartered in an MSA in each year from Compustat.[4] I also construct a variable that is the aggregate amount of assets these firms have using the Compustat data. The Compustat data is available only through 2014.

[4]The headquarters of a firm is not necessarily where all their economic activity takes place; see García and Norli (2012). The headquarters of a firm is readily available from firm financial statements, however, and papers studying urban geography and finance commonly use the headquarters as the location of the firm; see, for example, Ivković and Weisbenner (2005), Kose et al. (2011), and Dougal et al. (2015).

I take the natural log of these to get $lognfirms$ and $logfirmassets$. From 2001 onwards, the Bureau of Economic Analysis (BEA) provides real GDP at the MSA-level such that I have real GDP growth from 2002 to 2015.

Some of the MSA-level control variables I use are quite slow moving or the data is available only a few times throughout the sample. I measure the industry concentration in each city by constructing the Herfendahl-Hirschman Index (HHI) using employment in 2-digit NAICS code industries using the 2000 County Business Patterns (CBP) from the US Census. I term this variable emp_HHI. I also use the 2000 CBP data to construct the overall degree of competition between firms in a city by dividing the total employment in a city by the number of firms ($firmsperemp$). I take the share of the population with a four-year college degree or more education from the 2005 American Community Survey (ACS).

Table 4 provides summary statistics on the data. On average, delegated investors account for 23% of purchases. There is substantial variation in the share of transactions by delegated investors across cities and some variation within cities across years. Pittsburgh has the lowest share of delegated investors in the sample. In 2001 and 2002, delegated investors made none of the seven purchases of property in Pittsburgh. In 2007, delegated investors accounted for 72% of purchases of property in San Francisco. The number of transactions is quite small in some cities in some years making the overall ranking in Table 1, which averages across years, helpful to summarize city rankings. On average, 5.5% of the property stock transacts in an MSA in a year but less than one percent changed hands in several cities in 2009.

The average cap rate is 7.6%, roughly 400 basis points above the 10-year Treasury over this time period. Cap rates exhibit far less volatility over both time and across MSAs;

the standard deviation is just 0.9 percentage points. In some MSA-years, RCA does not have enough observations on property-level cap rates to construct an average cap rate. The average price per square foot is $133. The average MSA population is 2.9 million and ranges from 1.1 (Salt Lake City) to 19.6 million (New York City Metro).

3 Empirical Facts about Trade Frequency and Investor Composition

3.1 Trade Frequency and Investor Composition

Table 1 aggregates the data across years to show how investor type shares range across MSAs. The table presents the average shares of purchases by delegated investors and REITs in each MSA over the 2001-2015 period. Delegated investors comprised 38% of purchases in the Boston metro area but only 9% 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 over time, there is substantial persistence in delegated investor shares. Table 5 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 0.61.

Figure 1 illustrates that there is a positive relationship between ownership by delegated investors and trade frequency but does not control for any covariates. Furthermore,

Table 4: MSA-Level Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
numtransactions	585	205	232	7	1867
delshare	585	23.2	12.8	0.0	72.4
tf	578	5.5	3.2	0.5	20.6
caprate	530	7.6	0.9	5.1	10.3
logpop	585	14.9	0.6	13.9	16.8
occrate	585	93.9	1.0	92.2	95.3
occrate_CBRE	535	88.9	2.9	80.6	96.8
revgrowth	585	1.8	2.9	-2.2	6.9
rentgr	565	0.3	7.3	-32.6	40.3
lognfirms	546	4.6	0.9	2.5	7.0
logfirmassets	546	12.6	1.5	8.9	17.0
gdpgrowth	546	2.0	3.1	-11.6	12.3
emp_HHI	585	0.10	0.07	0.08	0.52
firmsperemp	585	0.047	0.005	0.037	0.058
college	585	31.3	6.3	18.9	46.0
logsize	576	16.8	0.4	15.7	18.6
logpsf	576	4.9	0.5	3.6	6.7
msa_avgqual	585	0.47	0.18	0.10	0.92

