# Liquidity Pricing of Illiquid Assets

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**ABSTRACT**

So far the main body of the asset pricing literature has computed liquidity risk premia for either markets or single assets. The vast majority of these studies have been focused on fairly liquid assets, but recently a greater attempt to price such an important component of the asset pricing factors in markets with high illiquidity (especially in real estate) has also started to take place.

The present paper brings these recent studies together, and estimates the liquidity premium of illiquid assets looking at three main sources – time on market, liquidation bias and market liquidity – using three main empirical estimation models and several liquidity measures suggested in the literature. We find strong evidence of a high premium that varies across sectors and periods. This estimation is robust to different measures of liquidity and model specifications.

**Keywords:** Lliquidity, Asset Pricing, Risk Premium, Real Estate

## 1. Introduction

Several studies have looked at the pricing of some liquidity drivers within real estate markets. Establishing the extent of such an important factor is key to explaining (even though only partially) the equity risk premium puzzle of real estate. In fact, a high return to risk profile makes this asset appealing for asset allocation choices but very few fund managers allocate more than 5%-10% to real estate. This fact would suggest that other features are considered by asset allocators when they decide how to distribute their investments. Secondly, the target rate of return (and hence premium) for real estate assets is time-varying and one of the drivers of such variation could be explained by the variation in liquidity available in the market.

In this study we provide an empirical analysis where, firstly, we compute several liquidity proxies that can be used to measure the liquidity premium. Along with publicly available portfolio metrics of the transaction activity within such markets (e.g. transaction volumes, turnover rates), we also compute some measures suggested in broader finance literature: Amihud (2002), Roll (1984) and Pastor and Stambaugh (2003). We believe that such measures – along with Time on Market (TOM) presented in the previous paper[1] – capture different dimensions of the liquidity phenomenon: tightness, depth, breadth, immediacy, resilience.

Secondly, we present the analysis using three different models to assess the ex-ante risk-return impact of liquidity premia for illiquid assets: time on market which leads to an underestimation of the ex-ante risk varying in both holding period and time on market; liquidation bias which leads to an overestimation of the return because only accepted bid prices (highest ones) are observed in transaction data; market liquidity which requires an extra return to compensate the investor for the exposure of assets to movements in liquidity levels recorded within their markets.

As a final step of our study, we empirically use these models to compute the liquidity premium to be embedded in the estimation of both ex-ante return and ex-ante risk for the UK real estate market. This empirical application is new for two main reasons: first it brings the estimation of several sources of liquidity together in one study allowing a comparison of the impact of such sources in determining the overall liquidity premium; second, it applies some of these models for the first time to the UK market, which offers by far the best databank of real estate assets under performance measurement – i.e. the transaction data refers to the properties whose performance is measured and it also reflects a good proportion of overall transactions taking place in the market. Thirdly, we offer an ex-ante perspective and estimation that can be compared to an ex-

[1] Devaney S. and Scofield D. (2014): "Time to Transact: Measurement and Drivers".

post analysis previously presented in the literature and suggesting an overall risk premium of real estate assets of around 2-4%.

The paper is structured as follows: the next section presents a review of the related literature. Main theoretical models and the data used in this study (along with the main measures of market liquidity) are described in sections 3 and 4.. Finally, sections 5 and 6 discuss the main empirical results and conclude the paper.

## 2. Literature Review

Liquidity in real estate markets has been studied for both direct and indirect markets. Corgel et al. (1995), Zietz et al. (2003), and Feng et al. (2011) provide a descriptive overview of exchange-listed REITs. The liquidity of REITs relative to alternative investments linked to real estate has great appeal especially to long term investors and this allowed the market to developed with a high institutional component in the ownership structure. Nelling et al. (1995) were the first to examine REIT liquidity. They analyze daily closing bid-ask spreads primarily for NASDAQ firms over the late 1980s. They find that REIT liquidity as measured by the percentage spread declined during the 1980s, i.e., percentage spreads widened, making REIT shares relatively expensive.

Following on this work, but using market microstructure data, Bhasin et al. (1997) examine REIT liquidity and find that percentage bid-ask spreads declined significantly over the period 1994-97 (a time which saw a significant growth in the number and market capitalization of REITs), also thanks to the "new REITs" – Cole (1998). They also use an empirical model of the spread developed by Stoll (1978) to provide evidence on the determinants of spreads, found to be a positive function of the price and dollar volume, and a negative function of the volatility of stock returns – see also Cannon and Cole (2011) who show significant improvements in overall liquidity around 200-2006. Finally, Clayton and MacKinnon (2000) confirm these results for the early 1990s by decomposing the percentage spread into three components (tightness, depth and resiliency) following Kyle (1985) and finding that most gains are attributable to improvements in depth rather than tightness.

Marcato and Ward (2007) develop the model in Clayton and MacKinnon (2000) to allow estimation with daily rather than intra-day data. Similar results are found in the US, with improving liquidity measured for both estimated spreads and market depth. The choice of the stock exchange is also found to be significant with even smaller REITs benefiting from listing in the NYSE as opposed to NASDAQ and AMEX – similar results to Danielsen and Harrison

(2002) who find that NYSE and AMEX to be preferable to NASDAQ. Weaker results are also found for other markets (UK and Australia). Brounen et al (2009) support the idea of studying several dimensions of liquidity in international markets and use three proxies for liquidity – dollar trading volume; turnover and a version of the Amihud measure – to avoid misleading conclusions. They document a significant and consistent role for market capitalization, nonretail share ownership and dividend yield as drivers of liquidity across markets. Finally, Subrahmanyam (2007) finds a liquidity risk priced in REITs and he is the first to explore order flow spillovers across NYSE stocks, finding that this phenomenon happens from REITs to non-REITs and that liquidity measures of the latter being a good predictor for the former.We now conclude with a series of works on REITs liquidity looking at different aspects of this asset pricing phenomenon. Hill et al (2012) examine the market value of REITs financial flexibility before and during the recent financial crisis. They define firm liquidity as lines of credit and cash holdings. The study provides mixed evidence of a positive association between firm value and unused credit line capacity. This suggests financial flexibility is more valuable during tight credit periods, consistent with internal liquidity mitigating underinvestment (i.e. cash-like holdings) when financing frictions are strong. Looking at the financing channel and the relationship between asset liquidation values and the capital structure, Giambona et al (2008) also find that liquid assets allow higher leverage and access to longer maturities. Still looking at the importance of liquidity of the underlying assets, Benveniste et al. (2001) compare the replacement value of assets held by a REIT to the value of the REIT itself and they find that securitization through the REIT structure increases the value of the underlying real estate assets by 10–20 percent. They also analyze cross-sectional determinants of liquidity as measured by dollar volume, and find that the market value of equity explains almost half the variation in dollar volume, but the statistical significance of this relation disappears when they include control variables for institutional ownership and property focus. Following from the evidence that REITs reflect partly equities and partly private real estate performances, Bond and Chang (2012) also study the cross-asset liquidity between these three markets/assets. In line with theoretical expectations, they find liquidity risk and commonality in liquidity to be generally lower for REITs than for other equities and causality going from public to private markets.

Characterising the intraday-trading behaviour, Below et al. (1995) find that (i) REITs have lower volume and fewer trades than non-REITs, (ii) mortgage REITs trade at narrower spreads than equity REITs, (iii) REITs with higher institutional ownership trade at narrower spreads that are closer to those observed for non-REITS.

Bertin et al (2005) point out that the use of raw spreads fails to consider that many transactions take place inside the quoted spread. Their study estimates several liquidity proxies classified as either friction or activity measures to determine whether or not REIT liquidity is similar to common stock liquidity. The results document that the liquidity of REIT stocks exhibits the well-known intraday U-shaped pattern that is typically found for common stocks. From an economic perspective, these results hold strong implications for REIT investors seeking to minimize trading costs by using the information revealed by the intraday patterns. The findings also reveal that the liquidity of REITs is generally lower than that of similar common stocks.

Finally, a recent study by Glascock and Lu-Andrews (2013) sheds light upon macroeconomic driving factors behind funding liquidity of REITs and the linkages between REIT funding liquidity and REIT market liquidity across the business cycle. The authors use the Amihud measure and the turnover ratio for market liquidity and debt service coverage ratio, loan-to-value ratio and number of loans from the American Council of Life Insurers (ACLI) for funding liquidity. The study shows contemporaneous and lagged macroeconomic effects on REIT funding liquidity, with negative effects from changes in inflation and default and term spreads, and a positive on from the banks' willingness to lend for commercial real estate investment opportunities.

There are fewer studies of liquidity for direct real estate investment than for either financial assets or REITs. In part, this stems from the decentralized and private nature of real estate markets that has, in the past, created difficulties in obtaining data and creating liquidity measures. Yet, in recent years, liquidity issues have been subject to more extensive study. For example, the debate summarised in IPF (2004) on the effects of liquidity on the risk of real estate investments has been taken further in by Lin and Vandell (2007), Bond et al. (2007) Lin and Liu (2008) and Cheng et al. (2013) amongst others. Meanwhile, work that considers the impact of liquidity on real estate price series has also developed substantially since IPF (2004) was published. This has resulted in the creation of liquidity indices in the US, though the assumptions and models required to produce such indices are methodologically complex. Further research has also been conducted with more traditional liquidity indicators such as volumes and time on market.

Two recent studies have explored the relationship between volumes and returns in private real estate investment markets. Fisher et al (2009) and Ling et al (2009) examine relationships between capital flows and investment returns in the US and the UK, respectively, to see whether they affect each other. Both studies use a vector autoregressive (VAR) approach where institutional capital flows and returns are specified as endogenous variables in a two-equation system. Fisher et al (2009) find that capital flows have a statistically and economically significant association with subsequent returns, which suggests weight-of-money effects in pricing. They do not find evidence for return chasing. Ling et al (2009) then find positive contemporaneous correlations between returns, absolute and percentage capital flows, and turnover, but their results did not support the idea that capital flows have a 'price pressure' effect in the UK.

