Illiquidity Measures and the Pricing Implication in Commercial Real Estate

Peng (Peter) Liu and Wenlan Qian[*]

[*]Liu is with the Department of Finance, Accounting and Real Estate, School of Hotel Administration, Cornell University, Email: peng.liu@cornell.edu. Qian (corresponding author) is with the Department of Finance, National University of Singapore, Tel : (65) 65163015, Wenlan.qian@nus.edu.sg.

I. Introduction

The relationship between illiquidity and asset prices has been examined extensively in the stock and bond market, where the cross-sectional and time-series variation in price impact,[1] is empirically proven to be priced in the expected returns (e.g., Amihud and Mendelson, 1986; Brennan, Chordia and Subramanyam, 1998; Amihud, 2002; Bekaet, Harvey and Lundblad, 2007; Bao, Pan and Wang, 2010).[2]

Given the substantial evidence on the liquidity premium in other asset markets, it is a plausible conjecture that liquidity plays a significant role in the real estate market, as real estate transactions are very costly.[3] On the other hand, the very long-term nature of investment in this market makes the significance of the liquidity premium in real estate less obvious. Moreover, the different market structure introduces new aspects of illiquidity that remain empirically under-explored in the literature. In addition to other factors that drive illiquidity,[4] search efficiency is a unique and significant aspect of trading frictions in the real estate market given the prolonged negotiated transaction process that involves costly search and matching (e.g., Wheaton, 1990).

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[1] There is a large theoretical literature in microstructure that models illiquidity as the price concession required in the presence of supply and demand imbalance as a result of asymmetric information, inventory risk and other effects (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987).

[2] In addition to the level of illiquidity, liquidity risk is shown to systematically influence asset prices in the stock market (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006) and in the bond market (Acharya, Amihud, and Bharath, 2010; Li, Wang, Wu, and He, 2010; Lin, Wang, and Wu, 2010).

[3] Transaction cost is estimated to be over three percent of the asset value (e.g., Haurin and Gill, 2002; Collett, Lizieri and Ward, 2003).

[4] It is well accepted that leverage and the down payment constraint amplifies negative demand shocks (Stein, 1995; Genesove and Mayer, 1997; Ortalo-Magne and Rady, 2006). Seller's behavioral limitation, such as loss aversion, leads to a lower probability of sale and a longer time to sale (Genesove and Mayer, 2001; Engelhardt, 2003). Sellers can also rationally delay sale timing due to the value of the option of waiting (Qian, 2012).

Despite its economic significance[5], empirical examinations on the relationship between illiquidity and real estate prices have been limited in scope. One major barrier to such endeavors is data availability. First, real estate is infrequently traded and direct measures of liquidity (e.g., bid-ask spread) are unavailable. Second, the popular proxy for search frictions, time-on-market (hereafter, TOM), is costly to gather for each individual transaction at the national level or for a lengthy time period.

The objective of this paper is study illiquidity and its pricing implication in real estate. Specifically, we focus on office buildings in the commercial real estate market. Buying and selling commercial real estate, in contrast to residential real estate, is purely investment-driven with the more sophisticated institutional investors being the major players. The office market is the key market in commercial real estate market, with a market capitalization of 6.5 trillion US dollars in the US at the end of 2010, which is slightly bigger than the U.S. treasury market and over half of the entire commercial market. Furthermore, the unique institutional features of the commercial real estate market make it ideal to identify search inefficiencies, a key aspect of illiquidity in over-the-counter markets in general.

We propose real estate illiquidity measures that are readily obtainable from transaction information. We take advantage of a salient feature of illiquidity in constructing our measures. Specifically, illiquidity leads to deviation of the transaction price from the asset's fundamental value, regardless of the underlying causes. This observation helps avoid the need to model directly the relevant determinants of illiquidity in real estate. Motivated by Amihud and Mendelson (2002), we first propose a price impact measure to reflect illiquidity when there is an

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[5] Illiquidity has important implications for understanding the price determinants (e.g., Turnbull and Zahirovic-herbert, 2010; Campbell, Giglio and Pathak, 2011), price index construction (Goetzmann and Peng, 2006) and portfolio allocation (Lin and Vandell, 2007).

imbalance between supply and demand. It is defined by the (absolute) price change (in percentage term) in market j from the time period $t\text{-}1$ to t divided by the dollar trading volume in this market at time t. Conditional on the level of the trading activity, a larger price movement implies a higher degree of illiquidity.

Moreover, we measure the market's search inefficiency as the ratio of the price impact (λ) measure of the subset of the less search-efficient properties in the same geographic market to that of the submarket of more search-efficient properties. Large, institutional investors trade commercial properties in a segmented market: typically they target larger, high quality, high-value properties. These investors are well-informed about the properties on the market, and the transactions are often taken place via auctions. In contrast, small, retail investors are more restricted in the smaller, no-prime markets, and they have to engage in lengthy and costly search, much as in the residential real estate, to complete the transaction. Therefore, within the same geographical location, there are two types of office buildings that are subject to similar macroeconomic fundamentals (such as local income and unemployment) but differ dramatically in search costs. The difference in price impacts between small and big properties within a market that shares the same fundamentals likely captures the level of search inefficiency in this particular market at the time.

Using a national sample of office market transactions in the U.S. from 2000 to 2011, we compute the two measures for each of 24 markets[6] at the quarterly level. We first study the applicability of the price impact and search friction measures by comparing them with characteristics of these transactions that are correlated with supply-demand mismatch or search frictions. Our proposed measures perform well. The price impact measure is negatively

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[6] The geographic market classification is defined by the data provider, CoStar COMP.

correlated with the trading volume, and is positively correlated with the proportion of distress sales in the market at a given time. The search friction measure is positively associated with the proportion of tax-deferred transactions and the proportion of properties sold with high vacancy or to out-of-state buyers. It is negatively associated with the proportion of tenant purchases in the market. Using the out-of-sample aggregate statistics on the commercial real estate market (such as total trading volume), we confirm our in-sample findings.

We also study how these two liquidity measures are related with macroeconomic variables. Price impact is significantly negatively correlated with local GMP and positively related with local market unemployment rate and funding/lending availability. On the other hand, the search friction measure is negatively associated with population density in the local market, interest rate, and the cap rate in the local market. In summary, these results suggest that price impact is positively associated with economic conditions, while search friction can be even more relevant in "hot" markets.

Next, we investigate the pricing implication of illiquidity using the price impact and search friction measures. Office buildings, both investment grade and non-investment grade, in markets at times with high price impact tend to command a higher return over the subsequent quarter. Search friction strongly predicts future returns in the non-investment grade submarket with costly search. We further gauge the return-illiquidity relationship in different market conditions. Illiquidity is likely to be particularly important during down markets (Brennan, Huh, and Subrahmanyam, 2012), either due to higher liquidity risk (Acharya and Pedersen, 2005; Acharyaet al., 2010) or due to capital constraints (Mitchell, Pedersen, and Pulvino, 2007; Brunnermeier and Pedersen, 2009; Hameed, Kang, and Viswanathan, 2010). We create a down market dummy for each market at quarter t if the quarter t return is negative. The illiquidity

premium is driven by the down period. For example, in the down market, a 10% increase in the price impact measure is associated with 0.86% increase in the annualized expected return in the cross section.

Lastly, we explore the variation in the liquidity premium among investment grade office properties and non-investment grade buildings within the same geographic market. Search friction is only relevant for future returns in the non-investment grade submarket. More interestingly, there is a flight-to-quality (liquidity) during market downturns. During such times, search friction and price impact strongly positively predict future returns in the non-investment grade properties. However, a higher search friction in the entire market during the down market predicts a negative return in the investment grade submarket over the next quarter. In addition, price impact does not predict a higher return over the next quarter for the investment grade properties at such times. These results suggest that investors flood to the submarket with better liquidity (i.e., lower price impact and little search frictions on average) during market distress and thus pay a price (liquidity) premium for the more liquid submarket.

The paper proceeds as follows. Section II introduces the two proposed illiquidity measures used in the study. Section III describes the office market transaction data. Section IV presents the empirical results, including evaluation of the price impact and search friction measures as well as the pricing implications of illiquidity in the context of the US office market. Section V concludes.