Notes: 1) *delsh* is the share of purchases made by delegated investors in %; tf is the percent of the property stock (in square feet) transacting; *caprate* is the average cap rate on properties in that market; $logpsf$ is the log of the average price per square foot in \$; *logpop* is the log of the population of the MSA in 2010; *occrate* is the average occupancy rate in that market from TREPP in %; $occrate\_CBRE$ is the average occupancy rate in that market from CBRE in %; $revgrowth$ is the average lagged revenue growth in that market from TREPP in %; $rentgr$ is the average growth in rents from CBRE in %; $lognfirms$ is the log of the number of publicly traded firms in the MSA; $logfirmassets$ is the log of the combined assets of all publicly traded firms in the MSA; emp_HHI is the Herfindahl-Hirschman Index of concentration of employment in the MSA based in 2000 using two-digit NAICS code industry classifications; $firmsperemp$ is the number of firms per employee in 2000; *college* is the share of the population that has at least a college degree in the 2005 ACS; *logsize* is the average size of a transaction in the MSA averaged where the property size in square feet is averaged across all years to mitigate the influence of which properties are transacting over time; 2) Each observation represents an MSA-year although *logpop* does not change across years. 3) $lognfirms$ and $logfirmassets$ are not available for 2015. 4) Property types included are office, industrial, and retail. 5) An observation corresponds to an MSA-Year. 6) Years included are 2001-2015.

Table 5: Persistence of Delegated Investor Share Over Time

	delsh 2008-2015
delsh 2001-2007	0.61***
	(0.09)
Constant	8.62***
	(2.18)
Observations	39
R^2	56%

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.

as I show in the model of the next section, 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. Nevertheless, it is worth considering a few explanations for the empirical relationship between the share of purchases by delegated investors and trade frequency other than the one this paper proposes. While an exhaustive empirical analysis of the determinants of ownership of CRE is beyond the scope of this paper, I consider five alternative explanations for the relationship in Figure 1. Because many of the control variables are highly correlated with one another (see Table 6), I limit the number of covariates in each specification rather than considering all of them simultaneously.

Large Cities

First, one might suspect that delegated investors focus their investments on the largest markets where there is both more information and more liquidity. That is, it might be the case that rather than having higher liquidity needs *per se*, delegated investors simply prefer larger markets and the greater availability of information in these markets also makes them more liquid. In column (2) of Table 7, I control for the population of the MSA in logs. The coefficient is positive but far from statistically significant. Delegated investors appear to be indifferent to the size of the MSA.

Asset and Tenant Quality

Second, 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 between delegated investor shares and trade frequency merely reflects delegated owners preferring higher quality assets and those assets also being more liquid. A related idea is that delegated investors prefer what is known as "credit tenants". Credit tenants are generally nationally known publicly traded firms and delegated investors may have a preference for such tenants because they can readily show measures of credit-worthiness to their investment boards. The argument is similar to the 'prudent-man' laws Del Guercio (1996) shows affect the choice of equity holdings of institutional investors.

In column (3), I therefore include three measures of tenant quality: the occupancy rate in the MSA (*occrate*), the average quality of properties transacting in the MSA (*msa_avgqual*), and the log of the assets of publicly traded firms headquartered in the MSA (*logfirmassets*). The coefficient on the occupancy rate is positive and marginally statistically significant. The coefficient on the quality of assets in the MSA in positive but statistically insignificant. The coefficient on the total assets of publicly traded firms is positive and statistically significant at the 5% level. The coefficient is positive in both specifications but statistically insignificant. The occupancy rate and assets of publicly traded firms have a correlation of 55% such that the lack of statistical significance when I include both variables may be an issue of power. I thus find modest support for the idea that delegated investors prefer high quality tenants. However, the coefficient on trade frequency is little changed after including measures of asset and tenant quality.

Herding

Third, delegated investors may herd into markets where rents are growing quickly. In column (4), I therefore include lagged revenue growth. The coefficient on trade frequency (tf) is little changed and the coefficient on $revgrowth$ is statistically insignificant.

Asset Size

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 the most expensive markets or markets with large properties where they can deploy a large amount of capital on a single property. In column (5), I therefore control for the log of average transaction size (in $). Since the goal is to proxy for the types of properties in the MSA, I average the physical transaction size across all years to mitigate the influence cyclical factors may have on which properties transact. The coefficient is positive and statistically significant at the 5% level consistent with delegated investors preferring markets in which they can deploy a large amount of capital in a single transaction.