These studies were facilitated by the fact that measures of absolute, if not relative, trading volumes are now available for most major real estate investment markets. In contrast, tightness, as captured by bid-ask spreads, is much more difficult to measure for direct real estate than for many financial assets as there is not an observable bid-ask spread for different assets in the real estate investment market. However, there is a distinction between the reservation price of a seller (the price at which they would be prepared to sell a real estate investment) and that of a buyer. The distance between these determines the likelihood of a sale taking place: where reservation prices meet or overlap, a buyer and seller will be able to conclude a trade, but, in cases where they do not, the asset concerned will stay unsold.

More generally, a distribution of reservation prices that reflects the views of potential buyers of real estate assets can be inferred as can a similar distribution of reservation prices that reflects views of potential sellers. Such distributions are proposed by Fisher et al. (2003); they describe how the shape and extent of overlap between these distributions influences the number of real estate assets likely to trade. They also argue that variations in the liquidity of the real estate market over time make the interpretation of real estate price series more difficult. This is because prices tend to adjust slowly to changes in real estate market conditions. In fact, the nature of real estate markets causes adjustments to occur in prices, volumes and the time to transact when market conditions change, as well as in the mix of assets that are traded. As such, Fisher et al. (2003) argue that real estate indices need to be adjusted to reflect the differential ability to enter and exit the market at different points of the real estate cycle.

Adjustments to create constant liquidity real estate price series are proposed and tested by Fisher et al (2003), Goetzmann and Peng (2006) and Fisher et al (2007). Subsequently, the relationship between constant liquidity and uncorrected price series for the US has been used by Clayton et al (2008) to derive a measure of market-wide liquidity, while Buckles (2008) proposes a liquidity index based on a more complicated procedure, but building from the same body of work. This area of research has resulted in the periodic publication of a liquidity series by the MIT Centre for Real Estate alongside the transaction-based price series resulting from the work of Fisher et al (2007). However, similar, constant-liquidity transaction price indices do not exist in other countries and are a prerequisite for creating a liquidity index of this nature.

The other major area of examination has been in regard to the time it takes to transact assets in the direct property market, i.e. time-on-market. A substantial body of research has explored time-on-market for residential property and key findings from this literature are considered in the chapter on time to transact. For real estate investment markets, there are fewer studies and those that exist tend to focus on measurement rather than explanation. For example, McNamara (1998) conducted survey work to establish perceived average times to transact for different real estate investments in the UK. For the sell side, he reported a marketing period of four to eight weeks and a due diligence period of four to twelve weeks depending on property type. However, subsequent work for the IPF by Crosby and McAllister (2004) found actual times to be longer, with a median time of 190 days (c.27 weeks) in their sample of transactions. This study also found considerable dispersion in transaction times. Finally, Scofield (2013), who considers time to transact from the buy side, finds that time to transact is time varying and that transactions were conducted more rapidly during the boom phase of the UK real estate cycle.

The nature of real estate markets (heterogeneous assets with limited numbers of buyers and sellers operating under various economic constraints) means that the length of the time-on-market is likely to be affected by many factors. Thus, when real estate investors come to sell a property, they face uncertainty not only in regard to transaction price (price risk), but also around the time it will take to sell (marketing period risk). In contrast, many financial assets can be sold instantaneously through public exchanges and so investors do not bear marketing period risk.

The nature and behaviour of marketing period risk is investigated in the work of Lin (2004) and Lin and Vandell (2007), who highlight the importance to real estate investors of the hidden risk exposure that occurs during the extended marketing period of a commercial real estate asset. Their models estimated the extent to which ex-post data on real estate performance understates the ex-ante risk exposure taken by real estate investors, because it does not take into account the asset risk exposure during the marketing period or the uncertainty of the marketing period itself. This work is extended by Bond et al (2007) who calibrate such models using the transaction time results found by Crosby and McAllister (2004). Their study suggests that the ex-ante level of risk exposure for a commercial real estate investor is around one and a half times that obtained from historical statistics, although this may decrease for investors who construct portfolios of real estate assets. Meanwhile, Lin and Liu (2008) consider how the level of risk may vary with the financial circumstances and investment horizons of different types of seller.

In summary, this work provides evidence of the importance of liquidity in direct real estate markets and, to some extent, the degree of liquidity for different types of property or in different periods. However, it is only recently that liquidity has attracted more extensive research. It is also the case that the range of measures produced and tested in a direct real estate context is much narrower than for either REITs or financial assets, and is less developed for real estate investment assets than for residential property markets, where data has traditionally been much richer.

A descriptive overview of the public non-listed REIT sector is provided by Corgel and Gibson (2008) for U.S. funds, and by Brounen et al. (2009) for European funds. Quite recently, new empirical work on the estimation of liquidity premiums for investment vehicles different from REITs has started to be developed in recent times and will probably be further analysed in the future. So far, however, only few articles have focused on European unlisted funds, debt products and American real estate mutual funds.

Particularly, Schweizer et al (2013) presents open-ended property funds (OPFs) which offer apparently perfect daily liquidity, but failed to do in market conditions when liquidity is most required (redemptions are suspended if a threshold of requests is passed). They find that these vehicles offer a liquidity premium (measured as discount to NAV, i.e. Net Asset Value) of about 6% in the short run, but are not affected by liquidity risk in the long-run and then represent an attractive investment tool for long-term investors (e.g. pension funds and other institutional players).

A recent working paper by Marcato and Tira (2013) builds upon the issue of suspended redemptions and tries to estimate the impact of traded volumes on the price of such vehicles. Interestingly, if no effect is seen for aggregate transaction volumes – in line with previous findings in the finance literature – an opposite effect is found for money flows entering and exiting funds. In fact a money smart effect is estimated for outflows (i.e. capability of disinvesting timely), suggesting that current investors have access to a better set of information. Instead, a return chasing behaviour seems to drive inflows (i.e. investors enter funds that performed well in the past) – see also Chou and Hardin III (2014) for US real estate mutual funds –, also thanks to the persistence of fund returns over time.

As further step in the analysis of indirect causes of liquidity for unlisted funds, Wiley (2013) links the problem of suspended redemptions to managerial incentives and finds that an increase in compensation increases the liquidity risk indirectly because it reduces the ability to generate revenues and to raise equity capital to be used to fulfil redemption requests.

Finally, as far as debt products are concerned, we clearly see a shift in the pricing of liquidity risk for such products. If before the last economic crisis Northaft et al (2002) estimated a very small liquidity premium for agency (e.g. Freddie Mac, Fannie Mae) products, Kim (2009) later found that a liquidity shock is more likely for mortgage backed securities (MBS) than for government bonds if there is a sudden and significant drop of trading activities (as we have observed back in 2008). Work from the Federal Reserve Bank of New York and Atlanta also reinforces these results linking the premium to vintage and a common factor (along with credit rating and idiosyncratic factor) – Dungey et al. (2013) – and showing the positive effect (around 10 to 25 b.p.) of the trading method on a "to-be-announced" (TBA) basis and no effect of the presence of a government credit guarantee.

## 3. Model and methodology

In this section we present three main models, which are helpful to understand the impact of liquidity on ex-ante measures of risk and return. In fact, when investors price the liquidity factor, their perceived risk attached to the investment (i.e. estimated ex-ante volatility) may be higher due to the presence of such risk factor. The first model captures this dynamic estimating the new ex-ante volatility for investors pricing the time necessary to transact their assets (i.e. time on market). Devaney and Scofield (2014) estimate TOM for different types of properties and during different periods. Our model intends to use this information to estimate what is the extra risk investors expect if they cannot transact their properties instantaneously as for financial markets such as equities and bonds.

Moreover, since properties are not transacted frequently and, at any point in time, transaction prices are only observed for a restricted sample of investable properties (i.e. not all properties are transacted at every point in time), investors may require a higher return because they want to be rewarded for the risk of not being able to sell their assets (or of needing to sell their assets at a discount) when they are in a position to do so. Hence, considering the impact of a liquidation bias, investors will increase the ex-ante return they require when they invest in real estate assets.

Finally, the third model also looks at the greater or smaller ability of a market to absorb order flows without affecting prices (i.e. matching demand and supply of transacted properties). In periods when markets are not able to absorb order imbalances, higher than expected price movements can be recorded. As a consequence, investors want to be paid for this extra-risk and they ask for a higher ex-ante return.

The following three sub-sections (3.1, 3.2 and 3.3) present the three different models in reference to the related literature and to give an intuition about interpretation and application.

### 3.1 TOM, risk and return

The first model we empirically estimate assesses the impact of the time on market (TOM) on the ex-ante risk of real estate. We want to build on the evidence obtained by Devaney and Scofield (2014), where a thorough data collection managed to achieve a sample of observable transactions and evidence will be used to determine the impact of TOM on the risk/return profile of real estate assets. Hence, we follow the stream of literature which theoretically models the ex-ante risk and return adjusting the ex-post measures. Particularly we follow Cheng et al (2010, 2013), Lin and Vandell (2007), Bond et al. (2007), Lin and Liu (2008) and Lin et al. (2009), and empirically test the models to compute a new measure of risk either assuming random real estate returns or deviating from this assumption.

Cheng et al (2013) build a simple model which is based on the transaction process of real estate assets, where in a round-trip (i.e. buy, hold and sell) transaction an investor faces the uncertainty of time on market (i.e. time to sell the asset) coupled with the uncertainty on the price for the successful sale. As a result of this process, the ex-ante return is a function of both variables: on one hand, the longer the TOM the higher the ex-ante return is because the liquidity premium will depress the price the buyer is willing to pay for the asset; on the other hand, the higher the selling price is, the higher the return is. This feature is different from financial assets where the uncertainty of TOM does not exist because transactions can be executed instantaneously. Hence, this market friction in real estate markets represents a liquidity risk which can be associated to a lower return expected by economic agents in case they need to sell quickly due to a liquidity constraint.

