Time Variation of Liquidity in the Private Real Estate Market: An Empirical Investigation

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Abstract

This paper characterizes the behavior of and evaluates competing explanations for time variation in private real estate market liquidity. In the first, sellers base their estimates of value on observations of signals from the market. The second incorporates the option value of waiting or the opportunity cost of not transacting into seller's optimal valuation strategy. In the third, we allow for the possibility of investors who are not fully rational in the sense that they trade on market sentiment and we link market-wide liquidity to investor sentiment. In this model, measures of aggregate liquidity act as an indicator of the relative presence (or absence) of sentiment-based traders in the market and therefore the divergence of asset price from fundamental value. Empirical findings are generally consistent with models of optimal valuation with rational updating and provide support for the opportunity cost approach.

> "The most important and perhaps obvious lesson from the recent market cycle, however, is the potentially awesome power of capital flows in the real estate industry. Ironically, the same could be said of the downturn in the early 1990s. Then, however, it was a lack of capital and liquidity that exacerbated the weak conditions in the physical space markets rather than the excess liquidity that has created distortions today."
>
> Charles Lowry, CEO, Prudential Real Estate Investors, 2004

Private real estate markets are characterized by a relative lack of liquidity, and the degree of liquidity can vary considerably over time. Strong (or "hot") markets with rising prices are characterized by both an increase in sales activity and a decrease in the average time-on-the-market required to sell a property. Conversely, falling (or "cold") markets typically exhibit a decrease in sales and a concomitant increase in average time-on-the-market. The relationship between market activity, liquidity, and prices has puzzled economists because it appears that property markets violate a fundamental tenet of economics; that prices adjust to equilibrate supply and demand. It seems that prices do not rise ‘‘enough’’ in up markets (resulting in increased sales) and do not fall ‘‘enough’’ and are downwardly rigid, in down markets (resulting in a decrease in sales).

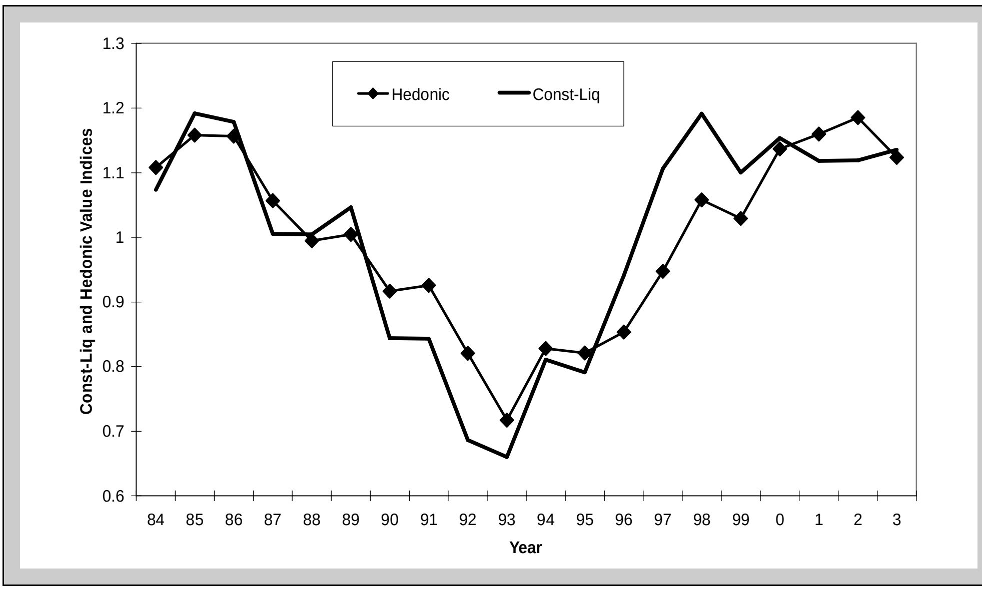
While widely understood as important, it is only recently that researchers have begun to formally model and empirically examine the dynamics of liquidity changes over time and the resulting effects on commercial property prices. Fisher, Gatzlaff, Geltner, and Haurin (2003), hereafter FGGH (2003), present a search-theoretic model of property transactions and pricing that explicitly recognizes that observed transaction prices are conditional on overall market liquidity at the time of sale (i.e., price and liquidity are jointly determined). They define a ‘‘constant liquidity value’’ of a property, as the value assuming no change in the level of market transaction activity, and derive a constant liquidity version of the National Council of Real Estate Investment Fiduciaries (NCREIF) property value index. The difference between this and a hedonic value index, based on observed transaction prices that implicitly reflect time variation in liquidity, provides a calibration of commercial property liquidity. Exhibit 1a plots both the constant liquidity and hedonic versions derived from NCREIF transaction data. As one might expect, the two series move closely together overall with the constant liquidity index displaying wider swings over time. The differences are particularly pronounced in market upswings and downturns. Relative to the transaction-based index, the constant liquidity index falls further in the major downturn of the early 1990s and rises more in the late 1990s market upswing; clearly liquidity has a large impact on reported transaction prices in these two periods.[1]

Goetzmann and Peng (2006) show that transaction prices in markets for heterogeneous goods provide misleading measures of both the market demand and market supply when buyers and sellers have different valuations (i.e., reservation prices) for the underlying goods. Transaction prices and trading volume are jointly determined by the distributions of, as well as the spread between, buyers’ and sellers’ valuations. Price indices constructed with transaction prices, with information contained in trading volume ignored, do not track the mean of buyers’ valuations, the mean of sellers’ valuations, or even the average of the two means. They propose a reservation-conditional unbiased index that tracks the mean of buyers’ valuations, and a seller reserve ratio that tracks the spread between the mean of buyers’ valuations and the mean of seller’s valuations. By using both the unbiased index and the seller reserve ratio, both market demand and market supply is tracked. Their reservation-conditional unbiased index is economically equivalent to the constant-liquidity index by FGGH (2003), which tracks the mean of buyers’ reservation prices, and their seller reserve ratio can be used to construct another type of constant-liquidity index that tracks the mean of seller’s reservation prices (i.e., the market supply).

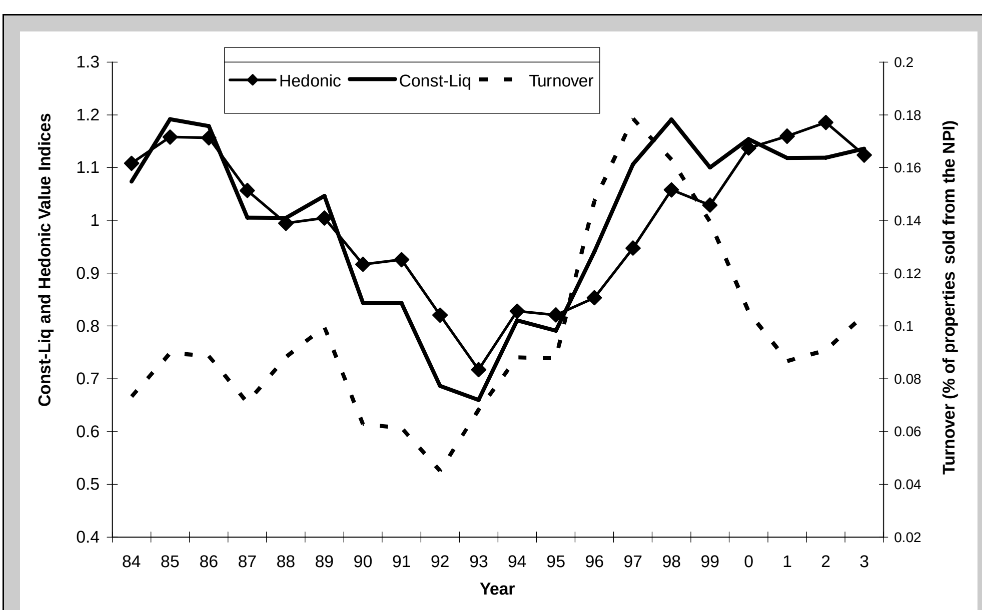
FGGH (2003) explain the positive relationship between price level and market activity within a search model in which changes in seller estimates of property value lag changes in buyer estimates. A slower relative reaction of sellers to

Exhibit 1 | Transaction-Based NCREIF Value Indices and Property Trading Activity, 1984–2003

(a) Hedonic (time-varying liquidity) and Constant Liquidity Value Indices



(b) Adding in Property Trading Activity (Turnover)



Notes: The hedonic (time-varying liquidity) index is derived from realized transaction prices of properties sold from the NCREIF Property Index (NPI). The constant liquidity (''Const-Liq'') index is derived from the same sample of transactions but utilizes an econometric approach to determine values assuming no change in liquidity. Both indices come from FGGH (2003), which develops the econometric procedure to produce the constant liquidity index. Property turnover data was provided by NCREIF, the National Council of Real Estate Investment Fiduciaries.

changing market conditions explains the relationship between prices and trading activity (liquidity). That is, in order for trading volume to be pro-cyclical to property prices, it must be the case that buyers respond more rapidly than sellers in updating property value estimates. FGGH (2003) do not directly explain why sellers would react more slowly than buyers to a change in market conditions. They take the observed relationship between market activity and price levels as given and structure a model consistent with that. It is our aim to dig a little deeper into the reasons underlying the differential response of buyer and seller distributions.

The goal of this paper is to provide new insights into the underlying causes of, or factors driving, time-variation in private market real estate liquidity.[2] More specifically, this paper empirically evaluates competing explanations of the time variation in private real estate market liquidity documented in FGGH (2003). We derive alternative testable hypotheses for why buyers respond more rapidly than sellers in updating property value estimates based on three different classes of models that have been proposed to understand the following: (1) time variation in liquidity in housing markets; (2) appraisal smoothing and the optimal valuation of noisy assets; and (3) commonality in, and intertemporal dynamics of, stock market liquidity. The essential elements and empirical implications of each are outlined below.

This phenomenon has received considerable academic attention as it relates to the owner-occupied housing market. The traditional explanation for sales activity decreasing with house prices has been a behavioral one with sellers ‘‘irrationally’’ refusing to recognize the decline in the value of their properties and continuing to list at higher than market values (Anglin, Rutherford, and Springer, 2003; and Case and Shiller, 2003). Time-on-the-market falls in hot markets because over-exuberant buyers have irrational house price expectations, formed by extrapolating recent price movements into the future rather than rationally considering the course of future market fundamentals (Case and Shiller, 2003). So-called ‘‘sellers’’ markets are characterized by abnormally high trading volumes, short marketing times (i.e., relatively high liquidity), and house price overshooting of intrinsic value.

Other researchers have offered rational explanations based on equity constraints and the dynamics of adjustment in housing consumption. For example, Stein (1995) and Ortalo-Magné and Rady (2006) develop models in which sales volume is pro-cyclical due to downpayment constraints and the market interaction between young credit-constrained households with older unconstrained households. Consistent with these models, Genesove and Mayer (1997) use sales data to show that seller reservation prices are affected by the loan-to-value ratio, while Lamont and Stein (1999) show that variations in price dynamics across metropolitan housing markets are related to differences in overall loan-to-value ratios across cities in a manner consistent with the model in Stein (1995). In a recent paper, Capozza, Hendershott, and Mack (2004) propose and test an empirical model of housing price dynamics that is similar to our approach but is concerned more with pricing than liquidity per se.

In considering whether these alternative explanations might carry over to income property markets, it is doubtful that either the behavioral-based downward price rigidity story, with sellers refusing to recognize a drop in house price, or the credit-constrained explanation will completely do so. As noted by Case and Shiller (2003, p. 335), ‘‘buyers and sellers in the housing market are overwhelmingly amateurs, who have little experience with trading.’’ In contrast, institutional income-property investors are more financially sophisticated and actively involved in property acquisitions, operations, dispositions, and portfolio management. In addition, it is unlikely that financing constraints play a large role in the liquidity dynamics documented by FGGH (2003) since NCREIF data contributors are large institutional investors that generally do not use significant debt financing. Income-property is an investment the value of which is derived from expected future cash flows, whereas owner-occupied housing serves as both an investment and consumption good. Institutional real estate investors are less likely to be as ‘‘emotionally attached’’ to their property. Finally, the consumption aspect of housing implies that most homeowners selling a house subsequently purchase another one. This is not necessarily the case with income-property investors, many of whom have more discretion with the timing of their investment decisions.