Table 6: Correlations Among MSA-Level Control Variables

	tf	*logpop*	*occrate CBRE*	*occrate*	*revgr*	*logsize*	*msa_avgqual*	*lognfirms*	*logfirmassets*	*gdpgr*	*emp_HHI*	*firmsperemp*	*college*	*logpsf*
tf	100%													
logpop	3%	100%												
occrate	12%	0%	100%											
occrate_CBRE	21%	2%	10%	100%										
revgrowth	-11%	1%	85%	-1%	100%									
logsize	29%	36%	3%	11%	2%	100%								
msa_avgqual	26%	28%	-11%	18%	-8%	41%	100%							
lognfirms	18%	68%	8%	5%	6%	50%	50%	100%						
logfirmassets	12%	55%	-4%	5%	-6%	59%	25%	78%	100%					
gdpgrowth	46%	-5%	8%	30%	-18%	6%	4%	4%	-2%	100%				
emp_HHI	-11%	-10%	0%	4%	0%	-10%	-21%	-12%	5%	-4%	100%			
firmsperemp	4%	24%	0%	21%	0%	12%	50%	14%	-6%	4%	-31%	100%		
college	24%	12%	0%	-6%	0%	49%	51%	52%	50%	7%	-18%	21%	100%	
logpsf	37%	39%	3%	18%	2%	76%	76%	55%	40%	11%	-19%	49%	52%	100%

Notes: 1) See Table 4 for variable definitions.

Economic Fundamentals

Delegated investors may also concentrate their investments in cities that the urban economics literature empirically shows will grow faster over the long run. Glaeser (2012) argues that the share of the population with a college degree increases MSA-level growth.[5]. Glaeser et al. (1992) show empirically that cities with more variety across industries and cities with more firm-level competition grow more rapidly. To the extent that delegated investors are more sophisticated than direct investors, they may be able to pick such long-term winners.

In column (6), I include $firmsperemp$, emp_HHI, and *college*. The coefficient on the share college educated is positive and highly statistically significant. Furthermore, the coefficient on tf falls by about 30% after including *college*. The coefficients on $firmsperemp$ and emp_HHI are far from statistically significant.

In column (7), I simultaneously include *occrate*, *msa_avgqual*, $logfirmassets$, *logsize*, and *college*. *logsize* continues to be significant at the 10% level and the coefficient on *college* remains positive and significant at the 1% level. The asset and tenant quality measures become insignificant. However the relationship between trade frequency and delegated investor share remains significant at the 1% level. The magnitudes indicate that a one percentage point increase in trade frequency is associated with a 1.4 percentage point increase in delegated investor share.

In column (8), instead of controlling for year fixed effects, which proxy for national differences in trade frequency across time, I include MSA fixed effects and a binary variable that takes a value of one if the observation comes from the years 2001-2007. Thus, in column (8), the relationship between delegated investor share and trade frequency is identified off of differences over time within an MSA. The coefficient on trade frequency is of similar

[5]See also Glaeser and Maré (2001), Moretti (2004), Shapiro (2006), and Dougal et al. (2018)

magnitude to the benchmark specification in column (7) and remains statistically significant at the 1% level.

Table 7: Delegated Investor Share and Trade Frequency: Multivariate Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tf	1.75***	1.78***	1.64***	1.75***	1.51***	1.26***	1.42***	1.61***
	(0.36)	(0.24)	(0.38)	(0.36)	(0.36)	(0.37)	(0.39)	(0.22)
occrate			1.59*				1.01	
			(0.87)				(0.85)	
msa_avgqual			3.09				-5.70	
			(4.29)				(4.41)	
logfirmassets			1.36**				-0.23	
			(0.64)				(0.56)	
logpop		1.27						
		(1.47)						
revgrowth				0.60				
				(0.41)				
logsize					6.79**		4.49*	
					(3.21)		(2.60)	
firmsperemp						-174		
						(166)		
emp_HHI						2.47		
						(5.80)		
college						0.60***	0.53***	
						(0.16)	(0.16)	
half1								-0.32
								(0.93)
Observations	578	578	539	578	570	578	531	578
R^2	23.3%	20.2%	26.1%	23.3%	27.4%	30.7%	31.5%	38.6%
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
MSA Fixed Effects	No	No	No	No	No	No	No	Yes

Notes: 1) Robust standard errors clustered by MSA in parentheses. 2) $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. 3) Dependent variable is share of purchases in MSA in a given year by delegated investors in %. 4) See Table 4 for variable definitions.