Consequently, if real estate returns were following a random walk (i.e. they were highly unpredictable because there was no time-dependency) the ex-ante return would simply be equal to the ex post single-period return (*ret*, e.g. average annual return from IPD) multiplied by the sum of holding period (*t*) and TOM ($t_{TOM}$)[2]:

$$ret_{ex-ante} = (t + t_{TOM}) * ret \quad (1)$$

[2] For financial assets with TOM equal to zero, the single period return would only be multiplied by the holding period.

And the risk – measured by variance (volatility squared) – would be represented by a combination of variances of returns within the holding period and variance of TOM (respectively $\sigma_t^2$ and $\sigma_{TOM}^2$) as follows:

$$\sigma_{ex-ante}^2 = (t + t_{TOM})\sigma_t^2 + ret^2 * \sigma_{TOM}^2 \tag{2}$$

Clearly, if TOM is equal to zero (as for financial assets), the second term of the equation disappears and the ex-ante variance is equal to the single-period variance ($\sigma_t^2$) multiplied by the holding period (*t*).

If we then assume 10% and 8% being the annual ex-post single period return and standard deviation of real estate respectively, Exhibit 1 reports ex-ante adjusted estimates of annual standard deviations for an investor considering the effect of TOM. Clearly, as the TOM increases, the ex-ante risk increases because it now includes the uncertainty about the time needed to sell the asset. For example for a 5 year holding period, the ex-ante risk perceived by the investor should pass from 8.0% (assumed to be the volatility for TOM = 0) to 9.4% when the time on market is 15 months (i.e. 1.4% difference). The marginal effect on the ex-ante risk is also smaller for longer holding periods (HPs) because the risk associated to TOM can be absorbed throughout the length of a longer investment period. In fact the effect on an increase of TOM from 0 to 15 months for a 15 year HP 'only' increases the ex-ante volatility from 8.0% to 8.6% (i.e. difference of 0.6%). In other words, the TOM (in our example of 15 months) has a bigger relative impact on the annualised 5 year holding period volatility (rising to 9.4%) than on the annualised 15 year holding period volatility (which only increases to 8.6%).

[ INSERT EXHIBIT 1 HERE ]

As a result of this 'extra' risk to be considered – i.e. in our example the difference between the new ex-ante volatility minus the original one of 8% – should lead to a higher ex-ante return required by the investor as a compensation for a higher risk. As a crude measure of the ex-ante return, we could apply the same ratio of modified vs original standard deviation to the original return. Returning to our example of an investor with 5 year holding period, the ratio of the two standard deviations would be 1.175 for a TOM equal to 15 months (9.4% divided by 8.0%). Hence, assuming an originally estimated return of 10% without considering the effect of the time on market, investors they should require a slightly higher ex-ante return around 11.75% (10%

multiplied by the ratio 1.175) if they also want to consider the uncertainty of not being able to sell the property immediately (i.e. TOM = 15 months). The new figures (9.4% and 11.75%) would then represent the ex-ante risk and return profile of the investment when we also consider the effect of TOM.

Previous literature – Geltner (1989), Booth and Marcato (2004) and Bond et al (2012) among others – has shown evidence of serial correlation (smoothing) in both residential and commercial markets and hence the assumption of intertemporal independence of return distributions is invalidated. In other words, we have to consider that real estate markets are cyclical and part of the cyclicality may be due to the use of appraisal-based (rather than transaction-based) indices. One way to approach this issue would be the creation of a version of the appraisal-based index corrected for smoothing. However, the extent to which the original index should be unsmoothed is not deterministic and hence we would be left in the uncertainty domain as to the statistical adequacy of such correction – refer to Key and Marcato (2007) for a study of the implications on asset allocation choices.

Hence we follow the work by Cheng et al (2013) who developed an estimate of the ex-ante risk correcting for both smoothing and the time on market:

$$\sigma_{ex-ante}^2 = (t + t_{TOM})(\beta^T)^2\sigma_t^2 + 2\sigma_t^2\beta^T(1-\beta^T) + \frac{\left(ret^2+\left(\beta^T\right)^2\sigma_t^2\right)\sigma_{TOM}^2+\sigma_t^2\left(1-\beta^T\right)^2}{t+t_{TOM}} \quad (3)$$

where $\beta^T$ represents the extent to which returns are smoothed.

The estimation procedure suggested by Cheng et al (2013) works as follows:

1. they compute time series of returns for different holding periods (from 1 to n quarters) and their standard deviations – we use annual observations as we are interested in annualised return and risk;
2. they calculate the ratio between each standard deviation and the standard deviation of one period returns (for period one, this ratio will be equal to one and it will increase as the holding period increases from 1 to n);
3. they run a regression using this ratio (minus 1) as dependent variable and the investment horizon (minus 1) as independent variable (with intercept equal to zero). The estimated coefficient is referred as $\beta^T$.

We have estimated values of $\beta^T$ for the different sectors of the UK real estate market which we directly report in section 5. The coefficient of the overall market using quarterly data is equal to 0.76, which is in line with the one computed by Cheng et al (2013) for the US market (respectively 0.9 and 0.6-0.7 for commercial and residential markets).

For our main exercise we are interested in annual risk and return, so we use the estimate using annual returns and this is equal to 0.53 for the overall property market. The fact that the number is smaller than for quarterly data reflects the less prominent need to correct the risk with annual data than with quarterly data (i.e. the issue of smoothing is more pronounced in the latter than in the former). Among sectors, retail and offices show estimates similar to the overall market while industrial reflects a lower degree of randomness than average.

As a final remark, it is worth noting that equation (3) shrinks back to equation (2) if there is no deviation from randomness. Intuitively, we can simply assume that equation (3) is the same as equation two, where we make an adjustment to the volatility we estimate from historical returns as follows:

$$\sigma_{adj} = (\sigma_t + \beta^T(t-1)\sigma_t)$$

And equation (3) can be rewritten as:

$$\sigma^2_{ex-ante} = (t + t_{TOM})\sigma^2_{adj} + ret^2 * \sigma^2_{TOM}$$

The intuition behind Cheng et al (2013) model is that without smoothing the computation of risk (measured as standard deviation) for different investment horizons should give a measure which is increasing as time increases, i.e. the risk of investing for 5 years should be smaller than the risk of investing for 10 years. At the same time, the impact of liquidity (measured as TOM) on the overall risk mitigates this effect because, as the holding period increases, the marginal impact of the time on market decreases (as we have already shown previously in Exhibit 1).

[ INSERT EXHIBIT 2 HERE ]

Applying the Cheng et al (2013) model, we present our results in Exhibit 2, which shows the modified ex-ante standard deviation if we both consider the time on market and correct returns for smoothing. Firstly the ex-ante risk is around 11% (for an investor with 5 year holding period) if returns are only corrected for smoothing and the time on market is equal to zero. As TOM increases, the ex-ante volatility increases from 11.2%to 13.3% (i.e. 2.1% difference) for a five year holding period and from 17.4% to 18.3% (i.e. 0.9% difference) for a 15 year investment horizon. Overall, the ex-ante risk reported in Exhibit 2 is bigger than the one shown in Exhibit 1 and this is mainly due to the correction for smoothing we introduced using the Cheng et al (2013) rather than the Lin and Vandell (2007) model. This finding is important because it shows that smoothing (non-randomness) causes an underestimation, not only of the total risk of real estate investment, but also of the impact of TOM on the ex-ante risk. In fact, for a short investment horizon (5 years, first column) the difference of ex-ante risk (between a market where TOM is equal to zero and another where it is equal to 15 months) is 2.1% rather than 1.4% (as in Exhibit 1). For a long investment horizon (15 years, last columns), instead, the difference is 0.9% rather than 0.6%.

### 3.2 Liquidation Bias

After a discussion about the impact of TOM on the ex-ante risk associated with real estate investment, we also want to consider another potential factor causing a deviation of ex-ante returns (i.e. return expected by the investor before the investment is made) from ex-post ones. We follow Lin and Vandell (2007) and model the so-called "liquidation bias", which reflects the inability of investors to sell their assets at observed market prices immediately, as it happens in financial markets. The evidence of this bias is represented by the low turnover and small portion of properties sold successfully, with many other properties sitting on the books of funds, and being offered to the market but not transacted because a counterparty is not found, or a price is not agreed.

Firstly, this bias is important for transaction-based indices because the observed prices are only reflecting the information on successful transactions (which may have different characteristics from the ones of unsuccessful transactions). Hence, returns only reflect the characteristics of a sub-sample of all potentially transacted properties (the ones which are actually transacted). Secondly, this bias is also relevant for valuation-based indices because appraisals used to construct valuation-based indices derive from comparables of transacted properties (and not from the full set of information of properties that may be potentially transacted). Finally, the liquidation bias also relates to the evidence that transacted properties may have been up for sale for a much longer time than the measured time on market – issue which is also related to the relisting phenomenon in housing markets.

Evidently, this bias would cause an overestimation of returns because the sub-sample of sold properties normally shows a price above the expected bid price at any point in time (i.e. the selling price will always have to be higher than the seller's reservation price which is the minimum price a seller would accept to execute a transaction). Moreover, for any observed sale price, we record a significant time lag between a property is included in the trading portfolio (ready to be sold) and the same property is actually transacted. Hence we can think of the liquidation bias as representing the impact that the sudden need of selling a property may have on the pricing of real estate assets. This effect can be translated into a reduced ex-ante return due to the potential sale price discount when this risk is considered.

Following the derivation of the formula for ex-ante return and volatility considering a liquidation bias – as in Lin and Vandell (2007) –, we compute the annualised return and risk measures correcting for the impact of holding period and marketing time as follows[3]:

$$ret_{ex-ante} = ret - \sqrt{3} * E\left[t_{Mktg}\right] * \sigma_t \quad (4)$$

$$\sigma_{ex-ante} = \left(1 + t_{Mktg}\right)\sigma_t \quad (5)$$

where $t_{Mktg}$ represents the average marketing time.

Intuitively, both the ex-ante return and volatility depend on the expected marketing period and the ex-post standard deviation[4], where an increase in marketing time and/or ex-post standard deviation determines a rise in both the ex-ante volatility – equation (5) – and the liquidation premium (reducing the ex-ante return – equation (4) – and hence increasing the difference between ex-ante and ex-post returns).