In contrast, recent papers by Krainer (2001) and Novy-Marx (2004) that propose richer theoretical underpinnings for state-varying housing market liquidity without appealing to either financing constraints or irrational behavior on the part of either buyers or sellers, appear to have significant potential to carry over to income-property liquidity dynamics. The authors both develop search-theoretic, rational agent models in which prices and liquidity (measured with time-on-the-market until a sale and directly related to trading volume) are jointly determined.[3] In their models, seller pricing and bargaining strategies must take into account the opportunity cost of failing to complete a transaction (or of keeping a property on the market). In down (up) markets, the opportunity cost of not completing a transaction is low (high), hence the value of waiting is high (low). Therefore, in down markets it is optimal for sellers to ‘‘fish’’ for higher valuation buyers, while in ‘‘hot’’ markets there is a greater chance that property values could fall next period, and hence sellers price the property relatively lower to avoid ‘‘paying’’ this high cost (Krainer, 2001; and Novy-Marx, 2004).[4] In Novy-Marx’s model, the opportunity cost is also directly related to the relative bargaining positions of buyers and sellers, and these vary systematically with the relative number of each. In modeling time varying commercial property liquidity, FGGH (2003) employ a similar search-theoretic framework. Hence the microeconomic, option-based explanation for the joint behavior of prices and liquidity across different states is one we consider.[5]

The second explanation we examine derives from models of property valuation or appraisal that assume seller estimates of property values lag ‘‘true’’ values because of an asymmetric information problem. Sellers, at least in part, base their estimates of value on observations of signals from the market, but the presence of noise means a change in signal is not fully reflected in sellers’ updated value estimates. A seller can be viewed as an appraiser who employs a partial adjustment-type updating model that has been widely utilized to ''unsmooth'' the NCREIF index and other appraisal-based return indices (Quan and Quigley, 1989; Clayton, Geltner, and Hamilton, 2001; and Childs, Ott, and Riddiough, 2003). In this framework, property transactions provide information that helps sellers learn about ''true'' property values over time. In a low transaction (low liquidity) environment, sellers are faced with a lack of new information with which to update prior valuations and hence place considerable weight on old and potentially stale information, causing list prices to be high relative to bids.[6]

Both the partial updating and costly-search literatures suggest that time variation in liquidity (pro-cyclicality of trading volume and pricing) is primarily the result of optimal behavior on the part of sellers interacting with rational buyers in a private market characterized by noise and significant frictions. Price-liquidity dynamics in these models are primarily driven by seller behavior, in response to exogenous demand shocks.

The third potential explanation we consider focuses on buyer behavior and specifically on the potential for excessive trading by overconfident investors in up markets. This argument derives from recent work on stock market liquidity and price dynamics. One of the more interesting findings in academic finance research in recent years is that there is considerable time variation in market-wide liquidity and that a significant portion of this changing liquidity is common across individual stocks (Chordia, Roll, and Subrahmanyam, 2001; Huberman and Halka, 2001; and Jones, 2002). Exactly what the underlying causes of time variation in liquidity are is an active area of research.

Baker and Stein (2004) develop a theoretical model with heterogeneous investors in which liquidity acts an indicator of investor sentiment.[7] Their model links time variation in liquidity to trading by irrational investors (those subject to waves of sentiment) in a world of short-sale constraints, and hence limited arbitrage. Aggregate liquidity in their model acts as an indicator of the relative presence of sentiment-based traders in the market place and therefore the divergence of asset price from fundamental value. Abnormally high aggregate liquidity (turnover or spreads) is evidence of overvaluation and in fact forecasts a future downturn in stock prices.[8] Gervais, Kaniel, and Mingelgrin (2001) put forward a similar hypothesis and suggest that in a world with constraints on short-selling, pessimistic traders will be on the sidelines and their opinions will not be incorporated into stock prices. They further argue that trading activity (volume) shocks affect a stock's visibility, demand, and therefore price, thereby providing a link between a liquidity proxy (volume or trading activity) and price that is not directly a liquidity phenomenon in the conventional sense, much in the spirit of Baker and Stein.[9]

This approach appeals to market frictions, including short sale constraints, to explain the link between trading activity and pricing in large, centralized, public stock markets that are generally regarded as highly liquid. Hence, it would seem that this ‘‘story’’ could be particularly relevant in the much more illiquid private real estate market where investors cannot sell property short and is comprised of heterogeneous investor groups.

The remainder of the paper proceeds as follows: Section 2 outlines a search-based model of income-property transactions and pricing, based on FGGH (2003) and Goetzmann and Peng (2004), and derives testable hypotheses based on the three classes of models discussed above to explain the positive relationship between pricing and transaction activity. Section 3 provides the empirical models and results. Section 4 summarizes the key findings and concludes.

Search Model Framework and Empirical Implications

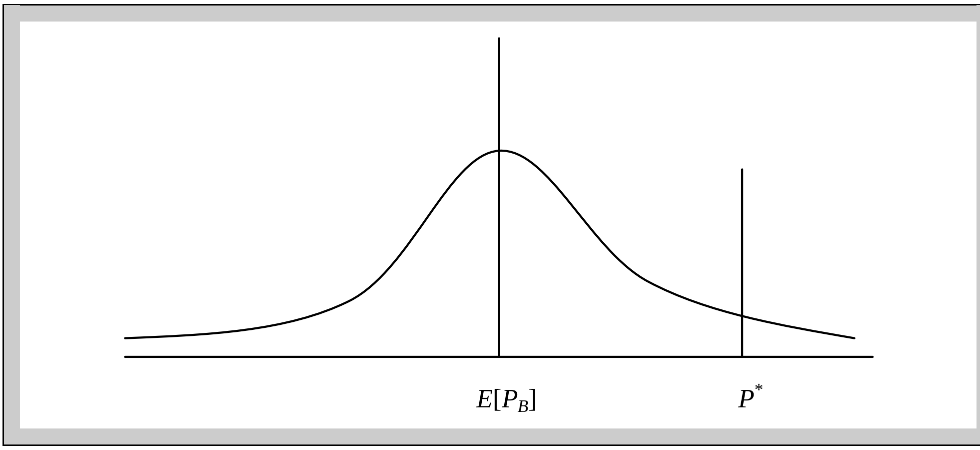
This section presents a simple model of a market for heterogeneous assets to highlight the key elements of search-based models such as FGGH (2003) and Goetzmann and Peng (2004), and then uses it as the basis to explore alternative explanations for why changes over time in transaction frequency are driven by buyer value distributions shifting more relative to seller distributions shifts in response to shocks.[10] As discussed above, these explanations include: (1) lagged seller price adjustment due to noise; (2) sellers’ option value of waiting (i.e., not transactions), both rational economic supply side explanations; and (3) over-optimism (or overconfidence) on the part of some buyers, coupled with market frictions such as the inability to sell property short, a demand-side force that exacerbates the turnover-value linkage caused by inertia in seller adjustments.

Consider a property and a potential buyer universe where individual buyers place different values on the property. Let the density function of buyers’ valuations be $b(P)$ and the cumulative distribution function be $B(P)$, where P is price. $B(P)$ therefore represents the proportion of buyers who have a valuation on the property of less than or equal to P. $B(P)$ represents the state of the property market, and we take the expected value, $E[P_B]$, of the distribution to be our specific measure of market conditions.

For expositional simplicity, assume a degenerate distribution of seller valuations at a single price, P^*. Under this simplifying assumption, the model can be interpreted as the market for a single property where the seller has a single specific reservation price. This reservation price will be set, at least partially, based upon the seller’s knowledge of market conditions. Assume that the seller knows the shape of the density function $b(P)$, knows the initial level of $E[P_B]$, but cannot fully observe changes in $E[P_B]$. Changes in the mean of the distribution must be inferred by the seller from offers made by buyers or comparable transactions.

Graphically, the market can be represented as in Exhibit 2. P^* being greater than $E[P_B]$ is intuitive as sellers are current holders of the property and therefore should have relatively high valuations on it.[11] From the diagram, the probability of a sale from a particular, randomly drawn buyer’s offer is $1\text{-}B(P^*)$. Assuming that one

Exhibit 2 | Search Model Setup



buyer comes forward each period, the expected time-on-the-market of the property is: $E[TOM] = 1/[1 - B(P^*)]$.

The distributions above can be used to derive supply and demand schedules for the property where demand at a specific price is $Q = 1 - B(P)$. The quantity, Q, here is actually the probability of selling the property during a particular time interval. However, in aggregate, if the probability of sale goes up for individual properties then aggregate sales and therefore market activity will increase. Given our simple assumption on the seller reservation price, the supply curve is perfectly elastic (Exhibit 3). Since we assume that P^* lies above $E[P_B]$, our interest lies in only the portion of demand curve above $E[P_B]$, as that is where equilibrium occurs.

Consider now an exogenous shift in market conditions. In the model, this is characterized as a shift in $b(P)$. Without loss of generality, assume a downward shift in the average buyer's valuation of the property. $b(P)$ will shift to the left, and the demand curve will also shift to the left. In response, the seller's valuation of the property will also shift down.

In Exhibit 4A, the shift in market conditions is fully incorporated into the seller's valuation. This is the perfect information case wherein P^* shifts left by the same amount as $E[P_B]$. Thus, demand shifts from D_1 to D_2 and supply shifts from P_1^* to P_2^*. In this case, quantity is unaffected and the full impact of the decrease in market valuation is felt on price. Exhibit 4B illustrates the case where information asymmetry implies that the seller's valuation only partially reflects the change in market conditions (at least initially). Note that in this case both price and quantity decrease following the exogenous negative shock to valuations.

The model shows how an exogenous shock to demand can result in changes to both property prices and to market activity. Following a decrease (increase) in