II. Measures of Illiquidity -- Price Impact (λ) and Search Friction

The first objective of this paper is to construct intuitive and easy-to-compute liquidity proxies using readily available data in the real estate market. The Amihud measure (Amihud,

2002) aims to capture illiquidity using the magnitude of the price movement conditional on trade size, and it performs well in capturing price impact (Goyenko, Holden and Trzcinka, 2009). Given the low frequency of our data which limits the direct application of the Amihud measure, we define our price impact proxy using price and volume data in a slightly different fashion.

$$\lambda_{j,t} = \frac{\left|\ln(\widetilde{price}_{j,t}) - \ln(\widetilde{price}_{j,t-1})\right|}{Dollar\ Volume_{j,t}} = \frac{\left|\ln(\frac{1}{N_{j,t}}\Sigma(\widetilde{price}_{i,j,t})) - \ln(\frac{1}{N_{j,t-1}}\Sigma(\widetilde{price}_{i,j,t-1}))\right|}{Dollar\ Volume_{j,t}} \tag{1}$$

$\lambda_{j,t}$ is the (absolute) price change (in percentage term) in market j from the time period t-1 to t divided by the dollar trading volume in this market at time t (equation (1)). The price change is computed based on the average transaction price (per square foot) in the market within the same quarter. To control for the effect of different property attributes, and more importantly to isolate the impact of the market trend on the price change in the market for a given quarter, we first estimate a hedonic pricing model (Rosen, 1974) in equation (2). We use the property size and age as the main hedonic variables, and we include a year-quarter dummy to capture the component of the transaction price that is attributable to the aggregate market trend. The R square of the pooled regression is 47%. We take the pricing residual $\varepsilon_{i,j,t}$ from equation (2) as our estimate of $\widetilde{price}_{i,j,t}$ for the office property i in the market j at quarter t.

$$\ln(psf_{i,j,t}) = \beta_0 + \beta_1 \ln(age_{i,j,t}) + \beta_2 \ln(size_{i,j,t}) + \beta_t + \varepsilon_{i,j,t} \tag{2}$$

The intuition of the price impact measure is the following. $\lambda_{j,t}$ measures the extent to which a given level of trading activity affects the absolute price change in the market. A liquid market with a low price impact is one in which prices do not move quickly in response to large trading volume. The larger the average price deviation conditional on the same level of trading activity, the bigger the mismatch between supply and demand, and the higher λ in the market at that time.

It is important to note that the limited set of explanatory variables (and R square) in equation (2) is not limitation of our pricing equation, as it is not meant to capture the hedonic determinants of office properties prices. The purpose of the estimation is to remove persistent time trends in prices given our low frequency observations, and is to control for the most salient differences in building attributes (such as age and size) to allow a meaningful measure of aggregate price and return. The residual estimate of $\widehat{price}_{i,J,t}$ should be interpreted as the de-trended office price of building i in MSA j at quarter t, controlling for size and age. We allow our estimate of $\widehat{price}_{i,J,t}$ to be a function of other property- or sale-specific attributes that may reflect liquidity of the transaction. This facilitates our identification of the liquidity measures, which are computed based on the estimated $\widehat{price}_{i,J,t}$. It also allows the subsequent empirical tests of the pricing of illiquidity based on changes in these prices.

The unique institutional features of the commercial real estate market make it ideal to identify search inefficiencies. Large, institutional investors trade commercial properties in a segmented market: typically they target larger, high quality, high-value properties. These investors are well-informed about the properties on the market, and the transactions are often taken place via auctions. In contrast, small, retail investors are more restricted in the smaller, no-prime markets, and they have to engage in lengthy and costly search, much as in the residential real estate, to complete the transaction. Therefore, within the same geographical location, there are two types of office buildings that are subject to similar macroeconomic fundamentals (such as local income and unemployment) but differ dramatically in search costs.

Given such, search friction is defined to be the ratio of the price impact (λ) measure of the subset of the less search-efficient office properties in a particular geographic market and that of the submarket with the more search-efficient properties (Eqn. (3)). The idea is that,

conditional on the average level of supply and demand mismatch in a given market, the incremental price impact of the relatively search inefficient submarket compared to the search efficient submarket measures the pricing outcome of search frictions. Based on the industry convention, we define the class A and B office properties as the search-efficient properties, due to high visibility and information transparency and since institutional investors are the major players in this sub-market and the transaction process involves little search. Class C office properties tend to be smaller, less expensive properties traded by retail investors with significant search frictions. As a robustness, we also identify search- (in)efficient submarkets based on size (either dollar value or the physical size). Small properties arguably have higher search frictions than bigger properties due to lower visibility and match quality. The results are qualitatively the same.

$$search\ cost_{j,t} = \frac{\lambda_{j,t}^{high\ search\ cost\ submarket}}{\lambda_{j,t}^{low\ search\ cost\ submarket}} \equiv \frac{\lambda_{j,t}^{small}}{\lambda_{j,t}^{big}} \qquad (3)$$

The main advantage of the two proposed measures is their simplicity and availability. Price and volume information are always accessible in any standard real estate data and thus we circumvent the need to access TOM data, which, as we indicated, are in general not readily available. One can also model the price impact by estimating the latent supply and demand using a structural approach (e.g., Fisher, et al., 2003, 2004). In this paper, we take advantage of a salient feature of illiquidity in constructing our measures. Specifically, illiquidity leads to deviation of the transaction price from the asset's fundamental value, regardless of the underlying causes. This observation helps avoid the need to model directly the relevant determinants of illiquidity in real estate.

Our measures are alternative to traditional proxies in the real estate market such as trading volume (or TOM). Specifically, they offer a more relevant proxy for understanding the pricing implication of illiquidity. Firstly, as we stated, TOM is a(n endogenous) function of the final transaction price. For example, a distressed sale with a heavy discount may have a low TOM, which does not provide any information on the general search condition in the market at that time. More generally, research shows the tradeoff between TOM and the selling price, which is incorporated into a seller's optimal listing decision (Haurin et al., 2010). Similarly, a large trading volume that greatly affects the transaction price (e.g., a bulk of distress sales with heavy price discounts) does not imply a liquid market. This suggests that one needs to incorporate price impact in measuring liquidity. Secondly, realized TOM is a lagging indicator of the search efficiency in the market, and thus is less helpful in understanding the expected returns. An increase in the search friction is revealed in the TOM measure only after the properties are sold, which could be long after the original shock. Lastly, we introduce both price impact and search friction measures to distinguish the different aspects of illiquidity.

III. Data Description

A.   *Office market transaction data*

Our sample consists of 88,561 office property transactions over a 144-month period (from Jan. 2000 to December 2011) drawn from across 24 largest real estate markets in the United States that span 15 states: Arizona, California, Colorado, Florida, Georgia, Illinois, Massachusetts, Michigan, New Jersey, New York, Nevada, Oregon, Pennsylvania, Texas, Washington, plus the District of Columbia. The data used in this study come from CoStar COMPS, a proprietary database provided by the CoStar group (NASDAQ: CSGP).

Headquartered in Washington D.C., CoStar maintains the largest and most comprehensive database of commercial real estate information[7]. CoStar collects data on commercial real estate transactions by contacting buyers, sellers, and brokers. Each transaction is then researched and verified by CoStar professionals to ensure accuracy. We are unaware of any sample selection issues materially affecting the dataset[8].

We removed all transactions that are indicated as non-arm's length and deleted outliers of size and price per square foot for those in the bottom 1%. We exclude transactions that are historic sites or built-to-suit, those associated with condominiums conversions or assemblages, or sales that involved damage from natural disasters or building contamination.The original dataset contains a rich set of property-level hedonics as well as transaction-level information. However, coverage varies among these variables. For example, not surprisingly, listing information, appraisal value as well as TOM information is available for only a small subset of all the transactions. To ensure power and accuracy of our analysis, we restrict ourselves to variables with either no or few missing values. The only exception is TOM, which we still include for the purpose of comparing with our own liquidity proxies.