[ INSERT EXHIBIT 3 ]

As an illustrative example, let us assume – as before – that the annual ex-post return and standard deviation are equal to 10% and 8% respectively. Exhibit 3 reports the ex-ante return (Panel A) and volatility (Panel B) for a series of combinations of marketing time and holding period applying the Lin and Vandell (2007) model to correct for the liquidation bias. As the marketing time increases, the expected ex-ante return decreases because the sale price may be

[3] Please refer to Lin and Vandell (2007) for the derivation of equations.

[4] The multiplicative factor $\sqrt{3}$ comes from a mathematical derivation of the final equation. Please refer to Lin and Vandell (2007) for further explanation.

lower than expected due to the discount investors may incur in. The difference between the original return (10%) and the newly computed (liquidation-adjusted) one represents the premium associated to the liquidation bias. As an illustration, for an investment horizon of 10 years and marketing time of 9 months, the average return of 6.8% suggests a liquidation premium of 3.2% (difference between 10% and 6.8%). Since the impact of the liquidation bias on returns decreases as the holding period increases, we also find that the premium is smaller for long investment horizons than for short ones (i.e. the impact of the sale price discount is spread across more years). Finally, Panel B shows the impact of the liquidation bias on the ex-ante volatility. Considering the risk of a price discount in the sale proceeds, we record an increase in risk as both marketing time and holding period increase, with the former having a bigger marginal impact than the latter.

### 3.3 Market Liquidity

Several models have previously attempted to price different risk factors jointly to capture the net impact of variations in liquidity levels on actual price movements and subsequently estimate the ex-ante liquidity risk premium. Within this framework, a smaller market liquidity premium represents the greater easiness to find counterparties to exchange assets at a specific point in time. The estimation of such models is very useful because it can also capture the time-varying nature of risk premia using market-wide information which is available to all investors – unlike the first and second moments (respectively average and standard deviation) of time on market. For financial assets such as bonds and equities, a series of asset pricing studies on liquidity have been published. Among them, we combine Fama and French (1993), Carhart (1997) and Pastor and Stambaugh (2003) to estimate a model that prices liquidity along with other risk factors. The inclusion of other factors which are not related to liquidity is important to isolate the liquidity risk premium and obtain an estimate which does not include other sources of reward. Alongside liquidity, according to standard finance literature, we include four main factors:

- market beta ($MKT_t$), which reflects the sensitivity of the asset to market movements, i.e. systematic risk. This risk is associated to market movements and it represents the amount of risk that the investor cannot diversify away;
- size ($SMB_t$) – spread between returns of small- and large-sized firms –, which represents the "small-firm effect" due to smaller firms outperforming large ones. It captures the loading on the extra-risk attached to smaller businesses which tend to be more volatile than bigger companies;

- value/growth *($HML_t$)* – spread between returns of value and growth stocks –, which captures the outperformance of value assets (high book-to-market ratio) on growth assets (low book-to-market). This factor has also been found significant for properties, with Jones Lang LaSalle now producing separate indices for value and growth properties (i.e. buildings with high income vs. properties with high potential growth) – Marcato (2004);
- momentum *($MOM_t$)* – spread between returns of highest and lowest performing firms, lagged one month –, which was introduced by Carhart (1997) to correct for the tendency of asset prices to show a degree of serial correlation (succession of returns above/below the average). This factor seems even more important for real assets than for financial ones.

The five-factor model developed by Pastor and Stambaugh (2003) we used in this part of our study can be represented as follows:

$$ret_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 LIQ_t + \varepsilon_t$$

where $\beta_1$ to $\beta_5$ are the estimated coefficients for the five risk factors in the asset pricing model. As a measure of liquidity, Pastor and Stambaugh (2003) suggest transaction volumes, with the sign being positive if the lagged excess market return is positive and negative otherwise. They focus on the aspect of liquidity capturing the link between temporary price changes and order flow. The simple intuition is based on Campbell et al. (1993) who argue that volume-related returns are caused by liquidity and the greater the order flow, the greater the compensation on future returns should be. The sign attached to the volumes is introduced because order flow *"should be accompanied by a return that one expects to be partially reversed in the future if the stock is not perfectly liquid"*.

In our estimation, we slightly modify the Pastor and Stambaugh (2003) liquidity measure using volumes with sign being positive if the lagged real estate return is above the risk free rate (rather than market return). The rationale behind this choice is the fact that real estate investors do not adjust their position instantaneously whenever the asset return is below/above the market return, but when there are major news which may lead to returns falling below the risk-free rate. Due to the presence of serial correlation in real estate returns, this liquidity measure tends to have the same sign of the left hand side variable (excess real estate return). Hence, we expect a positive estimated coefficient as a result. Alongside this measure (PS from now onwards), we also estimate the model using several other liquidity proxies suggested in the literature and presented in the next section. Normally we expect positive estimated coefficients when the measure reflects a liquidity proxy and negative ones when the measure refers to illiquidity.

## 4. Data Description and Market Liquidity Measures

In this study we analyze the pricing of liquidity in the UK real estate market. We use the IPD database which contains information on performance measures and transaction activity of a large part of the investable universe going back to December 1980 with an annual frequency and to December 1986 with a monthly frequency. Particularly in the annual database they cover 291 funds investing in 21,175 properties for a value of £ 152.6 billion as at December 2013. The three main sectors are retail (46.8%), office (26.5%) and industrial (15.4%). Part of these properties are also valued monthly and form the monthly database which is made by 58 funds investing in 3,407 properties for a total value of £ 35.5 billion as at December 2013. The proportion of sectors is similar and respectively equal to 43.9%, 31.8% and 18.7%.

In our study we use both databases, depending upon the analysis needed (if annual figures are needed, we directly use the annual database; for estimations, instead, we tend to use a monthly frequency to match studies in other asset classes and increase the statistical power of our results). A comparison of main descriptive statistics for the two databases is reported in Exhibit 4. Panel A shows that the annual average return is 9.45% for the overall market and ranges between 8.78% and 10.41% for the different sectors. The volatility is around 10% and the return distribution is slightly negatively skewed. Monthly figures are reported in Panel B which shows slightly smaller returns and higher single period swings (i.e. jumps in single months as suggested by high absolute values for minimum and maximum figures). The main difference is represented by volatility which tends to be underestimated using a monthly frequency. This feature is important because our findings using the annual database are different in magnitude from previous US studies. We argue that the direct use of annual performance for volatility measures is more appropriate and hence the impact of liquidity results less prominent than it would otherwise. In other words if volatility is underestimated due to the monthly/quarterly data frequency, the risk premium puzzle (and hence the liquidity premium) may appear even more significant than it is in reality.

[ INSERT EXHIBIT 4 ]

Since we use a model that formally accounts for serial correlation in the data to obtain the ex-ante return, we do not report annualized figures of standard deviation already corrected for smoothing issues[5] to avoid double counting. Moreover, we still find serial correlation in the return series with annual frequency. Hence, the extent of the correction will be measured on the basis of the amount of smoothing found in annual data.
The risk free rate is represented by the redemption yield of the 10 year benchmark of UK Government Gilt Index, while the equity factors of our model are taken from Gregory et al (2013).

In this section we also compute some measures of market liquidity that we will use to estimate the liquidity premium from the last model presented above. Particularly, we focus on measures using data which is publicly available in real estate markets. This has the advantage of offering a snapshot of different liquidity proxies that can be reproduced and updated by the reader at any point in time. All volume-related measures trending in time have also been normalized by using the inverse of the IPD capital value index (i.e. volumes have been used at current values).

**Trading Volumes**

Trading volume is an indirect but widely cited measure of market liquidity because of its simplicity and availability, with volume figures regularly reported for most assets. This measure indicates the amount of transaction activities over time. In periods with high volumes, we expect a greater easiness to sell properties and hence a reduced liquidity premium. We compute transaction volumes for a given period $t$ (i.e. the dollar volume traded $Vol_t$) as the sum of individual $i$ trades within the period (computed as prices $P_{it}$ times quantities $Q_{it}$):

$$Vol_t = \sum_{i=1}^{n} P_{it} Q_{it}$$

In our exercise volumes are computed as the sum of purchases and sales as recorded in the IPD database – refer to Ling et al. (2009) for a discussion of shortcomings in using this measure.

**Turnover Rates**

Turnover gives an indication of the number of times the outstanding volume of an asset changes hands within a specified time period and it is found to be negatively related to liquidity costs –

[5] Using the correction for autocorrelation, the annualized standard deviation would be c.ca 30% bigger than the unadjusted one.

Amihud and Mendelson (1986) – because market makers tend to charge a higher transaction cost to cover the risk of holding their position when the turnover ratio is low. The inverse of this measure also gives an indication of the average holding period for the asset. Turnover is computed as follows:

$$Turn_n = \frac{Vol_t}{\sum_{i=1}^{n} P_{it} S_{it}}$$

where $S_{it}$ is the number of outstanding assets and $P_{it}$ and $Vol_t$ represent respectively the average price of the *i* trades and the trading volumes computed in the previous liquidity measure.
In our modelling exercise, the denominator of the equation is measured by the value of the stock monitored by IPD rather than estimates of total market size because we need this measure on a periodical basis (every month). Clearly, this measure using IPD data reveals the turnover ratio of institutional investors (dominating players in the database) and not necessarily the one of the overall market.