Robustness

Table 8 explores the robustness of the results in Table 7. I take the specification in column (7) of Table 7 as the benchmark. In column (1) of Table 8, I control for the total number of publicly traded firms headquartered in an MSA rather than their total assets. In column (2), I take the occupancy rate from CBRE rather than TREPP. In column (3), I use the log of the price per square foot instead of the log size of the average transaction to control for the ability of investors to deploy a large amount of capital in one transaction. None of these three changes materially affect the magnitude or statistical significance of the coefficient on tf.

In column (4), I use the share of sales by delegated investors rather than purchases as the dependent variable. Using sales instead of purchases results in the coefficient on tf falling by about a third but the coefficient remains significant at the 1% level and is a little more precisely estimated. The coefficient on *college* becomes insignificant consistent with delegated investors choosing to buy, but not to sell, in cities with strong growth prospects over the long run. Given the consistent relationship between delegated investor share and the share of the population with a college degree, a proxy for economic growth prospects, in column (5) I directly control for MSA-level real GDP growth instead of the share with a college degree. The coefficient on tf rises slightly and the coefficient on *gdpgrowth* is actually negative and statistically significant at the 5% level.

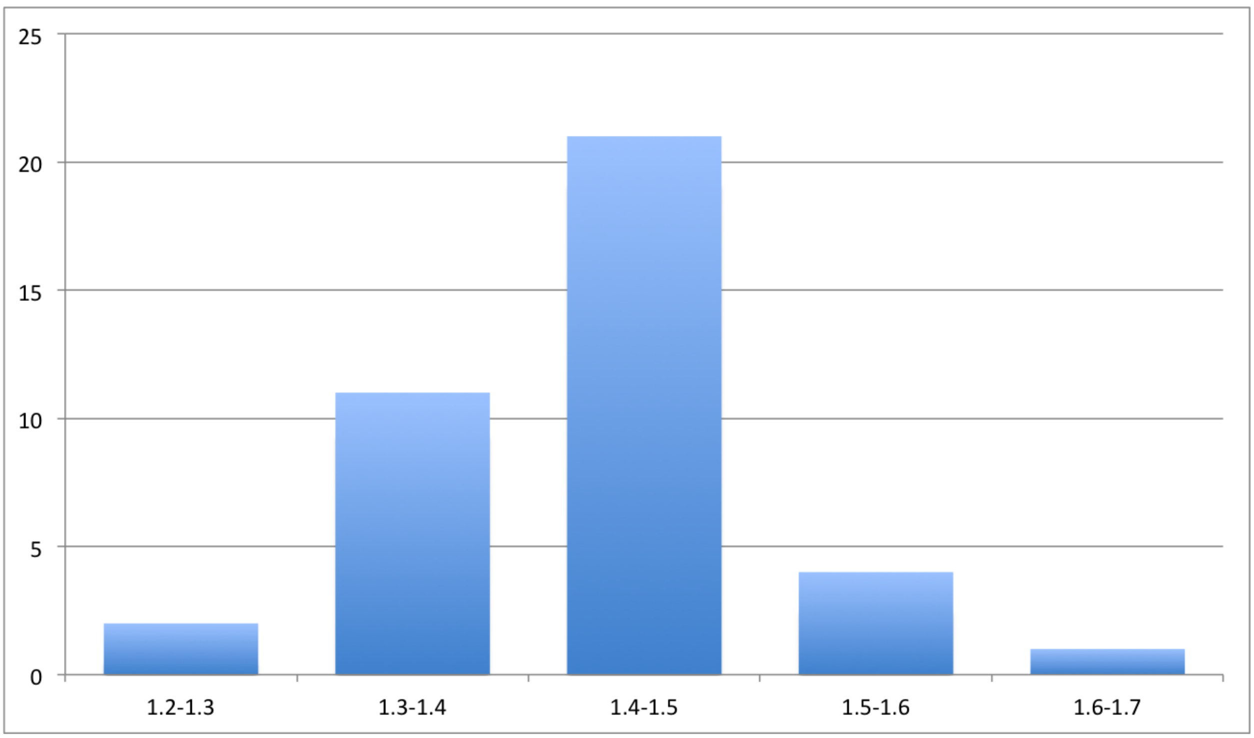
Figure 7 explores the robustness of the results to the MSAs included in the sample. It shows the coefficient on tf of the regression estimated in column (7) of Table 7 dropping one MSA at a time. The figure illustrates that the results are not heavily influenced by any single MSA.