Exhibit 3 | Aggregate Sales and Market Activity

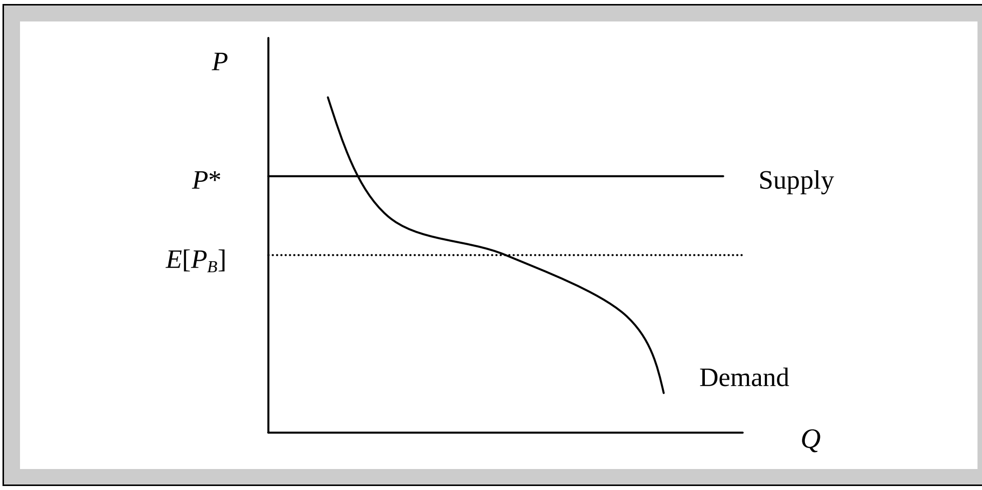
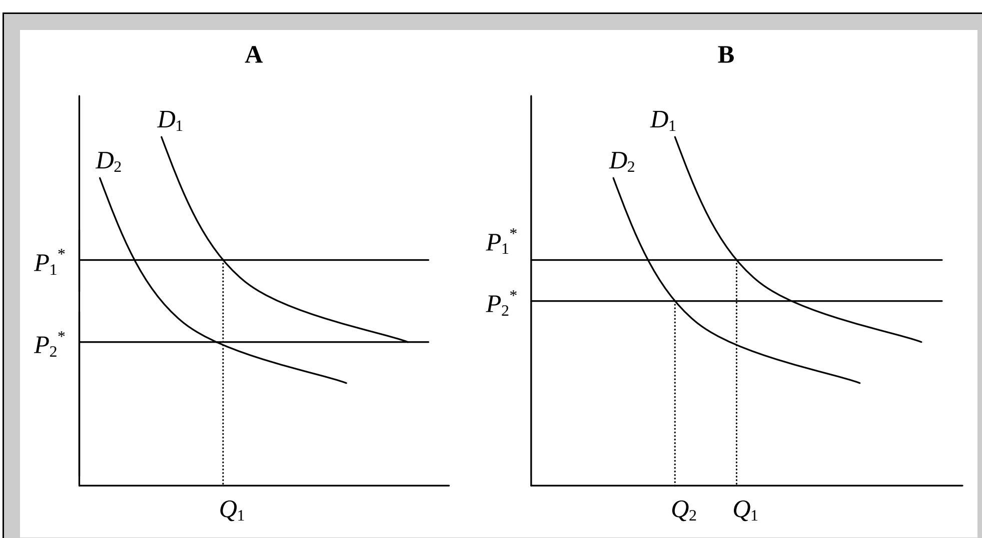


Exhibit 4 | Market Adjustment Dynamics



demand, prices fall (rise), market activity falls (rises), and average time-on-the-market ($1/Q$) increases (decreases).

Following FGGH (2003, 2004), buyers' and sellers' reservation prices can be specified as linear functions of asset-specific and ownership-specific characteristics, both of which primarily vary across properties cross-sectionally, and time variation in real estate and capital market factors that impact all properties. That is, buyer and seller reservation prices are given by:[12]

$$P_{it}^{b} = \sum \alpha_j^b X_{ijt}^P + \sum \beta_k^b D_{kt}, \tag{1}$$

$$P_{it}^{s} = \sum \alpha_j^s X_{ijt}^P + \sum \beta_k^s D_{kt}, \tag{2}$$

where P_{it}^b and P_{it}^s are the buyer's and seller's reservation prices, respectively, for asset i at time t. X_{ijt}^P is a vector of j property-specific and ownership structure attributes associated with property i and $\Sigma\ \alpha_j^b X_{ijt}^P$ and $\Sigma\ \alpha_j^s X_{ijt}^P$ represent the value impact of these attributes in terms of their impact on buyer and seller reservation prices.

Of particular interest are the second terms on the right-hand side of Equations (1) and (2). D_{kt} represents market-wide factors or valuation components common to both buyers and sellers. $\beta_k^b D_{kt}$ and $\beta_k^s D_{kt}$ capture the differential impact of market-wide factors on buyer and seller reservation prices and hence on transaction activity. These are common across all properties, represent systematic movements in the market as a whole, and are the focus in this paper.

A sale occurs if the buyer's reservation price equals or exceeds the seller's reservation price. That is if:

$$S_{it}^{*} = P_{it}^b - P_{it}^s = \sum (\alpha_j^b - \alpha_j^s) X_{ijt}^P + \sum (\beta_k^b - \beta_k^s) D_{kt} \geq 0. \tag{3}$$

Of course, S_{it}^* is not observable, only the sale or no sale outcome is observed, but this specification is useful in terms of illustrating the variables that impact the probability of sale and hence transaction intensity and hence liquidity. Our aim is to understand the factors driving the differential impact of market-wide factors on buyer and seller reservation prices and hence on transaction activity, as captured by the relative movement in $\beta_k^b D_{kt}$ and $\beta_k^s D_{kt}$. We consider the empirical implications of the three classes of models to derive testable hypotheses.

Consider first the ''appraisal-smoothing'' or rational updating in the presence of noise framework. Changes in sellers' property valuations lag those of buyers because sellers base their valuations, at least in part, on signals extracted from the market. These signals are taken from buyer behavior. However, the signals contain noise and therefore sellers will rationally only incorporate a portion of any change in signal in their own valuations. Over time, as noise is reduced through observation of sequential signals, sellers' valuations converge to those of buyers. This idea is captured in the simple partial adjustment framework introduced by Quan and Quigley (1989) and Geltner (1990), with the sellers reservation price, P_{it}^s, specified as a function of the full information reservation price, P_{it}, and the previous indication of value as captured by the lagged reservation price, as follows:

$$P^s_{it} = \lambda_t P_{it} + (1 - \lambda_t)P^s_{i,t-1}$$
$$= P^s_{i,t-1} + \lambda_t(P_{it} - P^s_{i,t-1}), \tag{4}$$

where λ is the weight that the seller places on new market information. It is sometimes termed the confidence factor and takes on a value between 0 and 1. The rate of adjustment in a seller's reservation price to signals about changes in property valuations varies inversely with the quality of the signals. We capture these dynamics by specifying the adjustment factor in the following way:[13]

$$\lambda_t = \gamma_0 - \gamma_1 noise_t. \tag{5}$$

Combining Equations (4) and (5) yields the following representation of adjustment in the seller's reservation price:

$$P^s_{it} = P^s_{i,t-1} + \gamma_0(P_{it} - P^s_{i,t-1}) - \gamma_1 * noise_t * (P_{it} - P^s_{i,t-1}). \tag{6}$$

The degree of adjustment is a function of the quantity and quality of new information. The ''noisier'' the information, the smaller the adjustment or update in seller reservation price. Noise is a function of transaction activity and specifically recent sales of properties similar to a particular seller's property. All else equal, we expect that greater property trading or transaction activity decreases noise and reduces lagging, implying that sellers' reservation prices are closer to constant liquidity valuations.[14]

The real option framework of Novy-Marx (2004) works in the same direction and therefore reinforces the effect in both the up and down directions. When transaction activity falls, noise increases and the volatility of transaction prices increases (we confirm this empirically later in the paper). Higher volatility (noise) increases the value of waiting and hence the incentive to sellers to not lower minimum acceptable prices and to fish for high valuation buyers. Similarly, on the upside in highly active property asset markets, volatility, noise, and the value of waiting are relatively low, or the opportunity cost of not transacting is high.

To illustrate this, consider an income-property owner who decides to sell a property. The owner chooses a minimum acceptable, or reservation, price based on his estimate of the risk-adjusted present value of future cash flows generated by the property. The value estimate will be a noisy indication of ''true'' value that can be viewed as an update of the initial (noisy) value the owner placed on the asset at the time of acquisition based on accumulated macroeconomic information and signals extracted from comparable sales of like property or related indications of value (Childs, Ott, and Riddiough, 2003). Signals extracted from the market could be due to offers that have been made on the property, sales of similar properties, or appraisals of the property that are, in turn, partly based on estimates of market conditions. If there is an exogenous change in market values, then sellers do not observe this directly, but rather must infer it from their market signal.

Take, for example, the case of a decline in market values. A property owner is attempting to sell and has a reservation price that reflects market conditions before the decline. The owner may receive an offer that is below the reservation price. Although not accepted, the low offer contains information about market conditions, specifically that the market value of the property may now be less than the seller previously thought. The seller will therefore adjust the reservation price to reflect this new information. However, the reservation price will only partially adjust. The offer may have been low because of a change in market conditions (i.e., a decline in the mean of the distribution of buyers' valuations), but it may also be due to the offer coming from a party that has a below average value on the property (i.e., a buyer from the left-hand tail of the distribution of buyers' valuations). Alternatively, the offer may have come from a party who has worse market information than the seller and has simply under-valued the property. Over time, as further signals are received from the market (e.g., further offers, observed sales of similar properties, etc.), the seller will move the reservation price downwards to fully reflect the decline in values that they are realizing has actually happened (conversely, if there has not been an actual decline in values then future signals will convince the seller that the first offer was a ''fluke,'' and the seller will readjust their reservation price back to the original level).[15]

The main point is that because of asymmetric information between buyers and sellers, sellers will observe buyer valuations with noise and will therefore only gradually adjust their own valuations to any observed changes. Note that the concept of the signal coming from actual offers on the property is only for expositional purposes. The source of the market signal and information asymmetry could just as likely come from something like sales of similar properties. In that case, the noise inherent in the signal would be due to things such as the possibility that a particularly high or low price for another property was due to differences in the precise characteristics of the property, a buyer with a value in the tail end of the distribution, or perhaps a distressed seller accepting a low offer.

This extension of FGGH (2003) offers a rational explanation for why seller valuations lag changes in the market, in terms of a well-established appraisal smoothing or rational updating mechanism from purely a valuation perspective, together with and reinforced by a real option mechanism that explicitly recognizes buyer and seller search dynamics in a model where the opportunity cost of not transacting plays an important role in price setting.

The final candidate explanation we examine involves the potential for ''excessive'' trading by overly optimistic buyers. In this case, apparent increases in liquidity as evidenced by higher turnover do not fully represent liquidity changes in the conventional sense as some of the increase is related to the excessive trading. Scheinkman and Xiong (2003) present a model in which differences of opinion result from overconfidence on the part of a subset of investors. Asset prices will then incorporate a speculative component, and trading activity is linked to overvaluation. Overconfident investors underestimate the variance of the returns to the risky asset, as their confidence intervals for the risky asset are too narrow. Under this hypothesis, overconfidence leads to more aggressive trading by individual investors and hence higher market-wide trading volume.[16] As noted in the introduction, Baker and Stein (2004) present a model with heterogeneous investors in which liquidity acts an indicator of investor sentiment. Changes in aggregate liquidity act as an indicator of the relative presence of sentiment-based traders in the market place and therefore the divergence of asset price from fundamental value. The major empirical implication that follows is that if abnormally high market-wide liquidity is indicative of a market dominated by overly optimistic, possibly uninformed buyers then liquidity measures will predict future decreases in property prices.

Analysis & Results

This section presents the results of our empirical evaluation of the competing explanations for time variation in the private real estate market liquidity documented by FGGH (2003). The analysis divides into two parts. First, we employ annual data from FGGH (2003) since they derive the constant liquidity index at the annual frequency and we want to work directly with this series to the extent possible. We examine the univariate statistical properties of key variables and then explore the dynamic linkages within a multivariate framework, employing a simple bivariate vector autoregressive (VAR) model and a cointegration/error-correction approach. An important component of this part is to empirically document the relationship as the annual frequency between the difference in the FGGH (2003) transaction and constant liquidity price indexes and trading activity.

The second stage of the empirical investigation employs higher frequency quarterly data. It is entirely possible, and in fact probable, that the dynamics between trading activity and prices resulting from relative shifts in buyer and seller value distributions take place at high frequencies and hence may not be detectable at the annual frequency. Based on our findings with annual frequency data, we use quarterly trading volume (turnover) as a proxy for liquidity with the caveat that one of our explanations for time variation in liquidity indicates that volume may problematic as a measure of liquidity.

Annual Data

In the FGGH (2003) model, market liquidity is strongly related to trading activity and liquidity is a function of the stage of the property pricing cycle. Exhibit 1b illustrates the strong positive relationship between turnover and property pricing, where turnover is the percentage of properties in the NCREIF index sold in a given year. It also indicates that periods of relatively high and low turnover are related to significantly larger differences between the constant liquidity and hedonic price indices. Turnover appears to lead price movements at major turning points on both the up and down sides, a result consistent with buyer value distributions moving first and sellers responding with a lag.