**Net Flows**

Previous studies have shown the importance of the direction of investment flows, along with their quantity. In other words, if there are greater imbalances in order flows, the price pressure (and hence illiquidity) may increase. In fact, for a player on the "wrong side" of the transaction (i.e. the one with very many competing players) a prompt matching with an opposite counterparty may prove to be difficult. We compute the measure of net flows as the difference between actual investments (purchases) and disinvestments (sales) in the market. Following Ling et al. (2012), we recognise that, if there were 100% market coverage, net flows would clearly be equal to 0 (accounting for transactions only, there must be always be two opposite counterparties). Over the last decade at least, we have seen the entry of non-domestic investors in particular segments of the market (e.g. London Offices) and this may have altered the overall amount of net flows to real estate investments. However, since the IPD database shows a very high coverage of institutional players[6], we may argue that these imbalances reflect the extent to which institutional investors (risk averse and liquidity lovers) decide to increase (positive net flows) or reduce (negative) their exposure to real estate. As a consequence, the negative value of this measure represents the extent to which more opportunistic players (e.g. hedge funds, private equity funds, etc.) may enter the market to exploit periods of liquidity dry-out. We compute net flows as the difference between purchases and sales, divided by transaction volumes (calculated as the sum of purchases and sales):

[6] At the present time, mainly domestic institutional investors.

$$NetFlows_t = \frac{Purch_t - Sales_t}{Vol_t}$$

**Amihud Measure**

The Amihud (2002) measure identifies the price impact of transaction volumes (i.e. the higher the measure the lower the liquidity of an asset/market) and it has been widely used in the literature. It represents a proxy of transaction costs – as discussed in Amihud (2002) – for studies looking at long time series and assets for which intra-day market data is not available. By construction, it represents the price pressure on assets: when this measure is low, it means that high transaction volumes do not impact significantly on the price and hence there is high liquidity in the market; vice versa, when its value is high, it means that relatively low volumes have a significant impact on prices and the market liquidity is low. Since we have a monthly (but not daily) frequency for UK real estate data, we modify the original Amihud (2002) measure and compute it as the ratio between the absolute value of the monthly return *($TR_t$)* and the monthly transaction volume *($Vol_t$)* as follows:

$$Amihud_t = \frac{|TR_t|}{Vol_t}$$

**Roll Measure**

Roll (1984) developed an implicit measure of the effective bid-ask spread based on the serial covariance of the changes in stock price, with the intuition that an illiquid asset should show a stronger autocorrelation pattern because it violates the two key assumptions of markets being informationally efficient and price changes being stationary. Since the autocorrelation coefficient is normally positive for real estate markets, we modify the Roll measure using the absolute measure of serial covariance, where $\Delta P_t$ indicates the price change at time $t$ and *cov* refers to the covariance operator:

$$Roll_t = 2 \times \sqrt{|cov(\Delta P_t, \Delta P_{t-1})|}$$

When the measure is high (low), we expect market liquidity to be high (low).

**Pastor-Stambaugh Liquidity Factor**

This liquidity dimension is associated with temporary price changes accompanying order flows. We follow Pastor and Stambaugh (2003) and use a modified version of the signed transaction volumes which are transaction volumes being positive if the excess real estate return above risk-free rate *($r_t^e$)* is positive and negative vice versa:

$$PS_t = sign(r_t^e) * Vol_t$$

As explained above, the original intuition behind this measure is simple: volume-related returns are caused by liquidity and an increase in the order flow requires a higher compensation on future returns, which are expected to be partially reversed if the asset is not perfectly liquid[7].

In our estimation, we slightly modify the Pastor and Stambaugh (2003) liquidity measure using volumes with sign being positive if the real estate return is above the risk free rate (rather than market return). The rationale behind this choice is the fact that real estate investors do not adjust their position instantaneously whenever the asset return is below/above the market return, but when there are major news such as returns below the risk-free rate. By construction, this liquidity measure tends to have the same sign of the left hand side variable (excess real estate return) and hence we expect a positive estimated coefficient as a result.

[ INSERT EXHIBIT 5 ]

We compute the different measures for the overall market using the IPD "All Property" indices, as well as for the three main sectors – Retail, Office and Industrial – making sure that they are not biased simply because of the coverage increase of the IPD database in time and the increase in volumes due to capital growth. Hence we correct the volume-based measures deflating them with the capital value index of IPD over time.

The correlation matrix of our computed liquidity measures is reported in Exhibit 5. Panel A shows that for the overall sample period (1987 to 2012) the different measures show some significant correlations with signs according to our expectations. Particularly, Amhiud, Roll and Return/Turnover are proxies for illiquidity, while the remaining ones are proxies for liquidity. Accordingly a negative correlation coefficient is found between these three measures and the remaining ones, with the only exception of transaction volumes (coefficient non significantly different from zero) which have been already proved to be a weak proxy for liquidity – e.g. Ling et al (2009). Some of the correlation coefficients are significantly high (in absolute terms) and the situation is improved when only the later part of the sample period (1996-2012) is used for the

[7] Please refer to section 2.3 for further discussion.

computation (Panel B). Finally, the PS measure seems to have the highest average correlation coefficient, embedding information contained in several other liquidity measures.

Finally, we find that these results generally hold (with some minor exceptions) when we analyze the different sectors separately. Exhibits A1, A2 and A3 in the Appendix report the correlation matrices of liquidity measures computed respectively for retail, office and industrial properties.

[ INSERT EXHIBIT 6 ]

Importantly, we want to guarantee that these proxies show patterns in line with expectations. Particularly, our liquidity measures should be able to capture market cycles, to reflect a signaling power particularly during phases of market distress such as the crisis at the end of the 1980s / beginning of 1990s and the most recent one starting at the beginning of 2007.

Exhibit 6 shows the cyclical pattern of all measures for the three different sectors. At a first glance, the different measures behave according to our predictions, signaling markets with liquidity pressure during periods of falling markets (i.e. spikes for illiquidity measures such as Amihud, Roll and Return/Turnover, and sharp declines for liquidity measures such as transaction volumes, turnover and net flows[8]). Transaction volumes, the Amihud measure and Return/Turnover suggest that industrial is the least liquid sector, with retail and office properties leading in the ranking at different points in time. Particularly over the last economic crisis, the illiquidity of office markets seemed to lag the ones in retail markets.

The only notable issue is the flat representation of the Amihud measure after 1995. This is primarily due to the high values of this measure in the first part of the sample period. However, if we only plot the time series from 1996, we clearly see the surge in illiquidity during the most recent crisis.

[ INSERT EXHIBIT 7 ]

Finally, as a cross-sector comparison, we also report average measures and their volatilities in Exhibit 7. The dominance of a sector is not clear from the statistics and hence we do not infer any significant differences in liquidity levels between different sectors. Turnover suggests Office being the most liquid, with Retail in a very similar position if we also consider the Amihud measure. Generally, we also find that the ranking of the three sectors by volatilities varies across measures and differences are not statistically significant in many cases.

[8] The PS measure is not reported because it is a signed version of the original transaction volumes.

Overall, we have computed several liquidity measures which show a certain degree of similarity. These measures are clearly not to be used as measures per se because they only identify proxies. In fact, it is of paramount importance to embed these measures in a formal modeling exercise that can allow us to price liquidity and hence estimate the premium an investor might expect.

In sections 2 and 3 we have presented the theoretical models and the data used for the estimation. In the next section we apply the three main models and discuss the main empirical results. Firstly, we report the impact of TOM on the standard deviation of returns. We then compute the liquidation bias, as a premium compensating investors for the inability to transact instantaneously. Finally, we estimate the premium associated to market liquidity using the five-factor model and the different proxies for market liquidity.

## 5. Empirical results

In this section we report the results of the three main models. The TOM bias leads to an increase of ex-ante risk perceived by investors and this worsens the return/risk profile of real estate investment. The liquidation bias reduces the return investors expect to achieve ex-ante because they may need to concede price discounts when they sell their assets. Finally, the overall market liquidity may lead investors to require a risk premium to invest in illiquid real estate assets.

### 5.1 TOM bias

The increase in ex-ante risk estimates due to TOM is reported in Exhibit 8. The average and standard deviation of returns for each property sector are computed using the IPD Annual Index. We also included some results from an estimation using the two main indices for the residential sector: Nationwide and Halifax. The average TOM is taken from averages of the sell-side sample of Devaney and Scofield (2014) for the commercial real estate market and the beta coefficients for the volatility ratio are computed as in Cheng et al. (2013) – but with annual data – and reported in the last column of the last two panels of the exhibit. The average TOM for residential markets has been taken from Rightmove for both house price indices.

[ INSERT EXHIBIT 8 ]

Panel A shows that, assuming the randomness of real estate returns, the adjustment to their volatility due to TOM is negligible and decreases as the holding period *(t)* increases. However, when we deviate from randomness (Panel B), volatilities are significantly different and they range between 12.3% (residential Nationwide for 5 year holding period) and 29.4% (Industrial for 15 year holding period). The ranking of sectors by risk is maintained and sectors with a high risk (e.g. industrial) see a higher impact of TOM on volatilities. As the holding horizon increases, the volatility increases (in line with expectation about the riskiness of asset returns and maturities, as represented by an upward yield curve). However, the marginal extra volatility exclusively due to TOM (hence excluding the complementary effect of non-randomness) decreases as the holding period increases because the impact of the same length on TOM for longer horizons should decrease when measured periodically – we report annual returns. Finally, we notice that the impact of TOM is significantly influenced by the deviation from the assumption of random real estate returns and this feature is dominant. In fact the size of the impact reported in Panel C is bigger than the one obtained assuming randomness – i.e. subtracting the original standard deviation from the one reported in Panel A.

### 5.2 Liquidation bias

The second bias we identified in the modelling section is due to the difficulty of a sudden liquidation, i.e. the inability of investors to sell their assets at observed market prices immediately, as it happens in financial markets. Exhibit 9 reports the annual risk premium associated to the liquidation bias in Panel A and the extra volatility (measured as adjusted minus original volatility) introduced by such bias in Panel B.

[ INSERT EXHIBIT 9 ]

Firstly, the annual risk premium (Panel A) for an investor with short holding period (5 years) is around 3.2% for commercial real estate (ranging from 2.9% for retail to 3.8% for offices) and around 1.5% for residential properties, which show a much lower time on market than the commercial segment. Secondly, this premium tends to decrease for longer investment horizons (15 years) to respectively 1.9% (ranging 1.7% - 2.3%) and 1.0%. Overall we can conclude that investors are expected to require an ex-ante premium due to liquidation bias which ranges between 1.0% and 3.5% depending upon the investment horizon (and given the assumptions on marketing time).