Table 8: Delegated Investor Share and Trade Frequency: Robustness

	(1)	(2)	(3)	(4)	(5)
Dependent variable	*delshare*	*delshare*	*delshare*	*delshare_sell*	*delshare*
tf	1.43***	1.38***	1.45***	0.95***	1.71***
	(0.38)	(0.38)	(0.39)	(0.25)	(0.35)
occrate	1.12		0.68	2.56***	-0.29
	(0.84)		(0.83)	(0.81)	(0.96)
msa_avgqual	-4.63	-7.37	-1.89	-4.71	0.77
	(4.56)	(4.38)	(5.45)	(3.85)	(3.56)
lognfirms	-0.64				
	(1.04)				
logsize	4.52*	4.97*		4.33*	6.25**
	(2.60)	(2.57)		(2.35)	(2.99)
college	0.53***	0.59***	0.58***	0.28	
	(0.15)	(0.16)	(0.16)	(0.17)	
occrate_CBRE		0.36*			
		(0.21)			
logfirmassets		-0.36	0.37	0.70	0.40
		(0.56)	(0.49)	(0.55)	(0.60)
logpsf			-0.93		
			(2.88)		
gdpgrowth					-0.52**
					(0.22)
Observations	531	496	531	531	496
R^2	31.6%	33.5%	30.5%	19.0%	29.9%
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
MSA Fixed Effects	No	No	No	No	No

Notes: 1) Robust standard errors clustered by MSA in parentheses. 2) $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. 3) Dependent variable in columns (1)-(3), and (5) is share of purchases in MSA in a given year by delegated investors in %; dependent variable in column (4) is share of sales. 4) See Table 4 for variable definitions.