Exhibit 5 examines the link between turnover and liquidity in more detail. Exhibit 5a compares the ratio of hedonic values to constant liquidity prices, a measure of inverse liquidity, to turnover. The two series are almost perfect mirror images of each other. The correlation between the ratio of hedonic values to constant liquidity value and turnover is a statistically significant −0.95. Exhibit 5b plots the ratio of constant liquidity to hedonic values, a direct liquidity measure, and property turnover. It clearly illustrates the direct link between liquidity and turnover in the FGGH (2003) framework.

Exhibit 6 reports detailed summary statistics for property value appreciation (or capital) returns, both hedonic and constant liquidity, and liquidity measures, property turnover, both actual or raw and detrended and the ratio of the hedonic

Exhibit 5 | Private Real Estate Market Liquidity and Transaction Activity Dynamics, 1984–2003

(a) Inverse Liquidity (Ratio of Hedonic to Constant Liquidity Index Values) versus Property Transacation Activity (Turnover)

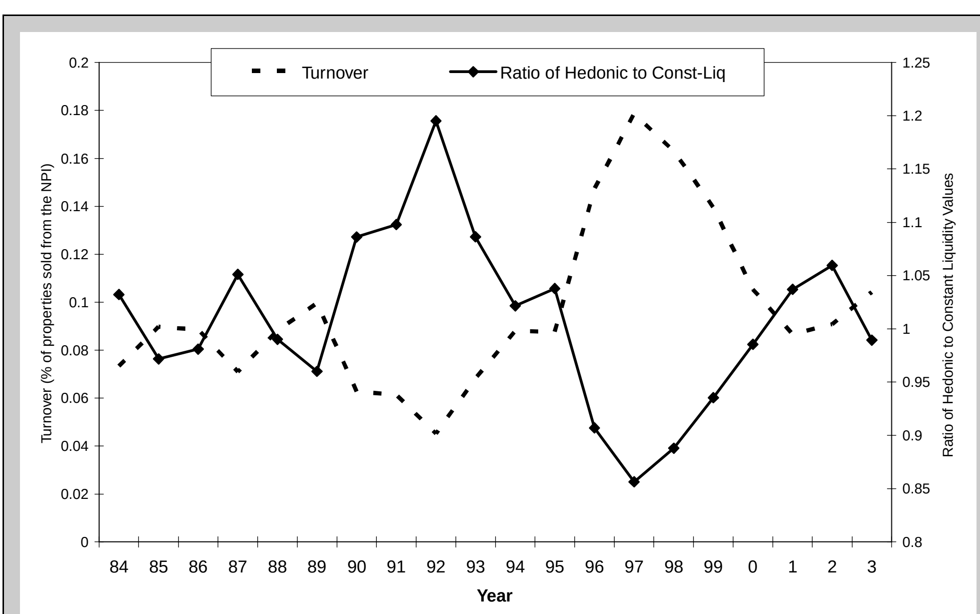
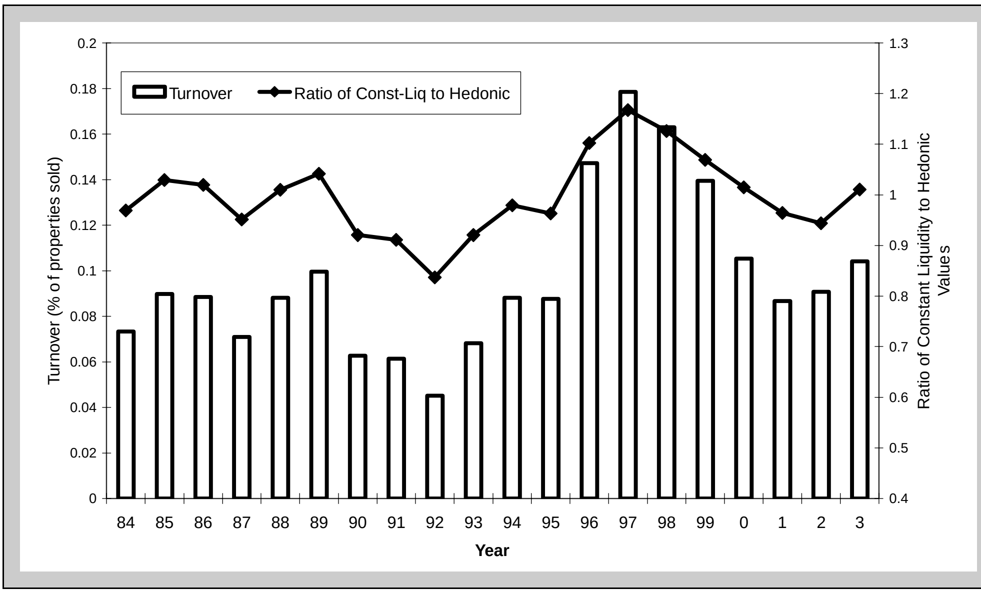


Exhibit 5 | (continued)

Private Real Estate Market Liquidity and Transaction Activity Dynamics, 1984–2003

(b) Liquidity (Ratio of Constant Liquidity to Hedonic Index Values) versus Property Transaction Activity (Turnover)



Notes: Liquidity is shown as the ratio of hedonic (time-varying liquidity) and constant liquidity value indices. The hedonic index is derived from realized transaction prices of properties sold from the NCREIF Property Index (NPI). The constant liquidity (''Const-Liq'') index is derived from the same sample but utilizes an econometric approach that holds liquidity constant. Both indices come from FGGH (2003), which develops the econometric procedure to produce the constant liquidity index. Property turnover data was provided by NCREIF.

to constant liquidity price level indexes.[17] The detrended turnover series is the residual series from a regression of raw turnover on a constant and a time trend. The turnover series, shown in Exhibit 1b and Exhibit 5, seems to be increasing over time, and recent work suggests that institutional investors do indeed have shorter holding periods on their property investment, and hence the need to consider a detrended series. The numbers in Exhibit 6 confirm several of the insights taken visually from the graphs. Looking first at the property value series statistics in Panel A in Exhibit 6, constant liquidity price changes, dlog(*constliq*), are more variable than observed transaction prices, dlog(*hedonic*) as evidenced by higher maximum and minimums, in absolute value terms, and a larger standard deviation. Constant liquidity prices are negatively skewed but hedonic prices are not. This implies that looking at the distribution of annual percentage change in property values, the larger changes, holding liquidity constant, are negative ones, a result that is consistent with recent findings in the stock market (Hong and Stein, 2003). The ratio of hedonic to constant liquidity price levels, (*Hedonic*/*Constliq*),

Exhibit 6 | Descriptive Statistics, Annual Data, 1984–2003

Panel A: Means and Standard Deviations

	dlog(*constliq*)	dlog(*hedonic*)	*Hedonic Constliq*	*TURNOVER* (raw)	*TURNOVER* (detrended)
Mean	0.00296	0.00007	1.00739	9.70158	0.35975
Median	−0.00071	0.00985	0.99260	8.98000	−0.12114
Maximum	0.20551	0.14396	1.19810	19.45000	8.35658
Minimum	−0.21510	−0.13464	0.85860	4.30000	−4.93273
Std. Dev.	0.11606	0.07944	0.08153	3.84031	3.87069
Skewness	−0.20250	0.03722	0.28204	1.06868	0.36402
Kurtosis	2.65222	2.18059	3.04885	3.67618	2.10105

Panel B: Correlations

	dlog(*constliq*)	dlog(*hedonic*)	*Hedonic Constliq*	*TURNOVER* (raw)	*TURNOVER* (detrended)
dlog(*constliq*)	1.00	0.82	−0.68	0.66	0.48
dlog(*hedonic*)	0.82	1.00	−0.63	0.62	0.37
Hedonic/Constliq	−0.68	−0.63	1.00	−0.90	−0.70
TURNOVER (raw)	0.66	0.62	−0.90	1.00	0.64
TURNOVER (detrend.)	0.48	0.37	−0.70	0.64	1.00

Panel C: Correlation Structures of FGGH (2003) Liquidity Measure and NCREIF Turnover

	Ratio of *HEDONIC/CONSTLIQ*				Detrended TURNOVER			
Lag	AC	PAC	Q-Stat	Prob	AC	PAC	Q-Stat	Prob
1	0.629	0.629	9.170	0.002	0.677	0.677	13.337	0.000
2	0.291	−0.174	11.235	0.004	0.247	−0.389	15.194	0.001
3	0.024	−0.139	11.249	0.010	−0.056	−0.054	15.291	0.002
4	−0.308	−0.377	13.860	0.008	−0.262	−0.198	17.563	0.002
5	−0.420	−0.029	19.042	0.002	−0.340	−0.050	21.566	0.001
6	−0.443	−0.161	25.212	0.000	−0.309	−0.070	25.049	0.000

Notes: "Hedonic" refers to a value index derived from realized transaction prices of properties sold from the NCREIF Property Index (NPI). "*Constliq*" refers to a constant liquidity index, which is derived from the same sample of transactions but utilizes an econometric approach to determine values assuming no change in liquidity. Both indices come from FGGH (2003), which develops the econometric procedure to produce the constant liquidity index. "Turnover" is the percentage of properties in the NPI that sold during the year. Detrended turnover is the residual series from a regression of actual or raw turnover on a constant and a time trend. AC is the autocorrelation, PAC is the partial autocorrelation, Q is Chi-squared test statistic of the null hypothesis of no autocorrelation and "Prob" is the *p*-value associated with this test.

our inverse liquidity measure, has a mean of 1, suggesting that on average the two series tend to have the same values over time and that time-variation in liquidity, captured by the difference between them, is mean reverting.

Panel B of Exhibit 6 reports the correlations between price changes and liquidity measures, while Panel C of Exhibit 6 examines the autocorrelation structure of the two key liquidity measures. The conclusions from Panel B of Exhibit 6 are as expected, with a high correlation between trading activity, liquidity, and price changes. Panel C of Exhibit 6 indicates that the ratio of hedonic values to constant liquidity prices, *Hedonic*/*Constliq*, and turnover have similar time-series properties. Both are highly positively autocorrelated over a one-year period, with the correlation weakening and then becoming negative after year 2. The positive followed by negative autocorrelations are again consistent with mean reversion in market-wide liquidity.

To shed additional light on the relationships between property pricing, liquidity, and trading intensity we estimate two simple VAR(1) models and test for Granger causality amongst the pricing and liquidity variables. Specifically, we estimate the following two systems and use them to test the direction of causality:[18]

Model 1

$$\begin{aligned} Hedonic_t &= a_3 + b_3 Hedonic_{t-1} + c_3 Turnover_{t-1} + e_{3t}. \\ Turnover_t &= a_4 + b_4 Hedonic_{t-1} + c_4 Turnover_{t-1} + e_{4t}. \end{aligned} \tag{7a}$$

Model 2

$$\begin{aligned} Hedonic_t &= a_1 + b_1 Hedonic_{t-1} + c_1 Constliq_{t-1} + e_{1t}. \\ Constliq_t &= a_2 + b_2 Hedonic_{t-1} + c_2 Constliq_{t-1} + e_{2t}. \end{aligned} \tag{7b}$$

If past information in a variable, x, improves forecasts of another variable, y, then x is said to "cause" y and vice versa. For example, with Model 1 we test whether *Turnover* causes *Hedonic* after controlling for persistence or autocorrelation in *Hedonic*. A positive finding would be consistent with partial adjustment of observed transaction prices to new information and consistent with initial adjustment impacting property turnover and then subsequently prices. The specific causality null hypothesis is: *Turnover* does not Granger-cause *Hedonic* if and only if the coefficient on $Turnover_{t-1}$ is zero, or H_0: $c_3 = 0$. The second equation in Model 1 is used to test for causality running in the other direction. Model 2 replaces *Turnover* with constant liquidity prices, *Constliq*.