Finally, as far as ex-ante risk measures are concerned (Panel B), the liquidation-adjusted ex-ante volatility seems to be around 30% to 40% (20% for residential properties) higher than the original one. This assumption leads to a perception of the risk/return profile of real estate investments which is worse than the one computed with original data. Consequently, this adjusted profile may also help to explain the lower than predicted allocations to property given by institutional investors. If allocators use the new estimated values of volatility, the Sharpe ratio of real estate decreases and hence optimization models should suggest a smaller percentage to be invested in this illiquid asset.

### 5.3 Market liquidity premium

The final step of our analysis aims to identify the premium linked to market liquidity. We estimate the Pastor and Stambaugh (2003) model using the different measures of liquidity we computed in section 3. Exhibit 10 shows the estimated coefficients and main statistics of the models using the full sample 1988-2012. Since some of the liquidity measures behave differently from mid 1990s, we also report the results using the sample 1996-2012 as a robustness check (see Exhibit 11). Generally, we find that market risk and the growth (HML) and size (SMB) factors are positive and significant. Furthermore, liquidity is important in explaining returns and this is consistent throughout all liquidity measures we use (each column represents the estimation of the model using a different liquidity measure). As expected, we find that proxies representing illiquidity rather than liquidity (i.e. Amihud, Roll and Return/Turnover) show a negative sign. The overall R-squared varies across models, with models using Turnover, Net Flows, Return/Turnover and PS showing the best fit and information criteria. When we estimate the models by sector (Panels B to D), we generally find a confirmation of our main results at the all property level, with some minor exceptions for the industrial sector.

[ INSERT EXHIBIT 10 and 11 ]

Furthermore, we compute the liquidity premia by multiplying the estimated coefficients of market liquidity with the average value of the liquidity measure over the sample period used in the estimation procedure. The top part of exhibit 12 shows the annualised liquidity premia estimated for the full sample. Firstly, premia at the all property level range from as little as 1%

(with Amihud) to as much as 12% (with Turnover). If these results may initially seem inconclusive, they are consistent with studies of other asset classes if we exclude turnover that clearly suggests a far too high premium (above 10% on average). Moreover, if we take a simple average of all the premia, we obtain a premium around 4.50% (or 3.26% if we exclude the estimation using turnover). When we estimate models by sector, we generally find consistent results with the exception of PS (showing a slightly smaller premium at sector than at all property level) and Amihud (showing a higher premium at sector than at all property level). Since the different behaviour of some liquidity measures after mid 1990s determines unexpected differences at sector level for some of our liquidity measures, we also report results for estimations using the restricted sample (1996-2012) in the bottom part of the table. We find that this set of results is even more coherent as the restricted sample gives a greater weight to the observations of the most recent crisis. Hence, we also find that the estimated coefficients are generally higher than the ones obtained for the full sample (around 1.0%-1.5% difference).

Finally, if we look at the difference between sectors, we may expect industrial to be the most illiquid market, with either retail or offices being the most liquid. However, we find that the liquidity premium of the retail sector is the highest (either 4.94% or 6.43% for the two sample periods), followed by offices (5.54% or 5.12%) and industrial (3.50% or 4.84%). One possible explanation may be offered by the information theory. In fact, retail and office sectors are much more competitive both nationally and internationally. Hence, the information set available in these markets is probably larger than the one in the industrial sector. This availability allows investors to readily embed this information in their behaviour and therefore the pricing may be reflecting more readily the information attached to the investment flows of economic agents.

[ INSERT EXHIBIT 12 ]

So far we estimated our models statically using a long sample period. However, we also want to show the time-varying nature of the models and to test their stability in predicting liquidity premia over time. Hence we estimate the Pastor and Stambaugh (2003) model monthly using a 5 year rolling window (i.e. 60 observations). Along with average and standard deviation of estimated liquidity premia, Exhibit 13 reports their values at three different points in time: before the crisis (December 2006), in the middle of the liquidity dry-out (December 2008) and at the end of the sample period (December 2012). Values are computed for all property and the three main sectors.

[ INSERT EXHIBIT 13 ]

The overall average of liquidity premia is around 7% (average excluding volumes and turnover) and confirms previous results obtained with a single estimation using the full sample (4.50%). In this rolling procedure, however, we find that both volumes and turnover show very high premia peaking at the end of 2008 to a level of 29% to 36% for all property. Since these values are clearly beyond reasonable expectation, we also present overall averages excluding these coefficients in the last column. In this case, we find that the overall average premium for all property is around 4.5% (in line with the static estimation), with a maximum premium of 10.2% (compared to 16.6% including the two measures) during the most recent economic crisis. At the end of 2006, both averages (last figure of the last two columns) suggested a premium of around 5% for all property.

Comparing results between sectors, we find that overall market liquidity risk seems to be highest for offices and retail. This result is in line with the greater swings of liquidity in this sector than in others which make this risk less predictable. However, during the recent economic crisis (December 2008) we find that, as in the previous estimation using the full sample, industrial recorded the highest liquidity risk premium.

Finally, among all liquidity proxies, we find that results are mostly stable using net flows and the Pastor and Stambaugh (2003) measure, which suggest an overall premium of 3.0% - 3.5% for all property and between 2.5% and 3.5% for different sectors. Accordingly, we report in Exhibit 14 the graph of the liquidity premia computed with the two measures from 2000 onwards. Premia were initially stable at around 2% to 4%, to find a slight temporary increase (mainly recorded by the PS measure) when transactions were low around 2004-06. Importantly the liquidity premia computed with the two different measures seem to be much more aligned over the most recent period. Just before the economic downturn, liquidity became an important factor and premia suddenly increased to 10% (for both measures) by the end of 2007. Since the middle of 2009 they have started to decrease back to the initial levels of 2%-3%, suggesting a reduction in the pressure of liquidity on the pricing of real estate assets.

[ INSERT EXHIBIT 14 ]

## 6. Conclusions

Overall, we have applied several models to understand the impact of liquidity on ex-ante return and risk profile of an illiquid asset such as real estate. We have found that time on market, coupled with non-random returns, can generate a perceived ex-ante risk which is 30% to 40% higher than the one observed in ex-post returns.

Using the argument of a possible liquidation bias – because investors cannot necessarily sell assets as and when they want – we also computed the impact of such stylized fact and found it to be even more significant than the TOM effect, with the impact on risk – mainly driven by the correction for serial correlation – almost double the one measured by ex-post measures and a liquidation premium varying between 2% and 3%.

Finally, the estimation of risk premia linked to market liquidity consistently showed the significance of this risk factor (with the exception of volumes in some models) throughout our specifications. Even if some of the estimated figures are clearly not in line with expectation (e.g. too high when transaction volumes and turnover are used), we find that, over time, premia are on average around 3.0%-3.5% and they range between 1.5% during rising markets (i.e. when it is easy to find a counterparty and transactions can happen very quickly) and 10% when a liquidity dry-out happens (e.g. during the most recent economic crisis). Our estimates are also in line with the ones suggested for more traditional asset classes (bonds and equities) by Hibbert et al (2009), which range between 0.1% (for very low risk bonds) and 3.5% to 5.5% (for either domestic or international equities).

Overall, considering both the liquidation bias approach and the market liquidity estimation, we find conclusive evidence that the ex-ante liquidity premium is around 3% on average and it varies over time ranging from 1.5%-2.0% to 10%. At the same time, investors normally use a rough estimate of 2% - 4% for the overall risk premium (including several factors such as obsolescence, tenant default and liquidity) to determine the required rate of return for real estate assets. Clearly our ex-ante figure seems to overestimate the liquidity premium according to such view, highlighting once more the presence of a risk premium puzzle. If on one hand, investors may argue that ex-post returns do not justify a 3% liquidity premium, on the other hand, the cost associated to illiquidity (i.e. inability to sell or to sell within a short period of time) is not necessarily recorded in IPD return data. In fact, if a property is not sold due to the inability to find a counterparty, this information remains hidden because the transaction price (and hence discount due to illiquidity) is not observed.

Moreover, our estimated liquidity premium does not necessarily imply a radical shift of required returns and consequent repricing of the asset class. As an illustrative example let us assume that the long-run risk free rate is around 3.0%-3.5%, obsolescence is estimated at 1.5% and the liquidity premium is around 3.0%. Adopting the practitioner's view, a newly constructed building with a good quality tenant and located in London should require an ex-ante return of around 7.0%-7.5%, which is in line with the ex-ante return (including potential future growth) required by investors for these types of properties.

Finally, we argue that our results are helpful for the real estate industry because some of the measures we suggested and tested in this paper may be periodically updated and offered to the market, along with the estimation of premia using the simple models we have illustrated.

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## Exhibits

Exhibit 1: Illustration of the effect of TOM on risk assuming returns are a random walk

| | t | 5 | 8 | 10 | 12 | 15 |
|---|---|---|---|---|---|---|
| $t_{TOM}$ (in months) | 0 | 8.0% | 8.0% | 8.0% | 8.0% | 8.0% |
| | 3 | 8.1% | 8.0% | 8.0% | 8.0% | 8.0% |
| | 6 | 8.3% | 8.2% | 8.1% | 8.1% | 8.1% |
| | 9 | 8.6% | 8.4% | 8.3% | 8.3% | 8.2% |
| | 12 | 9.0% | 8.7% | 8.5% | 8.5% | 8.4% |
| | 15 | 9.4% | 9.0% | 8.8% | 8.7% | 8.6% |

Note: The table reports the ex-ante standard deviation associated to different measure of holding period (HP, measured in years) and time on market (TOM, measured in months) when we assume that returns are independently distributed (no issues of smoothing at index level). Assuming an volatility of 8% with TOM equal to zero (first row), as TOM increases, the ex-ante risk increases because it includes the uncertainty about the time needed to sell the asset. The marginal increase is smaller for longer HPs (i.e. the effect of 6 months TOM is bigger for an investor with a 5 year HP than for an investor with 15 year HP).