We also obtain macroeconomic variables from different sources. The annual real Gross Domestic Product per capita by Metropolitan area (*GMP*) is obtained from Bureau of Economic Analysis under U.S. Department of Commerce. Population density (*DENSITY*) at MSA level is retrieved from U.S. Census Bureau. The unemployment rate (*UNEMP*), obtained from Bureau of Labor Statistics under U.S. Department of Labor, is a quarterly percentage of unemployment rate at the applicable MSA. The average 30-year fixed rate mortgage (*MB30*), aggregated by the

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[7]CoStar is the #1 commercial real estate company in the U.S. and U.K. Its proprietary database covers more than two million properties and more than 37 billion square feet of inventory in all commercial property types and classes.
[8]Studies that use CoStar COMPS data include Benmelech, Garmaise, and Moskowitz (2005), Garmaise and Moskowitz (2004).

Mortgage Bankers Association of America is used to measure the nation-wide real estate financing cost[9]. *TIGHTEN*, the net percentage of banks tightening standards for commercial real estate loans is from the quarterly senior loan officer opinion survey on bank lending practices. The average capitalization rate (*CapRate*) is the ratio of property rental income net of operating expenses divided by the transaction price, from the office sales reported by Real Capital Analytics. *INVENTORY* is the total square footage of completed properties that are competitively rented [10]. *OverSupply*, calculated as amount of new space added to market inventory (construction completions) during the time period divided by net change in occupied space (absorption) during the same time period.

B. *Descriptive statistics*

Panel A of Table 1 presents summary statistics on the properties in our sample and some key variables used in the analysis. Unit sale prices of office buildings range from $10.39 per square feet to $5,416.67 per square feet, while the average sale price per square feet is $174.18. Among 88,561 transactions that meet our data requirement, 35,243 sales contain information of the time-on-market (*TOM*), which is the numbers of days between the sale date of an office building and the date it is listed on the market.[11] The selection bias is a major issue for TOM, so we only use it as an indicative measure to compare with our liquidity proxies. Using the available information, the average marketing time for an office building is 263.53 days. The *Building Age* variable is computed as the difference between the property's built year and year it

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[9] We use the *MB30*, a key rate used in deciding mortgage rates for home buyers as the benchmark for the real estate market condition. Commercial mortgages are normally risker and of shorter term. However we don't access to the information of commercial mortgages rate.

[10] Owner-occupied, medical office buildings and buildings under construction are excluded from the inventory.

[11] We winsorize TOM at the top 1% tail.

is sold. The average building age is 34.79 years with standard deviation of 30.70 years.[12] The *Building Size*, measured as the total square footage of gross building area, varies significantly in the sample with a mean of 27,443 square feet[13]. The largest office building is about 3,781,045 square feet, while the smallest office space sold is only about eight hundred square feet. *Class A* is a dummy variable with a value of 1 if the property is a class A office building and 0 otherwise. Class A buildings are investment-grade properties that command the highest rents and sales prices in a particular market.

[Insert Table 1 about here]

We further create several dummy variables indicating atypical sale conditions: *Auction* is a dummy variable equal to 1 if the property is sold via auction and 0 otherwise; *Distressed Sale* is a dummy variable equal to 1 if the property is sold as a distressed property and 0 otherwise, *1031 Exchange* is a dummy variable equal to 1 if the property is sold as tax-deferred (1031 exchange) transaction and 0 otherwise, *High Vacancy* is a dummy variable equal to 1 if the property's vacancy rate is greater than 18% (sample median) or if the seller indicated that the property is of a high vacancy condition, *Tenant Purchase* is a dummy variable equal to 1 if the property is purchased by a current tenant and 0 otherwise, *Out of State Buyer* is a dummy variable equal to 1 if the property is sold to an out-of -state (sometimes out-of-country) buyer. The above atypical sale conditions are not mutually exclusive.

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[12] We treat the building age as zero, if the office building is sold in the same year or before the year it is built.

[13] Because size is one of the most important building characteristics in commercial real estate valuation, we try to verify and retrieve the size information as much as possible. If size variable in CoStar dataset is missing or erroneous, we use the ratio of sale price over price per square feet. If price per square feet is missing or erroneous, we compute the size using the product of number of floors and typical floor size. If none of the above information available, we approximate the building size using land area size.

Panel B of Table 1 shows the number and percentage of transactions by market to illustrate the geographical coverage of the data. Ranked by the total number of sales from 2000 to 2011, the sample includes 88,5361 office building sales in 24 largest real estate markets: New York Metro[14], Los Angeles, Chicago, Washington D.C., South Florida, Phoenix, Atlanta, Denver, Philadelphia, Boston, Seattle/Puget Sound, Tampa/St Petersburg, Orlando, Orange (California), San Diego, Sacramento, Portland, East Bay/Oakland, Dallas/Ft Worth, Detroit, Inland Empire (California), Las Vegas, South Bay/San Jose, and San Francisco. The top three markets: New York Metro (7,766 transactions), Los Angeles (6,046 transactions), and South Florida (5,122 transactions) account for a quarter of the sales in the sample, while the smallest market in the sample is San Francisco with 1,101 transactions. To reduce the influence of small sample bias and ensure robustness of our results, we remove market-quarters that have fewer than 10 transactions from the main analysis.

IV. Empirical Findings

A.   Empirical Estimates of λ and Search Friction

We estimate the hedonic pricing model in (2) in the pooled sample to obtain an estimate of $\widehat{price}_{i,J,t}$ and the quarterly price $P_{j,t}$ for market j at quarter t (by averaging $\widehat{price}_{i,J,t}$ across all transactions for market j at quarter t). Next, for each of the 24 office markets, we compute the price impact (λ) and search friction measures according to (1) and (3) for each quarter from 2001:Q1 to 2011:Q4.[15] Outliers of λ and search friction, defined to be the upper and lower 1%

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[14] The New York Metro market includes New York City, Northern New Jersey and Long Island.
[15] In the main analysis, we restrict our sample to post-2000 due to a more comprehensive coverage of markets of Costar after 2000.

tails, are winsorized. The values of both variables are roughly between 0.1 and 3 for all the markets in our sample period.

Before we study the pricing implication of illiquidity, we first investigate the time-series as well as cross-sectional properties of those measures. Table 2 provides annual time series of quarterly average statistics of common proxies of liquidity and price per square foot in the sample. The average price per square foot of transacted office properties in 24 markets, measured as dollar per square foot, has increased steadily since 1995. It peaks in 2007 and decreases afterwards. Both λ and search friction move over time but with a different pattern. In aggregate, price impact is high at the beginning of the sample period, reaches the bottom in 2007, and increases afterwards reaching the highest level after the 2008 crisis. This co-moves (negatively) with the aggregate price trend. The search friction is also high in the early sample period which decreases afterwards, but it also rises during the hot market period (2005-2007). At the beginning of the crisis (2008), search friction does not immediately increase but it is significantly higher in the period of 2009-2011.

[Insert Table 2 about here]

We further look into the cross-sectional variation in the time series pattern in Table 2. Figure 1 plots price and liquidity dynamics over time in Los Angeles, New York Metro, Dallas and Detroit markets. While there is commonality in the liquidity trends over time, both λ and search friction exhibit cross-sectional variation across different markets. For example, there is a much smaller increase in price impact in the New York metro market during the 2008 crisis, compared with the Los Angeles market. On the other hand, New York experienced a serious demand shock and high search frictions in the beginning of the sample period, resulting in a very

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high value of λ, search friction and abnormally low trading volume. For the less metropolitan markets such as Detroit and Dallas, the price impact and search friction series are much more volatile, and they in general have a higher search friction measure than either Los Angeles or New York Metro market.

[Insert Figure 1 about here]

B.   Are the proposed liquidity proxies measuring liquidity in the real estate market?

We answer the question by examining the cross-sectional and time-series correlation between our liquidity proxies and the variables that are shown to be related to the various liquidity aspects.

Existing literature suggests several variables that are correlated with search frictions and demand shocks. Campbell et al. (2010) suggest that distressed sales incur large price discounts, reflecting the impact of illiquidity via supply-demand imbalance and search inefficiency in the housing market. Turnbull and Sirmans (1993) find that out-of-state buyers pay a premium largely due to high search frictions. Ling and Petrova (2010) suggest three sale conditions that imply high search frictions in the commercial real estate market: tax-deferred (1031 exchange) transaction, distressed sale and purchase by out-of-state buyers find consistent evidence. Turnbull et al. (2010) show the vacancy effects on search friction and sale prices.