Panel A of Exhibit 7 reports the estimation results for both models and Panel B the Granger causality tests statistics. In both models, lagged constant liquidity prices are significantly positively related to current hedonic (observed transaction) prices, while lagged hedonic prices are not statistically related to current constant liquidity prices or turnover. Constant liquidity and turnover both show significant positive persistence, even after accounting for lagged hedonic prices. The high large positive value and statistical significance of the coefficient on Hedonic(−1) in Model 2, but not in Model 1, implies that *Constliq*(−1) does indeed capture both the pricing dynamics reflected in Hedonic(−1) and the time variation in liquidity related to changing transaction activity as captured by *Turnover*(−1). The

Exhibit 7 | FGGH (2003) Hedonic and Constant Liquidity Price Dynamics: Vector Autoregressive Models (VAR) and Granger Causality Tests, Annual Data, 1985–2003

Panel A: VAR Models

	Model 1			Model 2	
	Dependent Variable			Dependent Variable	
	HEDONIC	*CONSTLIQ*		*HEDONIC*	*TURNOVER*
HEDONIC(−1)	0.3010	−0.4946	*HEDONIC*(−1)	0.8348*	−7.3013
	(1.18)	(1.20)		(7.72)	(1.63)
CONSTLIQ(−1)	0.5005*	1.1816*	*TURNOVER*(−1)	0.0098*	0.7356*
	(2.42)	(3.53)		(2.53)	(4.59)
Constant	0.1980	0.3146	Constant	0.0710	9.9490*
	(1.77)	(1.74)		(0.64)	(2.16)
R^2	0.81	0.68	R^2	0.81	0.58
Adj. R^2	0.79	0.64	Adj. R^2	0.79	0.53

Panel B: Granger Causality Tests

Null Hypothesis	*F*-Statistic	Probability
CONSTLIQ does not Granger Cause *HEDONIC*	5.86	0.02775*
HEDONIC does not Granger Cause *CONSTLIQ*	1.43	0.24921
TURNOVER does not Granger Cause *HEDONIC*	6.38	0.02242*
HEDONIC does not Granger Cause *TURNOVER*	2.65	0.12280

Notes: Absolute values of *t*-Statistics are shown in parentheses.

*Denotes statistically significant at conventional significance levels.

test statistics in Panel B indicate that the null hypotheses that constant liquidity prices and turnover do not Granger cause hedonic prices is rejected at conventional significance levels. Overall the results are consistent with the notion that observed transaction prices do not fully adjust to new information. Part of the adjustment takes place via a change in liquidity.

As noted previously, it is possible that property prices are non-stationary series, which calls into question the VARs and Granger causality estimation and test results above using the levels of the variables. However, if this is the case, then it also suggests that there could be a long-run relationship between hedonic and constant liquidity prices that implies an error-correction framework to model short-run fluctuations and provide insight into the dynamic linkages between hedonic and constant liquidity prices. If the time variation in private market real estate liquidity, given by the difference between hedonic and constant liquidity prices, is a stationary process, then a regression of hedonic values on constant liquidity price levels as in Equation (8) below should yield a high positive coefficient on *constliq* and an AR(1) residual series that captures short-term adjustment to long-run equilibrium.[19]

$$\log(hedonic_t) = \alpha_0 + \alpha_1 \log(constliq_t) + u_t. \tag{8}$$

If there is a long-run relationship between *hedonic* and *constliq* (i.e., the two series are cointegrated) as shown in Equation (8), this implies that short-run dynamics are governed not only by changes in the two price variables but also by the extent to which the current situation departs from long-run equilibrium, as captured by the residual u, together in an error-correction framework, which takes the form:

$$\begin{aligned} d\log(hedonic)_t &= \lambda_0 + \lambda_1 d\log(constliq)_t \\ &\quad + \lambda_2[\log(hedonic)_{t-1} - \hat{\alpha}_0 - \hat{\alpha}_1 \log(constliq)_{t-1}] \\ &= \lambda_0 + \lambda_1 d\log(constliq)_t + \lambda_2 \hat{u}_{t-1}, \end{aligned} \tag{9}$$

where $\hat{u}_t$ is the OLS residuals resulting from estimation of Equation (8); λ_2 measures the speed with which the property asset market adjusts jointly through prices and liquidity back to long-run equilibrium between transaction and hedonic prices. We expect to find that λ_1 is positive but less than one, since adjustment of hedonic prices is more sluggish than constant liquidity prices, because the asset market adjusts through both transaction prices and liquidity jointly. Constant liquidity price assumes prices fully adjust, without any accompanying change in liquidity. Hence, information that is reflected in constant liquidity prices is not fully reflected in observed transaction (hedonic) prices, but in the joint behavior of hedonic prices and liquidity. In addition, we anticipate that λ_2 is negative and less than one in absolute value, suggesting that the change in hedonic prices also reflects the extent of departure from long-run equilibrium. When hedonic prices are high relative to constant liquidity prices, liquidity and trading volume are low. Hence, we expect to find that if *constliq* prices increase, then hedonic prices increase but not to the same extent and adjust even less in periods of low liquidity. In a period of unusually high liquidity, with constant liquidity price higher than hedonic price (i.e., $constliq > hedonic$), hedonic price changes are more responsive since greater transaction activity lowers noise and hence lowers the option value of waiting.

Exhibit 8 presents the results of estimating Equations (8) and (9). The positive significant slope coefficient and high R-squared in the levels regression, Equation (8), indicates a strong relationship between the two series, and statistical tests indicate that the residuals are positively autocorrelated and stationary. Exhibit 8 also presents three different versions of an error-correction model of property price changes, Equation (9) that derives directly from the levels regression, followed by two other specifications that employ alternative proxies for departures from long-run equilibrium. The results of estimating Equation (9) are:[20]

Exhibit 8 | FGGH (2003) Hedonic and Constant Liquidity Price Dynamics: Cointegration and Error Correction Estimation Results, Annual Data, 1984–2003

Dependent Variable	Explanatory Variables				
Levels Regressions	Constant	log(*constliq*)		R^2	Adj. R^2
log(*hedonic*)	0.0014 (0.1027)	0.7123 (9.58)		0.84	0.83
Error-Correction Models	Constant	dlog(*constliq*)	Level Residuals Lagged 1 Year		
dlog(*hedonic*)	−0.00104 (0.91)	0.4771 (5.91)	−0.5020 (3.20)	0.80	0.78
	Constant	dlog(*constliq*)	(*hedonic* / *constliq*) Lagged 1 Year		
dlog(*hedonic*)	0.0012 (0.153)	0.5493 (7.78)	−0.3877 (3.81)	0.83	0.81
	Constant	dlog(*constliq*)	*TURNOVER* Lagged 1 Year		
dlog(*hedonic*)	−0.0707 (2.96)	0.5203 (6.65)	0.0073 (3.10)	0.80	0.77

Note: Absolute values of *t*-Statistics are shown in parentheses.

$$
\begin{aligned}
d\log(hedonic)_t = {} & 0.477 * d\log(constliq)_t \\
& - 0.502 * [\log(hedonic)_{t-1}, \\
& - 0.7123 * \log(constliq)_{t-1}],
\end{aligned} \tag{10}
$$

with an R^2 of 80%. The coefficient estimates on both the change in log constant liquidity prices and the cointegration term have the expected signs and magnitudes and are statistically significant. The results are consistent with a market in which constant liquidity and observed transaction prices are tightly connected over long-run periods, but can diverge in the short-run. Shocks to the asset property market that cause changes in trading volume and hence liquidity are not fully reflected in observed transaction prices right away. The adjustment takes place in both liquidity and prices simultaneously and is influenced by the extent of departure from long-run equilibrium. The second error-correction type model replaces the lagged levels residual with the lagged ratio of hedonic prices to constant liquidity prices. It yields similar results. The third and final version uses lagged turnover in place of the levels residuals and also generates similar conclusions. This last finding provides additional evidence that fluctuations in liquidity are directly related to property transaction activity, as captured by turnover.

The analysis of the dynamics between FGGH (2003) hedonic prices and constant quality price series and property turnover generates a number of key findings that are largely consistent with the rational, partial updating of reservation prices by sellers as a major element of the explanation for the time variation in liquidity in the private institutional property market. These results must be viewed as "exploratory," however, since the annual frequency may be too low to detect the dynamics of price, volatility, and liquidity, not suitable for carefully investigating either the volatility and noise impacts, or the timing lead-lag relationships. In what follows we explore these considerations in more detail with an analysis of quarterly frequency data.

Quarterly Data

The FGGH (2003) constant liquidity index is constructed at the annual frequency, yet market important market dynamics relevant to this study likely occur at a higher frequency. This section employs quarterly data, the highest frequency available, at least with enough history to conduct meaningful empirical analysis. Moving to the quarterly frequency has advantages and disadvantages. As noted, the major advantage is that it is more relevant in terms of capturing important market dynamics. The major disadvantage, however, is that we do not have the FGGH (2003) constant liquidity or hedonic price indices at the quarterly frequency. Hence, we trade off a measure of time variation in liquidity, the difference between the hedonic and constant liquidity price indices, for higher frequency that permits analyses of turnover points, and volatility, as well as greater statistical precision by providing significantly more data points.

Income-property appreciation returns are measured by quarter-to-quarter percentage change in the Current Value Index or ''CVI'' version of the NCREIF index. The CVI index is based only on properties that are deemed to be revalued every quarter. Capital or appreciation returns are estimated using a ''repeat re-appraisal'' regression methodology that is widely used in the housing sector to generate house price indices, such as the one produced by OFHEO. While the CVI is an appraisal-based index, it does not suffer from a number of the problems that plague the raw NCREIF capital return index. The quarterly NCREIF index is essentially an annual index that is partially updated each quarter given that many of the properties are only revalued in the fourth quarter of each year. By including only properties that have been appraised, the CVI is more up-to-date and does not suffer from the same lagging and seasonality problems. In addition, given that the CVI is a current appraisal value index, for our purposes it can be viewed as the mean of the ''typical'' or marginal sellers pricing function. We employ a three-stage empirical investigation to examine the viability of the three candidate explanations proposed to explain time variation in market-wide liquidity, as follows:

- **Univariate Statistical Analysis**: Examine and compare the statistical properties and the dynamic linkages of property pricing, turnover, and market volatility (noise) at a basic level to generate key stylized facts to guide more formal models and tests of the three alternative explanations for time variation in liquidity.
- **Multivariate Econometric Model**: Investigate the joint dynamics of price changes and turnover in a vector autoregressive model that controls for exogenous demand factors. Impulse response functions trace out the market reaction to shocks in the asset demand for real estate.
- **Forecasting Future Property Appreciation**: A key empirical implication of the behavioral explanation of high turnover as ''sentiment'' is that current turnover should predict future return reversals. That is, if in a hot market buyers tend to be overly optimistic and overpay for property this implies that prices will eventually drop to return to fundamental or intrinsic value. We test the predictive ability of turnover, carefully controlling for other factors that could help explain future property appreciation.