Exhibit 2: Illustration of the effect of TOM on risk not assuming a random walk

| $t_{TOM}$ (in months) \ t | 5 | 8 | 10 | 12 | 15 |
|---|---|---|---|---|---|
| 0 | 11.2% | 13.3% | 14.6% | 15.8% | 17.4% |
| 3 | 11.4% | 13.5% | 14.8% | 15.9% | 17.5% |
| 6 | 11.8% | 13.8% | 15.0% | 16.1% | 17.7% |
| 9 | 12.2% | 14.1% | 15.3% | 16.4% | 17.9% |
| 12 | 12.7% | 14.4% | 15.5% | 16.6% | 18.1% |
| 15 | 13.3% | 14.8% | 15.9% | 16.9% | 18.3% |

Note: The table reports the ex-ante standard deviation adjusted by liquidity and violation of random walk assumption. For example for a 10 year holding period and 12 month TOM, the ex-ante standard deviation is 15.5%, compared to 14.6% if TOM were equal to zero (and assuming the same investment horizon). TOM represents time on market measured in number of months, while t indicates the investment horizon in years.

Exhibit 3: Liquidation Bias

Panel A: Ex-ante return

| $t_{TOM}$ (in months) | t | 5 | 8 | 10 | 12 | 15 |
|---|---|---|---|---|---|---|
| | 0 | 10.0% | 10.0% | 10.0% | 10.0% | 10.0% |
| | 3 | 8.5% | 8.8% | 8.9% | 9.0% | 9.1% |
| | 6 | 7.0% | 7.6% | 7.9% | 8.0% | 8.2% |
| | 9 | 5.7% | 6.5% | 6.8% | 7.1% | 7.4% |
| | 12 | 4.3% | 5.4% | 5.8% | 6.2% | 6.5% |
| | 15 | 3.1% | 4.3% | 4.8% | 5.2% | 5.7% |

Panel B: Ex-ante standard deviation

| $t_{TOM}$ (in months) | t | 5 | 8 | 10 | 12 | 15 |
|---|---|---|---|---|---|---|
| | 0 | 8.0% | 8.0% | 8.0% | 8.0% | 8.0% |
| | 3 | 9.5% | 9.7% | 9.8% | 9.8% | 9.8% |
| | 6 | 10.9% | 11.3% | 11.4% | 11.5% | 11.6% |
| | 9 | 12.2% | 12.8% | 13.0% | 13.2% | 13.3% |
| | 12 | 13.3% | 14.2% | 14.5% | 14.8% | 15.0% |
| | 15 | 14.4% | 15.6% | 16.0% | 16.3% | 16.6% |

Note: The table reports the ex-ante return (Panel A) and standard deviation (Panel B) when the liquidation bias is considered. The liquidation premium is computed by taking the difference between ex-post and ex-ante return. TOM represents time on market measured in number of months, while t indicates the investment horizon in years.

Exhibit 4: Descriptive statistics.

Panel A: Annual figures (Source: IPD Annual Database)

| *Annual figures* | *All Property* | *Retail* | *Office* | *Industrial* |
|---|---|---|---|---|
| Mean | 9.45% | 10.12% | 8.78% | 10.41% |
| Median | 10.24% | 12.01% | 8.35% | 10.52% |
| Standard Deviation | 10.03% | 9.56% | 11.34% | 10.65% |
| Kurtosis | 2.3 | 3.4 | 1.1 | 2.7 |
| Skewness | -0.9 | -1.5 | -0.5 | -0.1 |
| Minimum | -22.10% | -22.56% | -22.41% | -21.21% |
| Maximum | 29.51% | 24.85% | 31.14% | 39.31% |

Panel B: Annualised monthly figures (Source: IPD Monthly)

| *Annualised figures* | *All Property* | *Retail* | *Office* | *Industrial* |
|---|---|---|---|---|
| Mean | 8.68% | 8.41% | 8.08% | 10.50% |
| Median | 9.43% | 9.14% | 9.16% | 10.53% |
| Standard Deviation | 3.88% | 3.97% | 4.23% | 3.82% |
| Kurtosis | 6.5 | 7.6 | 4.6 | 5.1 |
| Skewness | -1.6 | -1.7 | -1.3 | -0.9 |
| Minimum | -47.76% | -51.02% | -48.01% | -44.90% |
| Maximum | 53.53% | 64.36% | 56.64% | 75.94% |

Note: Annualised figures are obtained by compounding monthly figures by 12 months. Annualised standard deviation is monthly standard deviation multiplied by $\sqrt{12}$.

Exhibit 5: Correlation Coefficients of Liquidity Measures.

Panel A: All Property 1988-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.19 | 0.42 | -0.43 | 0.12 | 0.07 | 0.62 |
| *Turnover* | | 1.00 | 0.40 | 0.03 | -0.16 | -0.32 | 0.34 |
| *Net flows* | | | 1.00 | -0.14 | -0.18 | -0.28 | 0.67 |
| *Amihud* | | | | 1.00 | 0.08 | 0.30 | -0.32 |
| *Roll* | | | | | 1.00 | 0.54 | -0.27 |
| *Ret/Turn* | | | | | | 1.00 | -0.36 |
| *PS* | | | | | | | 1.00 |

Panel B: All Property 1996-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.43 | 0.46 | -0.18 | 0.16 | 0.04 | 0.53 |
| *Turnover* | | 1.00 | 0.57 | -0.22 | -0.32 | -0.36 | 0.51 |
| *Net flows* | | | 1.00 | -0.30 | -0.32 | -0.38 | 0.75 |
| *Amihud* | | | | 1.00 | 0.52 | 0.86 | -0.40 |
| *Roll* | | | | | 1.00 | 0.60 | -0.31 |
| *Ret/Turn* | | | | | | 1.00 | -0.45 |
| *PS* | | | | | | | 1.00 |

Exhibit 6: Liquidity Measures by Sector.

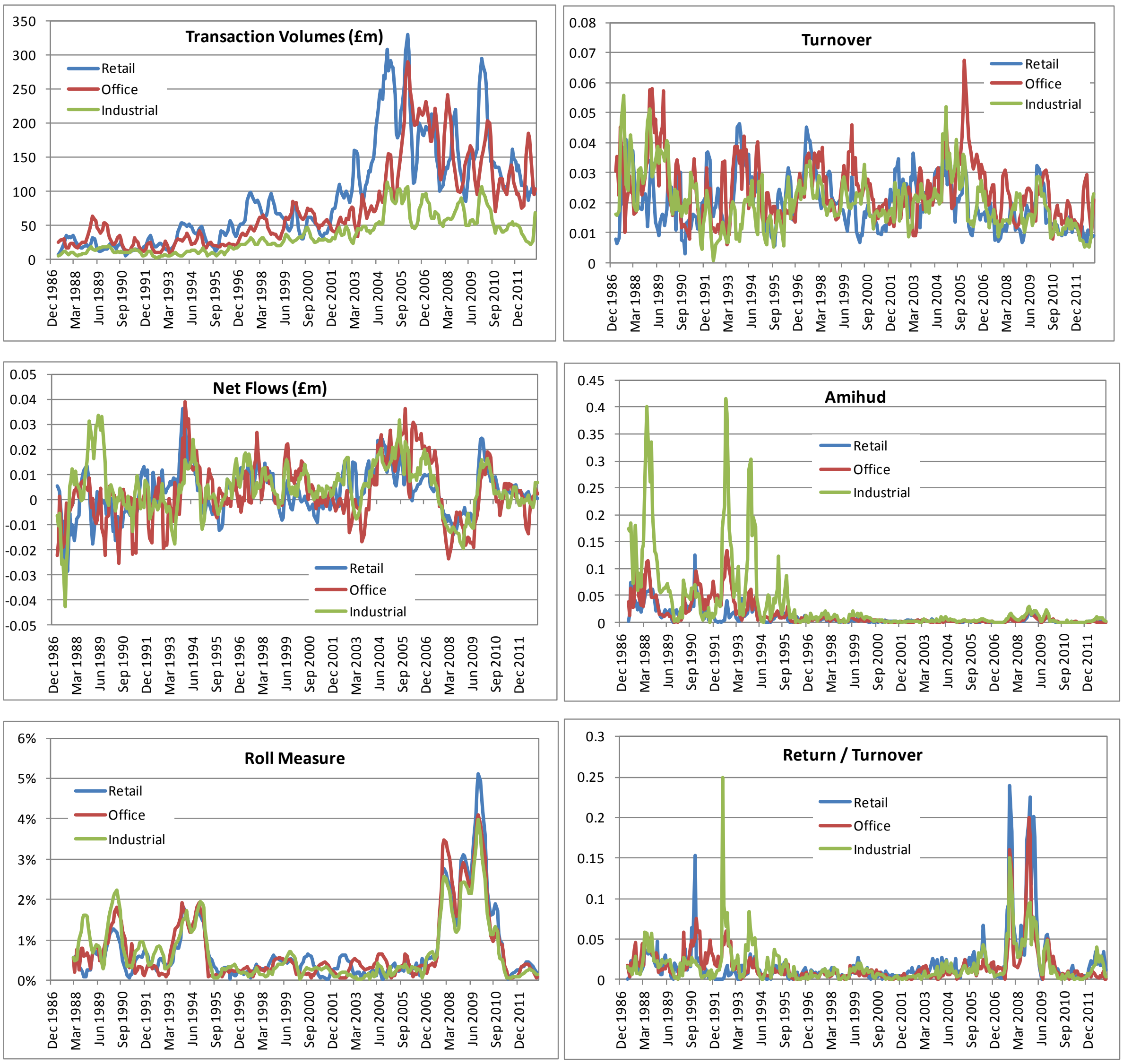


Table 7: Average and Standard Deviation of Liquidity Measures.