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

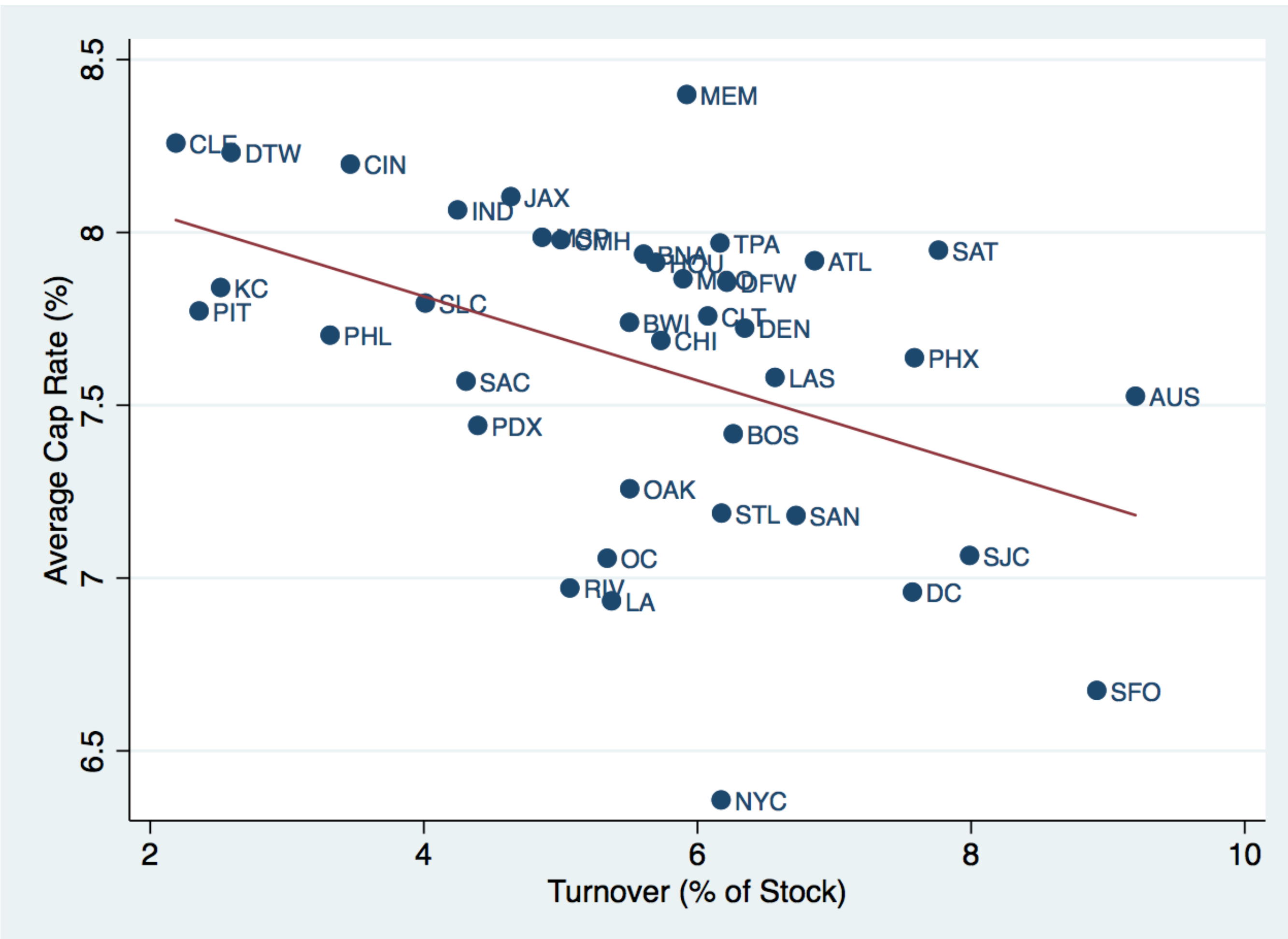


Notes: 1) All coefficients are statistically significant at the 1% level. 2) Bins respresent number of regression coefficients falling into range indicated.

3.2 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 turnover across MSAs ranges from two to nine percent of the stock.

Figure 8: Cap Rates and Trade Frequency are Inversely Related



Notes: 1) Cap rates for each MSA are averaged over 2001-2015. 2) Source: Real Capital Analytics (RCA) and author's calculations.

4 Explaining the Facts

I consider how well a search model with heterogeneous investors can explain the facts above. To do so, I calibrate 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. I require only that delegated investors have a higher average concentration of investors with frequent liquidity shocks for the model to have relevant empirical predictions; both delegated and direct investors can be individuals that frequently get valuation shocks and thus have high liquidity needs.

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 $1 - x$ and the intensity with which investors become low valuation agents is κ. In contrast to Duffie et al. (2005) and Duffie et al. (2007), once an agent becomes a low valuation agent, he remains a low valuation agent until he sells the property. Once he has sold the property, he exits the economy. Agents that become low valuation agents without having bought a property also exit the economy.

Agents differ in the likelihood that they will receive a valuation shock. Valuation shocks arrive at Poisson rate κ. If an investor switches to a low valuation type, he receives only $1 - x$. The density of investors that enter the economy is $f(\kappa)$ which I take as the uniform distribution over the interval $[\underline{\kappa}, \overline{\kappa}]$.

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

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

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

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

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

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.[6] I denote by $\mu_B^i(\kappa)$, $\mu_O^i(\kappa)$, and $\mu_S^i(\kappa)$, the density of agents with valuation shock frequency κ in market i that are looking

[6]Vayanos and Wang (2007) show that there also exist a continuum of symmetric equilibrium in which the measure of sellers is the same across both markets. In addition to being indeterminate, these equilibria are inconsistent with the facts I document about the US CRE market.

to buy the asset, that own the asset and remain high valuation, and that 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

$$\int_{\underline{\kappa}}^{\overline{\kappa}} \mu_B^i(\kappa) d\kappa = \mu_B^i \tag{3}$$

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

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

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

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

$$\frac{1}{\overline{\kappa} - \underline{\kappa}} \int_{\kappa^*}^{\overline{\kappa}} \frac{\lambda \mu_S^1}{k(k + \lambda \mu_S^1)} dk + \mu_S^1 = S \tag{6}$$

$$\frac{1}{\overline{\kappa} - \underline{\kappa}} \int_{\underline{\kappa}}^{\kappa^*} \frac{\lambda \mu_S^2}{k(k + \lambda \mu_S^2)} dk + \mu_S^2 = S \tag{7}$$

$$\begin{aligned} \mu_S^1 - \mu_S^2 + \mu_S^1 \frac{1}{2(r+\kappa^*)(\overline{\kappa} - \underline{\kappa})} \int_{\underline{\kappa}}^{\kappa^*} \frac{\lambda(r + \kappa^* + 0.5\lambda\mu_S^2)}{(k + \lambda\mu_S^2)(r + k + 0.5\lambda\mu_S^2)} dk \\ + \mu_S^2 \frac{1}{2(r+\kappa^*)(\overline{\kappa} - \underline{\kappa})} \int_{\kappa^*}^{\overline{\kappa}} \frac{\lambda(r + \kappa^* + 0.5\lambda\mu_S^1)}{(k + \lambda\mu_S^1)(r + k + 0.5\lambda\mu_S^1)} dk = 0 \end{aligned} \tag{8}$$