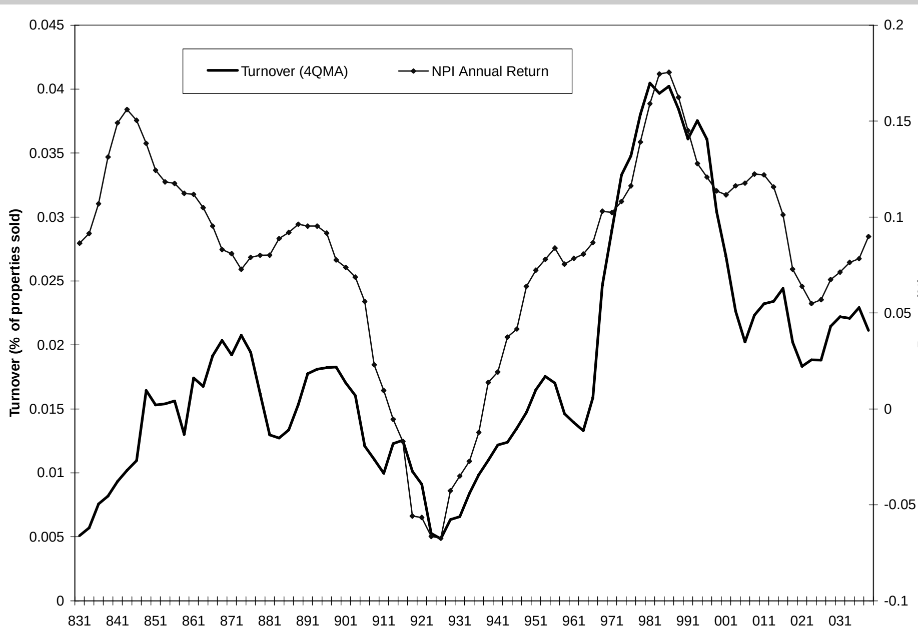
Exhibit 9 reports summary statistics for quarterly appreciation returns, dlog(cvi), raw turnover, NCREIF transaction capitalization rates, and the yield spread, which is the difference between ten-year and three-month Treasury yields. The yield spread provides a measure of the slope of the Treasury yield curve. It is used in the VAR analysis as an exogenous variable. Exhibits 10 and 11 display the price, return and turnover series. Exhibit 10 shows that year-to-year percentage change in the CVI index, or annual appreciation returns, tend to be coincident with

Exhibit 9 | Descriptive Statistics, Quarterly Data

Variables	Mean	Std. Dev.	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
Return [=dlog(cvi)]	−0.000	0.014	0.663	0.692	0.555	0.567
Turnover	0.019	0.011	0.554	0.405	0.436	0.631
Cap Rate	0.085	0.010	0.641	0.464	0.480	0.325
Yield Spread	0.020	0.011	0.859	0.709	0.543	0.351

Note: This table presents the means, standard deviations, and 1 to 4 quarter autocorrelations of the private real estate return, turnover, cap rate, and the spread between the 10-year Treasury yield and the 3-month Treasury yield.

Exhibit 10 | NCREIF Property Returns and Property Trading Activity (Turnover), Quarterly, 1983:1–2004:1



turnover, a result that FGGH (2004) suggest is consistent with buyer reservation prices moving first and seller reservation prices following. There do seem to be periods in which prices continue to rise while turnover drops off.

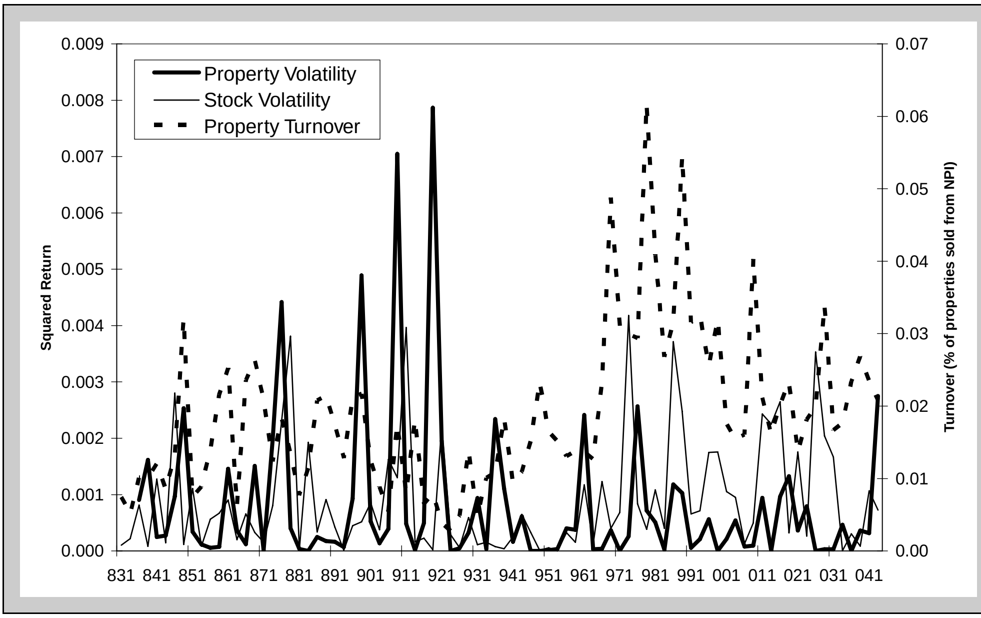
The option value of waiting, or opportunity cost of not transacting, plays a key role in Novy-Marx's (2004) theoretical model of time variation in liquidity.

Exhibit 11 | NCREIF Property Pricing (Transaction Cap Rate) and Property Trading Activity (Turnover), Quarterly, 1983:1–2004:1

Property price volatility is an important determinant of this option value. Exhibit 12 compares CVI capital return volatility and raw turnover. For comparison purposes, and to examine the potential for a capital flows effect between stock and real estate markets, conditional stock volatility is also shown. Property volatility is constructed as the squared residuals from a second-order autoregressive, or AR(2), equation fit to quarterly percentage change in the CVI index (i.e., quarterly appreciation rates). Stock market volatility derives from the changes in the S&P 500 Index. Since the Index is available monthly, we use monthly data to construct a quarterly index. Specifically, the quarterly stock volatility series is a three-month average of squared percentage changes in the S&P 500 Index within each quarter.

Property appreciation return volatility is considerably higher in the market downturn of the early 1990s, a period of abnormally low turnover and liquidity, and following other periods when turnover drops. In contrast, price volatility is relatively low in periods of rising returns—the mid 1980s and late 1990s. High (low) price volatility in cold (hot) markets would appear to provide support for both the appraisal smoothing/lagged seller adjustment and option-based opportunity cost of transaction explanations for time variation in liquidity. Exhibit 12 also shows that the real estate market may have gone through a structural

Exhibit 12 | Conditional Property Value and Stock Price Volatilities versus Property Transaction Activity (Turnover), Quarterly, 1983:1–2004:1



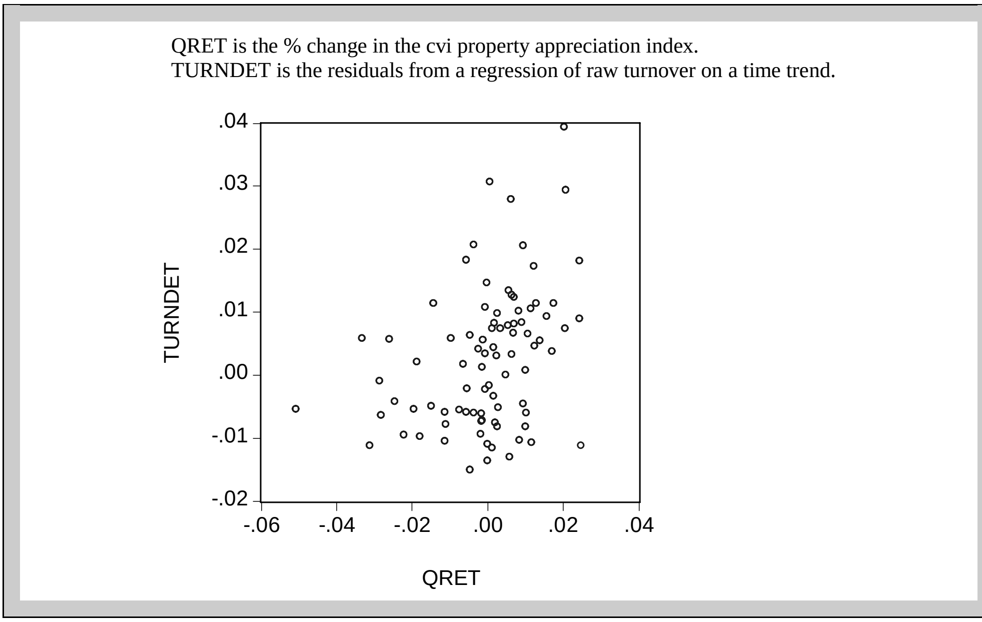
Notes: Property volatility is constructed as the squared residuals from a second-order autoregression time series model, or AR(2), equation fit to quarterly percentage change in the current value version of the NCREIF index (or CVI index) (i.e., quarterly appreciation rates). Stock market volatility derives from the changes in the S&P 500 Index. Since the index is available monthly, we use monthly data to construct a quarterly index. Specifically, the quarterly stock volatility series is a three-month average of squared percentage changes in the S&P 500 Index within each quarter.

regime change in the 1990s as the turnover series appears to shift dramatically, having both a higher mean and higher volatility.

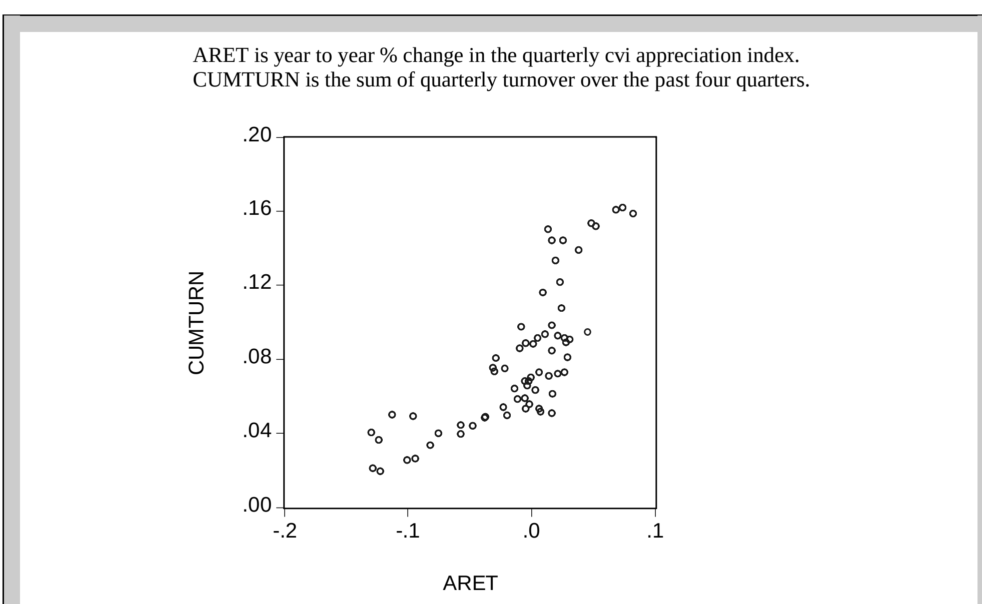
Exhibit 13 examines the relationship between contemporaneous appreciation returns and turnover with scatter plots, in two different ways. The top figure plots quarterly de-trended turnover against quarterly appreciation returns. Based on this picture, there does not appear to be a strong positive univariate relationship between the two series. It is possible the quarterly frequency is characterized by significant noise, making it difficult to detect a link. The bottom plot takes a longer-term view and examines the univariate relationship between year-to-year percentage change in the CVI value index (i.e., annual capital or appreciation returns) and cumulative turnover over the past four quarters. Eliminating some of the noise in quarterly changes reveals a positive relationship between price changes and transaction activity, but only when returns are "high" and "low."[21] When prices are not changing much, there does not appear to be a relationship between returns and volume. Hence, there appears to be a non-linear relationship between price change and volume that is a function of the return environment.

Exhibit 13 | Scatterplots of Real Estate Appreciation Returns versus Turnover Quarterly Data, 1983–2004

(a) Quarterly Percentage Price Change versus Detrended Turnover



(b) Annual Percentage Price Change versus Annual Detrended Turnover



The positive link between returns and cumulative turnover when returns are large in absolute value is consistent with an information story in which trading activity generates valuable information to investors that is employed to update reservation prices.