[Insert Table 3 about here]

Table 3 Panel A reports time series average of cross-sectional pairwise Pearson correlation coefficients among liquidity proxies and the market-specific and trade condition variables obtained in our data at the quarterly level. The simple univariate exercise suggests that our price impact and search friction measures are overall consistent with known proxies

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suggested by the literature. λ is positively correlated the proportion of distress sales, tax-deferred transactions, high vacancy buildings and tenant purchases in the market and negatively correlated with the proportion of out-of-state buyers in the market as well as volume and average transaction price. The search friction measure is positively related to TOM, high vacancy properties and purchases by out-of-state buyers. It is negatively correlated with the proportion of tenant purchases. In addition, λ and search friction is negatively correlated, suggesting that they capture independent illiquidity aspects in the office market. In particular, the result that search friction is positively correlated with transaction price and volume suggests that search friction is significantly manifested in the "hot" market conditions, whereas price impact is more related to bad market conditions.

Table 4 examines the performance of various liquidity proxies in a multivariate regression framework in the pooled sample. The multivariate results in general confirm the findings in Table 3. λ is significantly positively correlated with the proportion of distress sales and tenant purchases, and is negatively related with the proportion of tax-deferred exchange transactions (Panel A). The search friction measure is significantly positively correlated with high vacancy sales, out-of-state-buyer purchases, while it is negatively correlated with the proportion of tenant purchases. Search friction is also positively correlated with the proportion of tax-deferred exchange transactions, but it is not statistically significant.

[Insert Table 4 about here]

We run similar regressions using transaction volume and TOM as dependent variables (columns 3-4 of Panel A, Table 4). Transaction volume is in general not related to known proxies for illiquidity in the regression. There is a positive relationship between time on the market

(TOM) with the proportion of distress sales and out-of-state sales. However, TOM is also significantly negatively correlated with the proportion of tax-deferred exchange transactions, which is inconsistent with the prior literature that suggests that tax-deferred exchange transactions typically incur higher search costs.

We also control for volume and TOM in evaluating the independent effects of our liquidity proxies (column 5-6 of Panel A, Table 4). Our price impact (search friction) measure is negatively (positively) correlated with transaction volume (TOM). In addition, previous results still hold and remain strong. Taken together, these findings suggest that our proposed price impact and search friction are reasonable liquidity proxies. Furthermore, they capture beyond what is contained in the transaction volume and TOM. For example, a greater proportion of distress sales in a market at a given quarter is associated with a higher price impact, an insight shared by Campbell, et al. (2009). However, volume has an insignificantly positive relationship with the proportion of distress sales.

C   Price Impact, Search Friction and Macroeconomic Conditions

Next, we investigate how our price impact and search friction variables are correlated with the macroeconomic variables. We also use the aggregate statistics on the commercial real estate market conditions as an out-of-sample test of our findings in Panel A of Table 3 and 4. Panel B of Table 3 reports the simple correlation statistics between our liquidity measures and macroeconomic variables. Price impact, λ, is negatively correlated with local GMP, suggesting that liquidity is low resulting in a high price impact when the local market has low productivity. Similarly, a high price impact is associated with a high unemployment rate, high cap rate, a tighter lending standard, or a lower interest rate. Our price impact is also positively correlated

with high vacancy and negatively correlated with total trading volume in that local area, which confirm our in-sample finding in Panel A of Table 3.

Search friction is strongly negatively related to population density, consistent with traditional search theory. It is positively correlated with GMP, total trading volume and negatively correlated with unemployment and cap rate, suggesting that search frictions can be relevant in good economic conditions. For example, in "hot" markets, there are more buyers in the market and the seller's option value of waiting for a more attractive offer is higher, resulting in a less efficient searching and matching outcome (Novy-Marx, 2009).

In Panel B of Table 4, we carry out multivariate regressions. In columns (1)-(2), we regress our liquidity measures on macroeconomic variables (at the national level). In columns (3)-(4), we regress liquidity measures on the commercial real estate market-specific variables (at the market level). Results are qualitatively the same as the simple correlation statistics in Panel B of Table 3. Price impact is strongly negatively correlated with local GMP, total trading volume, and is positively correlated with unemployment rate, funding/lending availability and high vacancy. Similarly, search friction is strongly negatively correlated with population density, interest rate and cap rate. Coefficients on other variables are statistically insignificant.

D   The Relationship Between Expected Return and Illiquidity in the Office Market

Next we study whether the illiquidity level is priced in the expected returns in the office market in the U.S. We perform Fama-Macbeth regressions and the dependent variable is the one-quarter-ahead change in price as measured by the average transaction price (after de-trending and controlling for age and size, i.e., $\epsilon_{i,j,t}$ from Equation (2)). All liquidity variables are in logs. We also include the macro variables as control variables in columns (4)-(6) of Table 5.

High λ this quarter leads to a positive return over the next quarter, with or without controlling for the macroeconomic variables (Table 5). The effects are statistically significant at the 5% level. To interpret, a 10% increase in λ is associated with an increase in 10 basis points over the next quarter. In contrast, in the full sample of the office market, search friction does not seem to be relevant for the average office building prices, as a high search friction this quarter is not associated with the return in the subsequent quarter, with or without controlling for the macroeconomic variables.

E   Illiquidity Premium in the Normal versus Down Markets

The existing evidence in the literature points to a strong positive relationship between price impact and future returns, and results in Table 5 lend further support to the illiquidity-expected return relationship in the context of real estate. We next investigate whether the liquidity premium is particularly relevant in some periods or market conditions rather than others. A priori, illiquidity premium varies over time and is a function of the market conditions. In the real estate market, it is a general phenomenon that liquidity tends to dry up in crashes or in downturns (Stein, 1995; Krainer, 2001; Qian, 2012). Recent literature suggests that liquidity is more valuable in such times and extra compensation is required (Mitchell et al., 2007; Brunnermeier and Pedersen, 2009; Hameed et al., 2010; Brennan, et al., 2012).

We investigate the implication of illiquidity premium in different market conditions in Table 6. We create a dummy, *Down Market,* that is equal to one if the quarterly return of a market at quarter *t* is negative. By using zero return as the cut-off, our down market proxy is less subject to a look-ahead bias, compared to other thresholds based on the in-sample return

distribution. We interact our liquidity proxies with the down market dummies and repeat the analysis as in Table 5.

[Insert Table 6 about here]

Results in Table 6 present strong evidence consistent with our hypothesis. The premium associated with the price impact measure is driven by the down market. In the down market, a 10% increase in λ leads to a return increase of 26bps over the next quarter (statistically significant at the 1% level), which translates into 0.84% excess returns per annum. On the other hand, search friction proxy remains to have little predictive power on subsequent quarter returns in the full sample of office properties, regardless of down market or not.

F   Investment Grade versus Non-Investment Grade

As argued earlier, search friction is primarily relevant for the submarket where retail investors are the major players. Therefore, *ex ante,* one should the search friction measure to be priced in that submarket (instead of the full sample of office properties). In this subsection, we study the cross-sectional difference in the illiquidity premium associated with both search friction and price impact among different subsets of the office properties. We divide the market into Class A/B and Class C office properties, and examine the illiquidity-expected return relationship for the two sub-markets respectively. Class A and Class B buildings are more of investment-grade properties with higher quality, higher price and a larger institutional investor concentration. Class C buildings are typically smaller, cheaper and retail-investor-oriented. The dependent variable is the one-quarter-ahead return based on the average transaction price per square foot ($\epsilon_{i,j,t}$ from Equation (2)) for the two submarkets within the same geographic market j at time t respectively.

[Insert Table 7]

In all time periods, we continue to observe that price impact predicts the one-quarter-head return, as in Table 5 and 6 (Panel A of Table 7). However, the predictive power is driven by the positive relationship between price impact and future return in the investment grade properties. On the other hand, in the non-investment grade submarket, the positive relationship between price impact and future return is statistically insignificant. However, for that submarket, search friction plays an important role in pricing the office buildings, consistent with the notion that search friction is concentrated in the non-investment grade buildings. A 10% higher search friction is associated with 8 bps higher return over the next quarter in the non-investment grade submarket.