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

Transactions prices are heterogeneous in each market. While transactions prices have closed form solutions, in the interests of space, I do not reproduce the expressions for them from Vayanos and Wang (2007). I present 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.

Calibration

Given that the model has no role for heterogeneity in liquidity needs or technologies over time, I collapse the data to the means for each of the 39 MSAs. I then split the sample of cities into two sets of cities, high and low turnover. High turnover cities are the top half of cities by turnover while low turnover cities are those with turnover below or equal to the median. Table 9 shows that the most liquid cities have turnover of 6.85% while the least liquid cities have turnover of just 4.30%. The difference in turnover between the two sets of cities is more than 45% of the mean level of turnover. By comparison, the difference in the average cap rates across the two sets of cities is a mere 13 basis points or less than 2% of the average cap rate.

I fix z to 1 such that buyers and sellers have equal bargaining weight. I fix r at 5.45% which is considerably higher than the average yield on the 10-year US Treasury over 2001-2015. The risk-free rate in the model must be higher to match the data because, in the model, there is no credit risk. Given the moments in the data, I can fit the data relatively well by setting $\underline{\kappa}$, $\overline{\kappa}$, λ, and x to 0.035, 0.09, 3.0, and 0.39. The midpoint of the range of κ

is such that each high valuation agent faces a 6.25% chance of getting a liquidity shock in any given year and thus becoming a low valuation agent.

Table 9: Search Model with Investor Heterogeneity

	Data: US Cities			Model	
	All	High Turnover	Low Turnover	High Turnover Market ($\kappa > \kappa^*$)	Low Turnover Market ($\kappa \leqslant \kappa^*$)
Avg. Cap Rate	7.63%	7.51%	7.74%	7.51%	7.73%
Turnover	5.54%	6.85%	4.30%	6.80%	4.28%
Del. Share	23.2%	20.5%	26.0%		
N	39	19	20		
μ_B				0.45	0.34
μ_O				8.15	8.23
μ_S				0.43	0.36
Mos. to Sell				8.92	11.65
κ^*				0.056	
Illiquidity Premium (bp)				206	228

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

For these parameter values, the value of κ that separates the two sets of agents is $\kappa^* = 0.056$. As Vayanos and Wang (2007) point out, there are both more buyers and more sellers in the more liquid market. The equilibrium masses of buyers in markets 1 and 2 are 0.44 and 0.33 such that the equilibrium times on the market ($\frac{1}{\lambda\mu_B^i}$) are approximately 9 and 12 months. I am not aware of empirical estimates of the time required to sell in the commercial real estate market but these numbers seem within the plausible range for commercial real estate.[7]

The differences in cap rates between the high and low turnover markets is very small, a mere 22 basis points. In practice, the cashflows of CRE may differ across cities, which

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

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

Overall, however, the model implies a full two percentage point compensation for the illiquidity inherent in CRE, about 40% more yield than that of the perfectly liquid, risk-free asset. While the model is highly stylized, to my knowledge this is the first estimate of the illiquidity premium of CRE in the literature.[8] Consistent with CRE being much less liquid than financial securities, this is a substantially higher illiquidity premium than what the literature finds for funds that hold financial securities. Aragon (2007) reports a 4-7% percent higher return on hedge funds with lockup restrictions relative to unrestricted funds. Barth and Monin (2018) construct a measure of illiquidity based on the average number of days it would take to liquidate a portfolio. Using this measure and data from hedge funds' security holdings, they find an illiquidity premium of 82 basis points per year per additional log-day of illiquidity. Khandani and Lo (2011) estimate illiquidity premia of 2.74% to 9.91% in hedge funds and mutual funds.

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

5 Conclusions

I have 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 the CRE markets of 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. I also find that delegated investors prefer to invest in larger assets and in highly educated cities.

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

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

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