To examine the properties of turnover as a function of the return environment in more detail, Exhibit 14 reports the means and standard deviations of turnover, both raw and de-trended, in up and down periods, characterized by either positive or negative quarterly returns. As expected, on average turnover is significantly lower in the low return state. In contrast, the volatility (standard deviation) of turnover is higher in the high return state than in the negative return quarters. Viewing turnover as the proxy for liquidity change, this is consistent with the notion that low liquidity environments have low risk of liquidity change, whereas higher liquidity periods are riskier in a liquid change context. Combining the univariate findings on price volatility (Exhibit 12) and turnover volatility, we have that low return environments are characterized by ‘‘high price/low turnover’’ volatility while higher return environments are ‘‘lower price/higher turnover’’ volatility. Previously, we interpreted the low price volatility in more liquid markets as evidence in favor of the Novy-Marx (2004) option explanation with low price volatility implying a high opportunity cost of not transacting. The higher turnover volatility would seem to reinforce this since with greater volatility there is a higher probability that liquidity could decrease.

To examine the dynamic linkages between trading turnover and property appreciation, and to formally test for causality, we employ a bivariate vector autoregressive model. Exhibit 15 reports estimation and Granger causality test results. Based on the coefficient estimates, there is no evidence to suggest that turnover ‘‘causes’’ returns or that returns lead turnover. The only lagged variables that have statistically significant estimates are lags of the dependent variable. Consistent with this, we cannot reject the null hypothesis of no Granger causality in either direction, at least with quarterly data over this sample period. Hence,

Exhibit 14 | Characteristics of Returns and Turnover in Different Return Environments

	Average (%)	Std. Dev. (%)
Raw Turnover		
(a) returns < 0	1.438	0.697
(b) returns ≥ 0	2.248	1.240
t-test of difference in means	−3.860	
Detrended Turnover		
(a) returns < 0	−0.136	0.871
(b) returns ≥ 0	0.614	1.166
t-test of difference in means	−3.411	

Exhibit 15 | Vector Autoregressions and Granger Causality Tests, Quarterly Data

Panel A: Vector Autoregression

	Equation 1: Return		Equation 2: Turnover	
Variables	Estimate	*t*-Stat.	Estimate	*t*-Stat.
D_1	0.001	0.16	−0.006	−1.54
D_2	0.002	0.51	−0.006	−1.80
D_4	−0.004	−0.96	0.007*	2.15
R_{t-1}	0.351**	2.80	0.064	0.64
R_{t-2}	0.460**	3.64	0.003	0.03
R_{t-3}	0.104	0.76	0.128	1.19
R_{t-4}	0.144	1.14	−0.016	−0.16
R_{t-5}	−0.270*	−2.25	−0.067	−0.70
T_{t-1}	0.105	0.63	0.392**	2.99
T_{t-2}	−0.029	−0.17	0.193	1.44
T_{t-3}	0.136	0.79	−0.013	−0.09
T_{t-4}	0.143	0.85	0.146**	1.10
T_{t-5}	−0.131	−0.84	−0.006	−0.05
S_t	0.168	1.48	−0.044	−0.49
R^2	0.66		0.67	

Panel B: *F*-tests of Granger Causality

Hypotheses	*T* does not Granger cause *R*	*R* does not Granger cause *T*
F-Statistic	1.71	0.87
P-value	0.15	0.51

Notes: This table reports the regressions of the real estate appreciation rate on lagged appreciation rates, turnover, cap rate, and the spread between the 10-year Treasury yield and the 3-month Treasury yield, as well as *F* tests of Granger causality between returns and turnover. D_i is the dummy for the *i*th quarter, in time period *t*; R_t is the real estate return measured at the % change in the NCREIF cvi index; T_t is the turnover; and S_t is the yield spread.
*Significant at the 5% level.
**Significant at the 1% level.

volume does not appear to Granger cause (appraisal) returns and vice versa in high frequency quarterly data, once we control for persistence in the variables.[22] In an attempt to shed additional light on quarterly return/turnover dynamics, Exhibit 16 examines the return regression from the return/turnover VAR in more detail. Regression 1 includes only lagged returns as regressors, while Regression

Exhibit 16 | Predicting One Quarter Ahead Real Estate Appreciation Rates

Variables	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
D_1	−0.001	−0.002	−0.002	−0.002	0.000
	(−0.47)	(−0.37)	(−0.36)	(−0.37)	(0.03)
D_2	0.000	0.001	−0.002	−0.000	0.002
	(0.09)	(0.19)	(−0.39)	(−0.06)	(0.50)
D_4	−0.004	−0.005	−0.005	−0.005	−0.004
	(−1.36)	(−0.90)	(−1.08)	(−1.08)	(−0.95)
R_{t-1}	0.375**				0.297*
	(3.27)				(2.37)
R_{t-2}	0.431**				0.448**
	(3.65)				(3.66)
R_{t-3}	0.112				0.124
	(0.88)				(0.91)
R_{t-4}	0.183				0.157
	(1.54)				(1.26)
R_{t-5}	−0.293*				−0.265*
	(−2.61)				(−2.24)
T_{t-1}		0.504*			0.140
		(2.47)			(0.86)
T_{t-2}		0.086			−0.017
		(0.39)			(−0.10)
T_{t-3}		0.219			0.138
		(0.98)			(0.82)
T_{t-4}		0.188			0.141
		(0.86)			(0.86)
T_{t-5}		−0.225			−0.124
		(−1.12)			(−0.81)
C_{t-1}			−0.364*		−0.050
			(−2.21)		(−0.43)
S_{t-1}				−0.231	0.223*
				(−1.69)	(1.97)
R^2	0.63	0.30	0.08	0.05	0.67

Notes: This table reports the regressions of the real estate appreciation rate on lagged appreciation rates, turnover, cap rate, and the spread between the 10-year Treasury yield and 3-month Treasury yield. D_i is the dummy for the th quarter, in time period t; R_t is the real estate return; T_t is the turnover; C_t is the cap rate; and S_t is the yield spread. The t-Statistics are in parentheses.

*Significant at the 5% level.

**Significant at the 1% level.

2 includes only lagged turnover. Regression 2 results suggest that lagged turnover is positively related to future returns, but the results of Regression 1 imply that there is significant autocorrelation in appraisal-based returns that must be accounted for. Once these are put together in Regression 5, the significance of the turnover coefficient disappears.

Exhibit 17 reports the results of moving from the quarterly to the annual forecasting horizon. If high turnover represents more than a liquidity phenomenon and includes an "excessive" trading component systematically related to the

Exhibit 17 | Predicting One-Year Ahead Annual Real Estate Appreciation Returns

Variables	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
R_{t-1}	1.923**				1.567**
	(4.98)				(4.35)
R_{t-2}	1.177**				1.187**
	(2.95)				(3.26)
R_{t-3}	−0.056				0.262
	(−0.14)				(0.69)
R_{t-4}	−0.329				−0.242
	(−0.87)				(−0.69)
T_{t-1}		1.322*			0.712***
		(2.62)			(1.94)
T_{t-2}		0.631			0.426
		(1.18)			(1.14)
T_{t-3}		0.750			0.479
		(1.40)			(1.30)
T_{t-4}		−0.065			−0.179
		(−0.13)			(−0.50)
C_{t-1}			−0.540		0.410
			(0.69)		(0.93)
S_{t-1}				−0.422	1.511**
				(−0.89)	(4.26)
R^2	0.59	0.28	0.01	0.01	0.70

Notes: This table reports the regressions of annual real estate appreciation rates on lagged quarterly appreciation rates, turnover, cap rate, and the spread between 10-year Treasury yield and the 3-month Treasury yield. Quarterly dummies were employed but the coefficient estimates are not shown. R_t is the quarterly real estate return, T_t is the turnover, C_t is the cap rate, and S_t is the yield spread. The t-Statistics are in parentheses.

*Significant at the 5% level.

**Significant at the 1% level.

***Significant at the 10% level.

presence of uninformed investors, then high turnover should be related to future return reversals. As with the quarterly forecast horizon, we estimate variants of the forecasting equation employing only lagged quarterly returns, only lagged turnover and then combined. Regression 1 indicates a strong persistence in property price changes even at the annual horizon. Current and one period lagged quarterly price changes are positively and significantly related to one-year ahead percentage price change. Regression 2 again indicates that turnover is positively related to future price movements, ignoring the persistence in property price changes. This time however, putting these together in Regression 5, the significance of the coefficient on turnover does not completely disappear as it did in the quarterly forecast horizon. High turnover does appear to predict future appreciation returns (1 year head), but with a positive coefficient, even after accounting for autocorrelation in appraisal-based price changes.[23]

These findings appear to be consistent with our cointegration results in the first section (annual data) of the paper, which support the dynamic adjustment of the property market through both price and liquidity over time, in part as a function of the extent of deviation of liquidity from long-run equilibrium level as proxied by trading turnover. They appear to be at odds with the Baker and Stein (2003) model of turnover as a sentiment indicator, unless because of long adjustment periods the annual frequency is too short a period to capture this feature of property market adjustment.

Conclusion

This study aimed to disentangle competing explanations for time-variation in private market real estate liquidity. We extend the search-based models of property transactions and pricing of Fisher, Gatzlaff, Geltner, and Haurin (2003), or FGGH (2003), and Goetzmann and Peng (2004) to explore three alternative explanations for why changes over time in transaction frequency are driven by buyer value distributions shifting more relative to seller distributions shifts in response to shocks. These explanations include: (1) lagged seller price adjustment due to noise (i.e., rational updating in world of uncertainty and asymmetric information); (2) sellers' option value of waiting (i.e., not transaction), both rational economic supply side explanations; and (3) over-optimism (or overconfidence) on the part of some buyers, coupled with market frictions, such as the inability to sell property short, a demand-side force that exacerbates the turnover-value linkage caused by inertia in seller adjustments.

Overall the empirical findings are consistent with models of optimal valuation with rational updating, and also provide support for the option-based opportunity cost explanation for the pro-cyclicality of trading volume (liquidity) property pricing. There is little evidence to suggest that high turnover derives from the presence of over-optimistic "noise" traders, at least based on the NCREIF data sample employed in this paper.

Endnotes

[1] This indicates that ''true'' commercial returns are underestimated by the NCREIF index in hot markets and overestimated in down markets. Goetzmann and Peng (2006) also explore this issue and provide an econometric correction technique applied to a housing price index.

[2] Evidence to support the need to understand private market liquidity dynamics comes from a recent survey undertaken for the Pension Real Estate Association (PREA) by Dhar and Goetzmann (2005). The authors find that liquidity risk is one the main risks of real estate investment as perceived by institutional investors. Consistent with this, the Investment Property Forum (IPF) in the United Kingdom has shown a keen interest in studying liquidity in commercial property markets and recent papers by Lin and Vandell (2005) and Bond, Hwang, Lin, and Vandell (2007) examine the implications of liquidity risk for pricing biases and optimal portfolio allocations, respectively.

[3] Wheaton (1990) also develops a search and matching theoretic foundation for the co-movement of prices and trading volume in the housing market. In his model, time to sale, which is negatively related to turnover, and house price are jointly determined.

[4] Cauley and Pavlov (2002) propose an option-based explanation for the downward rigidity of house prices in cold markets. They view levered ownership of a house as owning a call option on the house with the mortgage balance as the strike price. Selling the house involves exercising the option. Following a negative shock to demand, the value of retaining the option to sell may be greater than actually selling. Hence, rational owners may delay selling after a decrease in demand in order to retain the potential for a rebound in price in the future. Along similar lines, Krainer, Spiegel, and Yamori (2004) offer a model that extends Krainer (2001) to incorporate the effects of debt on market liquidity in response to negative demand shocks.

[5] Anglin (2003) also provides a theoretical foundation for the joint nature of changes in liquidity and value in response to changes in housing market conditions.

[6] Capozza, Hendershott, and Mack (2004) propose a model of price dynamics in illiquid markets applied to single-family housing markets in which transaction frequency can affect the rate of information dissemination. Markets with a high number of transactions, in theory, have lower information costs, which implies that prices should adjust relatively more quickly to long-run equilibrium values in response to shocks.