In Panel B of Table 7, we interact the liquidity measures with the down market dummy in the submarket analysis. The search premium for the non-investment grade properties is concentrated in the down market. In addition, price impact is priced in the non-investment grade properties in distress market times (column (2) and (4)). More interestingly, for the investment grade submarket in which liquidity is comparatively higher, the one-quarter-ahead return is more negative when the overall office market in that area experiences a shock in search frictions. In addition, during the down market, a price impact does not predict a higher return over the next quarter for the investment grade properties. Taken together, this set of results are consistent with the notion of flight-to-quality (-liquidity) in the 2008 crisis (e.g., Acharya et al., 2010) in the office market. It suggests that, during market downturns, investors flood to the submarket with better liquidity (i.e., lower price impact and little search frictions on average) and thus pay a price (liquidity) premium for the more liquid submarket.

V. Concluding Remarks

We examine the pricing implication of illiquidity in a very illiquid market—real estate. Specifically, transactions in this market occur over-the-counter with costly search and bilateral bargaining. Direct measures of illiquidity are unavailable due to low transaction frequency and data quality issues. We compute two indirect illiquidity measures from transaction price and volume data. The first illiquidity proxy measures price impact, and the second illiquidity proxy measures the search friction that is a significant source of illiquidity in this market.

Using a national sample of transactions in 24 major office markets in the U.S. from 2000 to 2011, we show that illiquidity is an important determinant of expected returns in commercial real estate. The conventional illiquidity measure, price impact, is strongly priced in the market. Search frictions, on the other hand, are also associated with future returns in the submarket with costly search. The illiquidity premium is stronger in market downturns. Moreover, we find evidence consistent with a flight-to-quality effect during the down markets. Specifically, at such times, investors are willing to pay a higher price for more liquid properties in the investment-trade submarket, while requiring a higher price discount in the less liquid, non-investment grade submarket.

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Table 1. Summary Statistics

Panel A of this table provides summary statistics of the hedonic and sale-condition dummy variables used in the study, and Panel B provides the geographic distribution of data (market is defined by the data provider CoStar COMPS). The sample covers 24 office markets in the U.S. from 2000:Q1 to 2011:Q4. *Price per s.f.* is sale price per square foot, *TOM* is time on market in days, *Building Age* is the number of years between the building's sale date and its built year, *Building Size* is total square foot of building space, *Auction* is a dummy variable with value of 1 if the property is sold via auction and 0 otherwise; *Distressed Sale* is a dummy variable with value of 1 if the property is sold as a distressed property and 0 otherwise, *1031 Exchange* is a dummy variable with value of 1 if the property is sold as tax-deferred (1031 exchange) transaction and 0 otherwise, *High Vacancy* is a dummy variable with value of 1 if the property's vacancy rate is greater than 18% (sample median) or the seller indicated that the property is of a high vacancy condition , *Tenant Purchase* is a dummy variable with value of 1 if the property is purchased by a current tenant and 0 otherwise, *Out of State Buyer* is a dummy variable with value of 1 if the property is sold to an out of -state (sometimes out-of-country) buyer, *Class A* is a dummy variable with value of 1 if the property is a class A office building and 0 otherwise. Small buildings are defined to be those below the market-specific median of the size distribution.

Panel A

Variables	N	Mean	StdDev	Min	Max
Price per s.f. ($)	84,069	174.178	140.34	10.39	5,4016.67
TOM (day)	35,243	263.53	301.42	1	1,111
Building Age (year)	79,510	34.79	30.70	0	291
Building Size (s.f.)	88,561	27,443	84,7332	842	3,781,045
Class A (%)	88,561	6.27	N.A.	0	1
Distressed Sale (%)	88,561	2.84	N.A.	0	1
1031 Exchange (%)	88,561	6.47	N.A.	0	1
High Vacancy (%)	88,561	8.60	N.A.	0	1
Tenant Purchase (%)	88,561	2.20	N.A.	0	1
Out of State Buyer (%)	88,561	14.76	N.A.	0	1

Panel B

Location	N	%	Location	N	%
New York Metro	7,766	8.77	Seattle/Puget Sound	2,348	2.65
Los Angeles	6,046	6.83	Orange (CA)	2,209	2.49
South Florida	5,122	5.78	San Diego	2,203	2.49
Phoenix	4,645	5.24	Dallas	2,049	2.31
Chicago	4,642	5.24	Detroit	1,980	2.24
Philadelphia	4,433	5.01	Sacramento	1,933	2.18
Atlanta	4,200	4.74	Inland Empire (CA)	1,868	2.11
Washington D.C.	4,000	4.52	Las Vegas	1,801	2.03
Denver	3,688	4.16	East Bay/Oakland	1,733	1.96
Tampa/St Petersburg	3,189	3.60	Portland	1,703	1.92
Boston	2,922	3.30	South Bay/San Jose	1,320	1.49
Orlando	2,448	2.76	San Francisco	1,101	1.24
Total				88,561	100

Table 2. Time Series Pattern of Price and Illiquidity proxies

This table provides annual time series of quarterly average statistics of common proxies of liquidity and price per square foot in the commercial real estate market. The sample covers 24 office markets in the US from 2000:Q1 to 2011:Q4. λ_t is our estimated price impact measure in each market at quarter t(Equation(1)), and Search friction$_t$ is our estimated search friction measure in each market at quarter t(Equation (3)). Our two liquidity measures are winsorized at the 1% and 99% level. TOM$_t$ is the average time on the market in each office market at quarter t, Volume$_t$ is the total transaction volume in each market at quarter t.

Year	λ (Basis Points)	Search Friction	Volume	TOM	PSF
2000	31.674	34.16	44.94	177.56	120.70
2001	35.596	21.54	42.04	173.85	144.10
2002	29.958	15.21	47.58	110.11	136.61
2003	26.777	11.45	50.89	158.94	144.12
2004	21.325	27.21	60.11	128.05	149.91
2005	15.652	42.47	53.55	177.39	178.34
2006	13.389	26.94	56.08	199.43	179.23
2007	10.788	34.70	66.90	249.38	206.36
2008	20.251	19.43	56.35	297.81	205.03
2009	46.104	21.81	40.01	311.14	162.91
2010	44.099	42.38	49.41	324.36	155.49
2011	51.519	44.63	61.11	461.41	134.84

Table 3.Correlation statistics of key variables at the market quarter level

This table provides correlations statistics. Panel A reports the time series average of the cross-sectional pairwise Pearson correlation coefficients between our liquidity measures and the average market and property characteristics/price in our data, and Panel B reports the correlation between our liquidity measures and the macroeconomic variables (either at the federal or at the market level). The sample covers 24 office markets in the US from 2000:Q1 to 2011:Q4. λ_t is our estimated price impact measure (from Equation (1)) in each market at quarter t, and $Search\ friction_t$ is our estimated search friction measure (from Equation (3)) in each market at quarter t. TOM_t is the average time on the market in each office market at quarter t, $Volume_t$ is the total transaction volume in each market at quarter t, $Distress\ Sale_t$ is the percentage of distress sales at quarter t, $1031\ Exchange_t$ is the percentage of sales involving 1031 exchange terms, $High\ Vacancy_t$ is the percentage of sales of high vacancy properties, $Tenant\ Purchase_t$ is the percentage of transactions with tenant buyers and $Out\ of\ State\ Buyer_t$ is the percentage of transactions with out-of-state buyers. GMP is real Gross Domestic Product per capita by Metropolitan area. $DENSITY$ is the Population density at the MSA. UNEMP is a quarterly percentage of unemployment rate at the applicable MSA. $MB30$ is average 30-year fixed rate mortgage rate. $TIGHTEN$ is the net percentage of banks tightening standards for commercial real estate loans is from the quarterly senior loan officer opinion survey on bank lending practices. $CapRate$ is the average capitalization rate office sales reported by Real Capital Analytics. $OverSupply$, calculated as amount of new space added to market inventory divided by net change in occupied space (absorption) during the same time period.