[7] Investor heterogeneity can result from differences across investors in terms of (1) information access or processing, (2) beliefs about the future (optimistic versus pessimistic), or (3) behavioral biases, such as overconfidence, that imply some investors not fully rational in the sense that they overestimate the precision of information signals or trade on ''market sentiment.'' Hence, investors can be alternatively classified as informed versus uninformed, optimistic versus pessimistic, or rational versus noise traders.

[8] Jones (2002) shows that high turnover predicts lower future returns, a result consistent with a behavioral effect; stocks become overpriced due to noise trading, which also lowers spreads and increases trading activity. See also Piqueira (2004).

[9] Additional recent research suggests that trading volume is related to value and momentum-based investment strategies and calls into question the common interpretation of trading volume as simply a liquidity proxy (Lee and Swaminathan, 2000; and Hong and Stein, 2003).

10 The basic model setup is a simplified version of the one proposed by Goetzmann and Peng (2004) to explain how transaction prices may not adequately capture both the demand and supply in markets for heterogeneous assets, such as housing markets.

11 Alternatively, this can be interpreted as the seller having in the past, been a buyer of this property and therefore to have made a successful bid, they would have a relatively high valuation on the property.

12 This section draws heavily from FGGH (2004).

13 Related to our specification, Quan and Quigley (1989) show that in a model of optimal valuation with Bayesian updating, $\lambda = Var[P]/(Var[P] + Var[e])$, where Var[$P$] is the variance in "true" price changes over time and Var[e] is the cross-sectional dispersion or noise in information provided by comparable sales. All else equal, the greater the quantity and quality of information provided by recent transactions of similar properties, the smaller is Var[e] and hence the closer the seller's estimate of property value to the "true" value.

14 Clayton, Geltner, and Hamilton (2001) provide empirical support for this model and show that lagging in prices can be viewed as lagging in cap rate adjustment.

15 Hendershott and Haurin (1988) discuss the implications of imperfect information in the context of the rental market. They state that if there is an *unperceived* decline in rental demand, then the duration of vacancy will rise with no effect on rents. Rents will be lowered only when landlords recognize the lowered demand. The effect of asymmetric information on prices in other, non-real estate markets has also been studied. In the equity markets, the effect of asymmetric information is the underpinning of much of the market microstructure literature. There, most models assume that market makers adjust prices in response to transactions, but the amount of the price adjustment depends on the probability of the transaction having been initiated by a better informed investor. Prices will therefore adjust only partially to a buy (sell) order, as there is a chance that it is from an uninformed trader. This is similar to the idea presented here where property sellers do not adjust their reservation prices fully in response to low market signals as the signal is noisy and the low signal may not be due to an actual decline in market conditions.

16 Consider a risky property with liquidation value, P, which is drawn from a normal distribution $\tilde{P}$ of potential values, with variance $\sigma^2_{\tilde{P}}$. Buyers receive noisy signals, $\tilde{S} = \tilde{P} + c\tilde{e}$, where c is a constant. In this setup, $c = 1$ is rational, whereas $0 < c < 1$ implies overconfidence. $\tilde{e}$ is a normally distributed, zero mean error term with variance $\sigma^2_{\tilde{e}}$; $\tilde{P}$ and $\tilde{e}$ are independent. The implication is that conditional on a noisy signal realization, S, $Var[\tilde{P}|\tilde{S} = S] = Var[\tilde{P}] - Cov(\tilde{P}, \tilde{S})/Var[\tilde{S}] = \sigma^2_{\tilde{P}} - [\sigma^4_{\tilde{P}}/(\sigma^2_{\tilde{P}} + c^2\sigma^4_{\tilde{e}})]$ with $c < 1$ investors underestimate the variance of price changes.

17 The "hedonic" index is a constant attribute bundle. It is derived from the prices of properties sold from the NCREIF index and controls for differing property characteristics so that changes in the index measure pure property transaction prices changes.

18 We recognize that the validity of the causality tests requires that turnover and both the hedonic and constant liquidity price series are stationary, which may not be the case. Moreover, we regard the VARs and causality tests undertaken here as preliminary data analysis tools, in part also because they consider only lead-lag relationships and therefore neglect potentially valuable information contained in contemporaneous data.

19 We use "log" prices so that differences, used in subsequent estimations, represent percentage changes as opposed to absolute index level differences.

[20] This equation is similar to the dynamic housing price model proposed by Capozza, Hendershott, and Mack (2004) that is given as Equation (2) in the paper and specified as: $\Delta P_t = \alpha \Delta P_{t-1} + \beta(P^*_{t-1} - P_{t-1}) + \gamma \Delta P^*_t$, where P is transaction price and P^* is the long-run equilibrium house price determined by economic conditions. α measures the extent of serial correlation or persistence and β the speed of mean reversion.

[21] Regressions of price change on turnover confirm the findings suggested by the data plots. With quarterly data we find $R_t = 0.49{*}T_t$ with a t-Statistic of 3.85 and R^2 of 15%, suggesting that quarterly turnover and percentage change in price are significantly positively correlated. However, once we account for serial correlation in the residuals (persistence in price changes), the coefficient on turnover is not statistically significant. With annual percentage change in price and cumulative four-quarter turnover data, we obtain $R_t = 0.72{*}T_t$ with a t-Statistic of 5.86 and R^2 of 30%. With lower frequency annual data, however, the coefficient on turnover remains statistically significant after accounting for serial correlation in the residuals (coefficient is 0.42 with t-Statistic of 2.80]. The finding of a stronger link between turnover and price change at the annual versus quarterly frequency is consistent with results in, and search-based explanation suggested by, Berkovec and Goodman (1996).

[22] We also estimated a three-variable VAR with appreciation returns, turnover, and return volatility. The inclusion of volatility did not improve the model fit or affect the coefficient estimates in the turnover or return equations.

[23] We also estimate variants of the following model: $AR_{t+4} = c + a_1 AR_t + a_2 AR_{t-4} + b_1 CUMT_t$, where AR is annual return or percentage change in property value and $CUMT$ is cumulative annual turnover. The coefficients on lagged annual returns are positive and negative at lags 4 and 8, respectively, suggesting positive persistence in the short-term and mean reversion in the long term. The coefficient on cumulative turnover is positive and significant.

References

Anglin, P. The Value and Liquidity Effects of a Change in Market Conditions. Working Paper, University of Windsor, 2003.

Anglin, P., R. Rutherford, and T. Springer. The Trade-off Between the Selling Price and Time-on-the-Market: The Impact of Price Setting. *Journal of Real Estate Finance and Economics*, 2003, 26, 95–111.

Baker, M. and J. Stein. Market Liquidity as a Sentiment Indicator. *Journal of Financial Markets*, 2004, 7, 271–99.

Berkovec, J. and J. Goodman. Turnover as a Measure of Demand for Existing Homes. *Real Estate Economics*, 1996, 24, 421–40.

Bond, S., S. Hwang, Z. Lin, and K. Vandell. Marketing Period Risk in a Portfolio Context: Theory and Empirical Estimates from the UK Commercial Real Estate Market. *Journal of Real Estate Finance and Economics*, 2007, 34:4, 447–61.

Capozza, D., P. Hendershott, and C. Mack. An Anatomy of Price Dynamics in Illiquid Markets: Analysis and Evidence from Local Housing Markets. *Real Estate Economics*, 2004, 32, 1–32.

Case, K.E. and R.J. Shiller. Is There a Bubble in the Housing Market? *Brookings Papers on Economic Activity*, 2003, 2, 299–362.

Cauley, S. and A. Pavlov. Rational Delays: The Case of Real Estate. *Journal of Real Estate Finance and Economics*, 2002, 24, 143–65.

Childs, P., S. Ott, and T. Riddiough. Optimal Valuation of Noisy Real Assets. *Real Estate Economics*, 2003, 30, 385–414.

Chordia, T., R. Roll, and A. Subrahmanyam. Market Liquidity and Trading Activity. *Journal of Finance*, 2001, 56, 501–30.

Clayton, J., D. Geltner, and S. Hamilton. Smoothing in Commercial Property Valuations: Evidence from Individual Appraisals. *Real Estate Economics*, 2001, 29, 337–60.

Dhar, R. and W. Goetzmann. Institutional Perspectives on Real Estate Investing: The Role of Risk and Uncertainty. Pension Real Estate Association Research Report, 2005.

Fisher, J., D. Gatzlaff, D. Geltner, and D. Haurin. Controlling for the Impact of Variable Liquidity in Commercial Real Estate Price Indices. *Real Estate Economics*, 2003, 31, 269–303.

——. An Analysis of the Determinants of Transaction Frequency of Institutional Commercial Real Estate Investment Property. *Real Estate Economics*, 2004, 32, 239–64.

Genesove, D. and C. Mayer. Equity and Time to Sale in the Real Estate Market. *American Economic Review*, 1997, 87, 255–69.

Gervais, S., R. Kaniel, and D. Mingelgrin. The High Volume Return Premium. *Journal of Finance*, 2001, 56, 877–919.

Goetzmann, W. and L. Peng. Estimating Housing Price Indices in the Presence of Seller Reservation Prices. *Review of Economics and Statistics*, 2006, 88, 100–12.

Hendershott, P. and D. Haurin. Adjustments in the Real Estate Market. *Journal of the American Real Estate and Urban Economics Association*, 1988, 16, 343–53.

Hong, H. and J. Stein. Differences of Opinion, Short Sale Constraints, and Market Crashes. *Review of Financial Studies*, 2003, 16, 487–525.

Huberman, G. and D. Halka. Systematic Liquidity. *Journal of Financial Research*, 2001, 2, 161–78.

Investment Property Forum. *Liquidity in Commercial Property Markets*. IPF Educational Trust Research Report, London, 2004.

Jones, C. A Century of Stock Market Liquidity and Trading Costs. Working Paper, Graduate School of Business, Columbia University, 2002.

Krainer, J. A Theory of Liquidity in Residential Real Estate Markets. *Journal of Urban Economics*, 2001, 49, 32–53.

Krainer, J., M. Spiegel, and N. Yamori. Asset Price Declines and Real Estate Market Liquidity: Evidence from Japanese Land Values. Working Paper 2004-16, Federal Reserve Bank of San Francisco, 2004.

Lamont, O. and J. Stein. Leverage and House-Price Dynamics in U.S. Cities. *Rand Journal of Economics*, 1999, 30, 498–514.

Lee, C. and B. Swaminathan. Price Momentum and Trading Volume. *Journal of Finance*, 2000, 55, 2017–69.

Lin, Z. and K. Vandell. Illiquidity and Pricing Biases in the Real Estate Market. Working Paper, University of Wisconsin, 2005.

Lowry, C. Four Lessons of the Disconnect. Institute of Fiduciary Education. Prudential Real Estate Investors, Fall 2004.

Novy-Marx, R. The Microfoundations of Hot and Cold Markets. Working Paper, University of Chicago Graduate School of Business, 2004.

Ortalo-Magné, F. and S. Rady. Housing Market Dynamics: On the Contribution of Income Shocks and Credit Constraints. *Review of Economic Studies*, 2006, 73, 459–85.

Piqueira, N. Trading Activity, Illiquidity Costs and Stock Returns. Princeton University Working Paper, 2004.

Quan, D. and J. Quigley. Inferring an Investment Return Series for Real Estate from Observations on Sales. *Journal of the American Real Estate and Urban Economics Association*, 1989, 17:2, 218–30.

Scheinkman, J. and W. Xiong. Heterogeneous Beliefs, Speculation and Trading in Financial Markets. Working Paper, Princeton University, 2004.

Stein, J. Prices and Trading Volume in the Housing Market: A Model with Down-Payment Effects. *Quarterly Journal of Economics*, 1995, 110, 379–406.

Wheaton, W. Vacancy, Search, and Prices in a Housing Market Matching Model. *Journal of Political Economy*, 1990, 98, 1270–92.

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