Panel A

	λ_t	$Search\ Friction_t$	TOM_t	$Volume_t$	PSF_t	$Distress\ Sale_t$	$1031\ Exchange_t$	$High\ Vacancy_t$	$Tenant\ Purchase_t$	$Out\ of\ State\ Buyer_t$
λ_t	1.00									
$Search\ Friction_t$	-0.24	1.00								
TOM_t	0.03	0.023	1.00							
$Volume_t$	-0.67	0.16	0.07	1.00						
PSF_t	-0.13	0.05	-0.05	0.08	1.00					
$Distress\ Sale_{t\,t}$	0.01	0.02	-0.01	0.03	-0.13	1.00				
$1031\ Exchange_t$	0.02	-0.04	-0.24	-0.14	-0.04	-0.00	1.00			
$High\ Vacancy_t$	0.02	0.13	0.01	-0.06	-0.01	0.09	0.07	1.00		
$Tenant\ Purchase_t$	0.08	-0.07	-0.00	-0.09	-0.04	-0.04	0.09	0.00	1.00	
$Out\ of\ State\ Buyer_t$	-0.09	0.24	0.13	0.08	0.06	-0.02	-0.17	0.08	-0.09	1.00

Panel B

	λ	Search Friction	GMP	DENSITY	UNEMP	VOLUME	CapRate	TIGHTEN	OverSupply	MB30
λ	1									
Search Friction	-0.08	1								
GMP	-0.23	0.06	1							
DENSITY	-0.11	-0.11	0.06	1						
UNEMP	0.28	0.00	-0.18	0.14	1					
VOLUME	-0.40	0.12	0.46	0.10	-0.35	1				
CapRate	0.17	-0.08	-0.25	0.02	0.07	-0.40	1			
TIGHTEN	0.02	-0.07	-0.01	0.00	0.21	-0.19	-0.01	1		
OverSupply	0.00	0.04	-0.11	-0.08	0.00	0.04	-0.06	0.00	1	
MB30	-0.11	-0.03	-0.01	-0.06	-0.65	0.16	0.13	0.15	0.00	1

Table 4: Evaluation of Price Impact and Search Friction Proxies

This table evaluates measures of liquidity by examining their relationship with common proxies of liquidity in the commercial real estate market (Panel A) as well as macroeconomic variables (Panel B). The sample covers 24 office markets in the US from 2000:Q1 to 2011:Q4. All liquidity variables are in logs. Please refer to Table 3 for variable definitions. Standard error is clustered at the market level and the associated t statistics are included in the parenthesis. *, **, *** refer to statistical significance at the 10%, 5% and 1% level.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
	λ_t	$Search\ Friction_t$	TOM_t	$Volume_t$	λ_t	$Search\ Friction_t$
TOM_t					0.326***	0.016
					(3.99)	(0.12)
$Volume_t$					-	0.448***
					1.758***	
					(-15.40)	(3.91)
$Distress\ Sale_t$	4.076***	0.088	2.156***	0.221	3.770***	-0.043
	(3.39)	(0.09)	(5.92)	(0.44)	(5.76)	(-0.05)
$1031\ Exchange_t$	-0.122	0.018	-	-1.014	-1.254**	0.517
			1.944***			
	(-0.09)	(0.02)	(-9.93)	(-1.63)	(-2.58)	(0.66)
$High\ Vacancy_t$	-0.010	4.371***	0.161	-0.580	-1.121	4.652***
	(-0.01)	(4.45)	(0.73)	(-0.86)	(-1.33)	(4.91)
$Tenant\ Purchase_t$	7.293***	-4.765***	0.210	-	2.438***	-3.546**
				2.813***		
	(5.20)	(-3.12)	(0.51)	(-4.49)	(2.99)	(-2.24)
$Out\ of\ State\ Buyer_t$	-0.716	2.898***	0.900***	0.279	-0.505	2.779***
	(-0.83)	(3.98)	(7.58)	(0.81)	(-0.97)	(3.77)
Constant	-	0.653***	5.241***	3.848***	-	-1.17
	7.438***				2.383***	
	(-19.25)	(3.81)	(105.02)	(21.20)	(-3.80)	(-1.27)
Observations	1645	1622	1682	1683	1644	1621
R-squared	0.04	0.09	0.33	0.05	0.48	0.11

Panel B

	(1) λ_t	(2) *Search Friction*$_t$	(4) λ_t	(5) *Search Friction*$_t$
GMP_t	-2.478*	0.605		
	(-1.99)	(0.71)		
$DENSITY_t$	-0.202	-0.470***		
	(-0.56)	(-2.94)		
$UNEMP_t$	0.172**	-0.091		
	(2.61)	(-1.60)		
$MB30_t$	-0.035	-0.334**		
	(-0.24)	(-2.25)		
$TIGHTEN_t$	0.004*	-0.000		
	(1.72)	(-0.12)		
$Volume_t$			-0.585***	0.365***
			(-5.30)	(3.76)
$CapRate_t$			-1.509	-15.319**
			(-0.26)	(-2.65)
$OverSupply_t$			-0.001*	0.001**
			(-1.88)	(3.73)
$High\,Vacancy_t$			0.093***	0.050
			(4.76)	(1.37)
Constant	19.638	0.442	8.724***	-4.740**
	(1.40)	(0.04)	(3.46)	(-1.03)
Observations	1177	1172	990	989
R-squared	0.14	0.04	0.36	0.07

Table 5.The Effect of Liquidity Measures on Quarterly Returns in the Office Market

This table studies whether the liquidity level is priced in the quarterly returns in the office market in the US. We perform Fama-Macbeth regressions in the sample of 24 office markets in the US from 2000:Q1 to 2011:Q4. All liquidity variables are in logs. The return variable is the quarterly change in the average trend-adjusted and characteristic-adjusted price (i.e., $\epsilon_{i,j,t}$ estimated from Equation (2) in each office market at quarter t).$\lambda_{t-1}$is our estimated price impact measure (from Equation (1)) in each market at quarter t-1, and Search Friction$_{t-1}$ is our estimated search friction measure (from Equation (3)) in each market at quarter t-1. Please refer to Table 3 for variable definitions of other explanatory variables. The associated t statistics are included in the parenthesis. *, **, *** refer to statistical significance at the 10%, 5% and 1% level.

VARIABLES	(1) Quarterly Return$_t$	(2) Quarterly Return$_t$	(3) Quarterly Return$_t$	(4) Quarterly Return$_t$	(5) Quarterly Return$_t$	(6) Quarterly Return$_t$
λ_{t-1}	0.010***		0.009***	0.009**		0.009*
	(3.08)		(2.91)	(2.22)		(2.04)
Search Friction$_{t-1}$		-0.000	0.001		-0.003	-0.002
		(-0.04)	(0.24)		(-1.23)	(-1.06)
GMP$_{t-1}$				-0.210	-0.375	-0.163
				(-0.80)	(-1.46)	(-0.66)
DENSITY$_{t-1}$				-0.520	-0.253	-0.552
				(-0.78)	(-0.38)	(-0.77)
UNEMP$_{t-1}$				-0.001	-0.002	-0.001
				(-0.14)	(-0.27)	(-0.16)
MB30$_{t-1}$				0.007	0.005	0.006
				(0.65)	(0.49)	(0.58)
Constant	0.057***	0.002	0.056***	5.999*	5.914*	5.735*
	(2.85)	(0.67)	(2.82)	(1.84)	(1.96)	(1.74)
Observations	1607	1585	1585	1177	1172	1172

Table 6: Liquidity Premium in the Normal versus Down Markets

This table studies the liquidity effect in explaining returns in normal versus down market conditions using Fama-Macbeth regressions. The sample covers 24 office markets in the US from 2000:Q1 to 2011:Q4. All liquidity variables are in logs. $Down\ Market_{t-1}$ is a dummy that takes 1 if the quarterly return (i.e., the quarterly change in detrended and characteristics-adjusted prices) for a market at quarter *t-1* is negative. Please refer to Table 3 for definitions of the rest of the variables. The associated t statistics are included in the parenthesis. *, **, *** refer to statistical significance at the 10%, 5% and 1% level.

	(1) Quarterly Return$_t$	(2) Quarterly Return$_t$	(3) Quarterly Return$_t$
$Down\ Market_{t-1}$	0.448***	0.121***	0.451***
	(9.92)	(12.03)	(9.36)
λ_{t-1}	-0.020***		-0.019**
	(2.97)		(2.53)
$Search\ Friction_{t-1}$		0.004	0.002
		(1.01)	(0.54)
$Down\ Market_{t-1} \times \lambda_{t-1}$	0.046***		0.047***
	(7.39)		(6.66)
$Down\ Market_{t-1} \times$ $Search\ Friction_{t-1}$		-0.010*	-0.004
		(-1.97)	(-0.66)
GMP_{t-1}	-0.131	-0.545	-0.325
	(-0.43)	(-1.44)	(-0.93)
$DENSITY_{t-1}$	-0.923	0.237	-0.378
	(-1.20)	(0.27)	(-0.40)
$UNEMP_{t-1}$	0.003	-0.003	0.001
	(0.37)	(-0.28)	(0.13)
$MB30_{t-1}$	0.005	0.005	0.006
	(0.45)	(0.43)	(0.48)
Constant	7.535*	4.214	5.941
	(1.96)	(1.04)	(1.37)
Observations	1177	1172	1172

Table 7. Liquidity Premiums: Investment Grade versus Non-Investment Grade Office Markets

This table studies the liquidity effect in explaining returns in Class A/B versus Class C properties using Fama-Macbeth regressions. Panel A reports the full sample results, and Panel B reports the result by down market. The sample covers 24 office markets in the US from 2000:Q1 to 2011:Q4. All liquidity variables are in logs. For each market in each quarter, we create the average price (i.e., $\epsilon_{i,j,t}$ in Equation (2)) for Class A/B and Class C properties respectively, based on which we compute the return variables. Please refer to Table 3 for definitions of the rest of the variables. The associated t statistics are included in the parenthesis. *, **, *** refer to statistical significance at the 10%, 5% and 1% level.

Panel A

	(1) $Quarterly$ $Return_t$ Investment Grade	(2) $Quarterly$ $Return_t$ Non Investment Grade	(3) $Quarterly$ $Return_t$ Investment Grade	(4) $Quarterly$ $Return_t$ Non Investment Grade
λ_{t-1}	0.010**	0.008	0.011	0.006
	(2.08)	(1.61)	(1.64)	(0.77)
$Search\ Friction_{t-1}$	-0.005	0.008**	-0.009***	0.008*
	(-1.60)	(2.04)	(-2.88)	(1.99)
GMP_{t-1}			-0.054	-0.157
			(-0.16)	(-0.45)
$DENSITY_{t-1}$			-0.329	-0.529
			(-0.35)	(-0.74)
$UNEMP_{t-1}$			-0.008	0.004
			(-0.76)	(0.59)
$MB30_{t-1}$			0.001	0.009
			(0.09)	(0.79)
Constant	0.069**	0.036	3.355	5.261
	(2.23)	(1.21)	(0.67)	(1.16)
Observations	1582	1582	1172	1171

Panel B

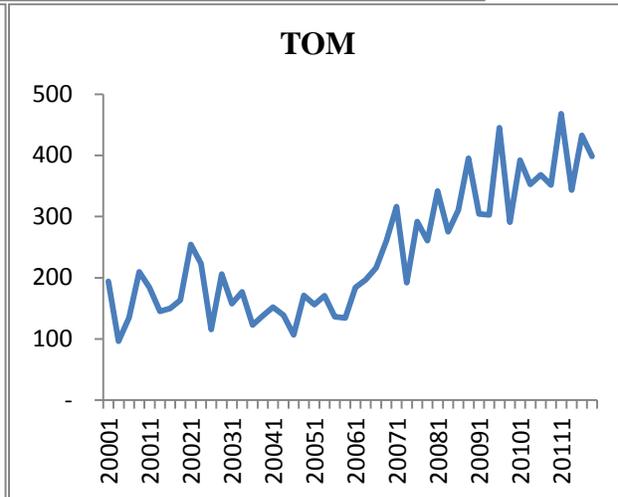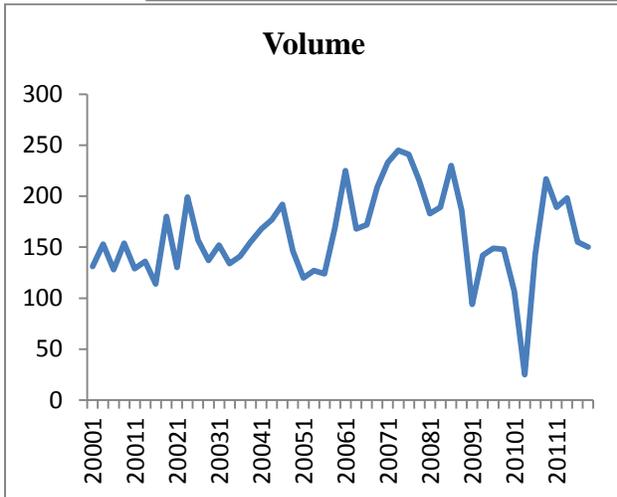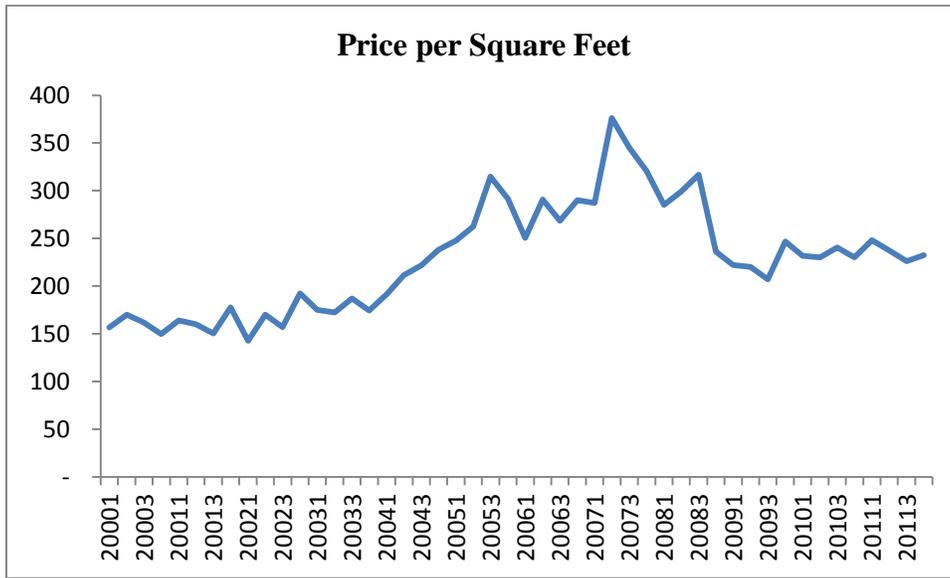|	(1) Quarterly Return$_t$	(2) Quarterly Return$_t$	(3) Quarterly Return$_t$	(4) Quarterly Return$_t$
	Investment Grade	**Non Investment Grade**	**Investment Grade**	**Non Investment Grade**
Down Market$_{t-1}$	0.312***	0.326***	0.349***	0.367***
	(4.28)	(5.23)	(4.02)	(4.13)
λ_{t-1}	0.002	-0.011	-0.004	-0.017
	(0.24)	(-1.60)	(-0.36)	(-1.36)
Down Market$_{t-1}$ × λ_{t-1}	0.014	0.034***	0.019	0.040***
	(1.23)	(3.82)	(1.54)	(3.13)
Search Friction$_{t-1}$	0.019***	-0.017**	0.010**	-0.024***
	(3.94)	(-2.48)	(2.31)	(-3.11)
Down Market$_{t-1}$ × *Search Friction$_{t-1}$*	-0.035***	0.042***	-0.030***	0.050***
	(-4.12)	(6.00)	(-4.03)	(5.55)
GMP$_{t-1}$			-0.517	0.157
			(-0.78)	(0.37)
DENSITY$_{t-1}$			0.993	-0.930
			(0.54)	(-1.08)
UNEMP$_{t-1}$			-0.010	0.014
			(-0.90)	(1.13)
MB30$_{t-1}$			0.000	0.013
			(0.01)	(0.83)
Constant	-0.116**	-0.138***	-1.031	4.202
	(-2.06)	(-2.97)	(-0.14)	(0.72)
Observations	1582	1582	1172	1171

Figure 1. Price and Liquidity Measures in Selected Office Markets

The figure plots the average transaction price (per square foot), trading volume, average TOM, λ, and search friction (estimated from equation (1) and (3)) in four selected markets: Los Angeles, New York Metro, Detroit and Dallas from 2000:Q1 to 2011:Q4.
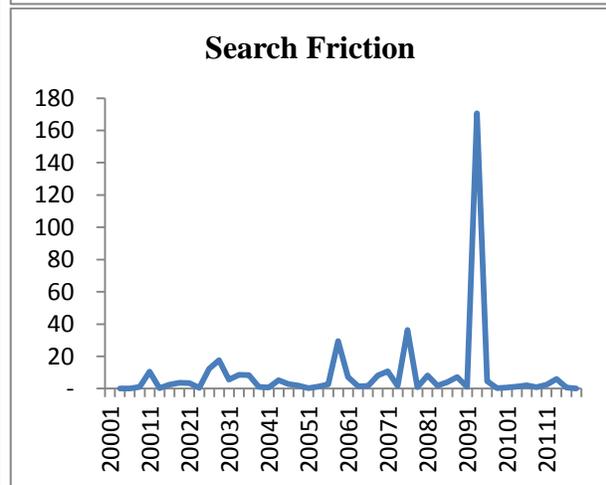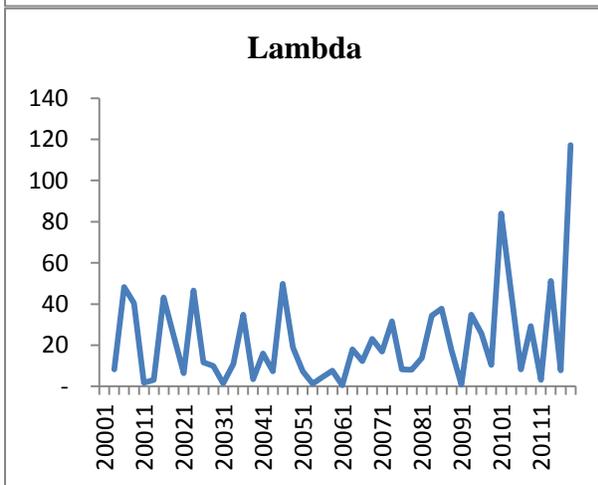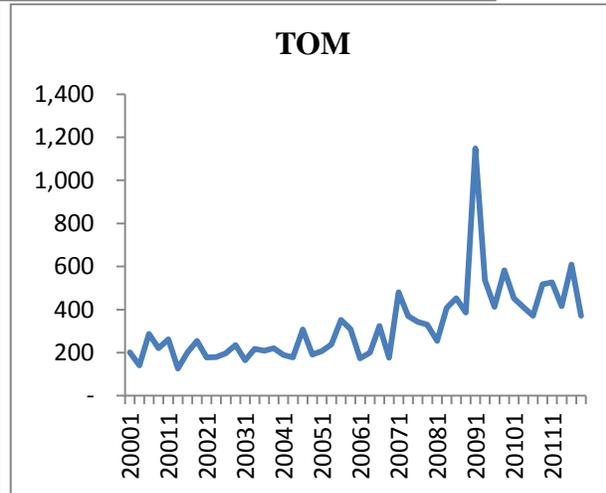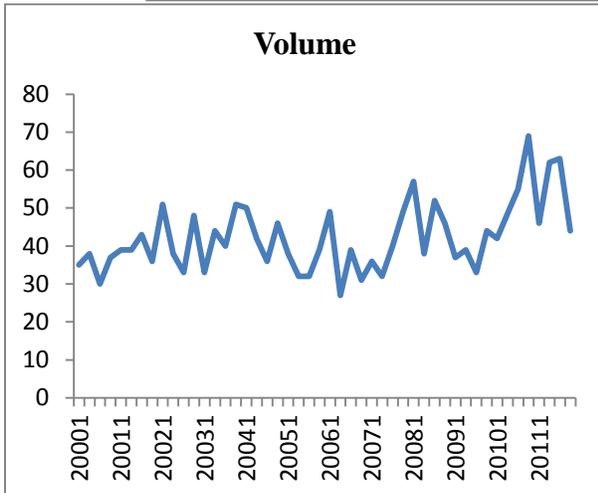
Panel A. Los Angeles
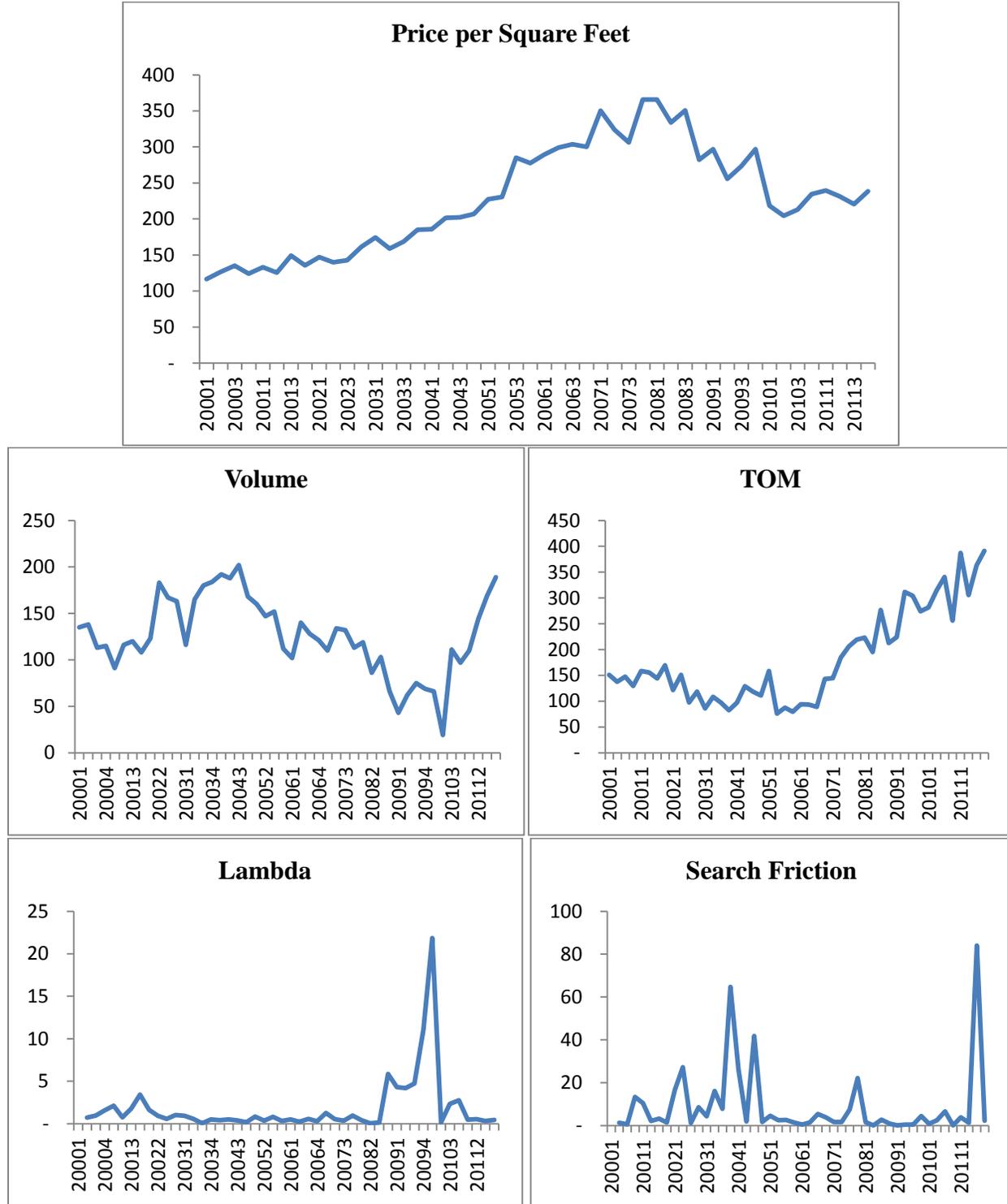
Panel B. New York Metro Area

Price per Square Feet

Volume

TOM

Lambda

Search Friction

Panel C. Detroit

Price per Square Feet

Volume

TOM

Lambda

Search Friction

Panel D. Dallas/Ft Worth

Price per Square Feet

Volume

TOM

Lambda

Search Friction