Panel A: Sample 1988-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| **Average** | | | | | | | |
| All Property | 183.7 | 2.0% | 0.4% | 0.4% | 0.7% | 1.9% | 117.6 |
| Retail | 91.8 | 2.0% | 0.4% | 0.9% | 0.7% | 2.0% | 50.6 |
| Office | 77.0 | 2.4% | 0.3% | 1.4% | 0.7% | 1.7% | 41.1 |
| Industrial | 35.0 | 2.0% | 0.5% | 3.1% | 0.7% | 1.8% | 21.8 |
| **Standard Deviation** | | | | | | | |
| All Property | 148.6 | 0.8% | 0.8% | 0.7% | 0.8% | 3.1% | 205.3 |
| Retail | 74.9 | 0.9% | 0.9% | 1.4% | 0.8% | 3.3% | 107.3 |
| Office | 62.9 | 1.0% | 1.2% | 2.3% | 0.9% | 2.5% | 90.6 |
| Industrial | 26.7 | 0.9% | 1.0% | 6.7% | 0.9% | 2.5% | 38.2 |

Panel B: Sample 1996-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| **Average** | | | | | | | |
| All Property | 241.2 | 1.9% | 0.5% | 0.1% | 0.7% | 2.0% | 171.8 |
| Retail | 123.4 | 1.9% | 0.5% | 0.3% | 0.7% | 2.2% | 73.4 |
| Office | 100.8 | 2.3% | 0.4% | 0.3% | 0.8% | 1.4% | 60.9 |
| Industrial | 46.8 | 1.9% | 0.6% | 0.6% | 0.7% | 1.5% | 31.7 |
| **Standard Deviation** | | | | | | | |
| All Property | 147.2 | 0.8% | 0.8% | 0.2% | 1.0% | 3.6% | 225.2 |
| Retail | 70.7 | 0.8% | 0.8% | 0.4% | 1.0% | 3.8% | 122.2 |
| Office | 62.7 | 0.9% | 1.2% | 0.4% | 1.0% | 2.7% | 102.2 |
| Industrial | 24.5 | 0.7% | 0.9% | 0.6% | 1.0% | 2.1% | 42.2 |

Exhibit 8: Changes in Volatilities Due to TOM.

Panel A: Effect of TOM on volatilities

| | Average | St.Dev. | TOM (months) | Holding Period t (years) 5 | 8 | 10 | 12 | 15 |
|---|---|---|---|---|---|---|---|---|
| All Property | 9.45% | 10.03% | 5.2 | 10.2% | 10.1% | 10.1% | 10.1% | 10.1% |
| Retail | 10.12% | 9.56% | 4.9 | 9.7% | 9.7% | 9.6% | 9.6% | 9.6% |
| Office | 8.78% | 11.34% | 5.4 | 11.5% | 11.4% | 11.4% | 11.4% | 11.4% |
| Industrial | 10.41% | 10.65% | 5.2 | 10.8% | 10.8% | 10.7% | 10.7% | 10.7% |
| Nationwide | 6.63% | 8.95% | 2.7 | 9.0% | 9.0% | 9.0% | 9.0% | 9.0% |
| Halifax | 6.26% | 9.66% | 2.7 | 9.7% | 9.7% | 9.7% | 9.7% | 9.7% |

Panel B: Combined effect of TOM and non-randomness on volatilities

| | Average | St.Dev. | TOM (months) | Holding Period t (years) 5 | 8 | 10 | 12 | 15 | βt |
|---|---|---|---|---|---|---|---|---|---|
| All Property | 9.45% | 10.03% | 5.2 | 14.5% | 17.1% | 18.6% | 20.1% | 22.1% | 0.53 |
| Retail | 10.12% | 9.56% | 4.9 | 14.3% | 17.0% | 18.6% | 20.0% | 22.0% | 0.56 |
| Office | 8.78% | 11.34% | 5.4 | 17.6% | 20.9% | 22.9% | 24.7% | 27.3% | 0.58 |
| Industrial | 10.41% | 10.65% | 5.2 | 18.5% | 22.3% | 24.5% | 26.6% | 29.4% | 0.68 |
| Nationwide | 6.63% | 8.95% | 2.7 | 12.3% | 14.6% | 15.9% | 17.1% | 18.8% | 0.51 |
| Halifax | 6.26% | 9.66% | 2.7 | 13.3% | 15.7% | 17.2% | 18.5% | 20.3% | 0.51 |

Panel C: Extra volatility exclusively due to TOM assuming non-randomness

| | Average | St.Dev. | TOM (months) | Holding Period t (years) 5 | 8 | 10 | 12 | 15 | βt |
|---|---|---|---|---|---|---|---|---|---|
| All Property | 9.45% | 10.03% | 5.2 | 0.6% | 0.4% | 0.4% | 0.3% | 0.3% | 0.53 |
| Retail | 10.12% | 9.56% | 4.9 | 0.5% | 0.4% | 0.4% | 0.3% | 0.3% | 0.56 |
| Office | 8.78% | 11.34% | 5.4 | 0.7% | 0.5% | 0.5% | 0.4% | 0.4% | 0.58 |
| Industrial | 10.41% | 10.65% | 5.2 | 0.8% | 0.6% | 0.5% | 0.5% | 0.4% | 0.68 |
| Nationwide | 6.63% | 8.95% | 2.7 | 0.2% | 0.2% | 0.2% | 0.1% | 0.1% | 0.51 |
| Halifax | 6.26% | 9.66% | 2.7 | 0.2% | 0.2% | 0.2% | 0.2% | 0.1% | 0.51 |

Note: Commercial real estate returns are taken from IPD. Nationwide and Halifax represent the main residential indices used in the UK market. TOM is the sell-side time on market measured by Devaney and Scofield (2014). TOM for the residential market (for both indices) is taken from Rightmove.com.

Exhibit 9: Liquidation Bias Estimates.

Panel A: Risk Premium for Liquidation Bias

| | Average | St.Dev. | TOM (months) | Holding Period t (years) | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | 5 | 8 | 10 | 12 | 15 |
| All Property | 9.45% | 10.03% | 5.2 | 3.2% | 2.6% | 2.3% | 2.1% | 1.9% |
| Retail | 10.12% | 9.56% | 4.9 | 2.9% | 2.3% | 2.1% | 1.9% | 1.7% |
| Office | 8.78% | 11.34% | 5.4 | 3.8% | 3.1% | 2.8% | 2.5% | 2.3% |
| Industrial | 10.41% | 10.65% | 5.2 | 3.4% | 2.7% | 2.5% | 2.3% | 2.0% |
| Nationwide | 6.63% | 8.95% | 2.7 | 1.5% | 1.2% | 1.1% | 1.0% | 0.9% |
| Halifax | 6.26% | 9.66% | 2.7 | 1.6% | 1.3% | 1.2% | 1.1% | 1.0% |

Panel B: Extra Volatility for Liquidation Bias

| | Average | St.Dev. | TOM (months) | Holding Period t (years) | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | 5 | 8 | 10 | 12 | 15 |
| All Property | 9.45% | 10.03% | 5.2 | 3.2% | 3.6% | 3.7% | 3.8% | 3.9% |
| Retail | 10.12% | 9.56% | 4.9 | 2.9% | 3.2% | 3.4% | 3.5% | 3.5% |
| Office | 8.78% | 11.34% | 5.4 | 3.8% | 4.3% | 4.4% | 4.5% | 4.7% |
| Industrial | 10.41% | 10.65% | 5.2 | 3.4% | 3.8% | 4.0% | 4.1% | 4.2% |
| Nationwide | 6.63% | 8.95% | 2.7 | 1.5% | 1.7% | 1.8% | 1.8% | 1.8% |
| Halifax | 6.26% | 9.66% | 2.7 | 1.6% | 1.8% | 1.9% | 1.9% | 2.0% |

Note: Commercial real estate returns are taken from IPD. Nationwide and Halifax represent the main residential indices used in the UK market. TOM is the sell-side time on market measured by Devaney and Scofield (2014). TOM for the residential market (for both indices) is taken from Rightmove.com.

Exhibit 10: Estimated model (full sample: 1988-2012)

| **Panel A: All Property** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | -0.001 | -0.008*** | -0.002*** | 0.002*** | 0.003*** | 0.006*** | -0.002*** |
| RMRF | 0.039** | 0.037** | 0.028** | 0.042*** | 0.04** | 0.03** | 0.026** |
| SMB | 0.059*** | 0.065*** | 0.063*** | 0.057*** | 0.056*** | 0.029 | 0.032** |
| HML | 0.049** | 0.043* | 0.043** | 0.046** | 0.042* | 0.013 | 0.019 |
| UMD | 0.028 | 0.026 | 0.016 | 0.027 | 0.025 | 0.008 | 0.015 |
| LIQ | 0.014*** | 0.476*** | 0.84*** | -0.172* | -0.204*** | -0.196*** | 0.035*** |
| Adjusted R-squared | 0.08 | 0.15 | 0.41 | 0.05 | 0.06 | 0.30 | 0.41 |
| F-statistics | 5.93 | 11.20 | 43.02 | 4.27 | 5.12 | 26.37 | 42.57 |
| Akaike info criterion | -6.13 | -6.21 | -6.58 | -6.10 | -6.12 | -6.40 | -6.58 |
| Schwarz criterion | -6.05 | -6.13 | -6.51 | -6.03 | -6.04 | -6.33 | -6.50 |
| Hannan-Quinn criter. | -6.10 | -6.18 | -6.55 | -6.07 | -6.09 | -6.37 | -6.55 |

| **Panel B: Retail** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | -0.002* | -0.01*** | -0.001** | 0.002*** | 0.003*** | 0.006*** | 0.001 |
| RMRF | 0.045*** | 0.041*** | 0.034** | 0.049*** | 0.046*** | 0.034** | 0.041*** |
| SMB | 0.057*** | 0.058*** | 0.055*** | 0.054** | 0.054** | 0.021 | 0.046** |
| HML | 0.05** | 0.041* | 0.031 | 0.043* | 0.04* | 0.018 | 0.031 |
| UMD | 0.033* | 0.026 | 0.013 | 0.031* | 0.029 | 0.021 | 0.027 |
| LIQ | 0.036*** | 0.592*** | 0.78*** | -0.111** | -0.181** | -0.198*** | 0.034*** |
| Adjusted R-squared | 0.09 | 0.22 | 0.38 | 0.06 | 0.06 | 0.33 | 0.15 |
| F-statistics | 7.15 | 17.87 | 37.84 | 4.77 | 4.69 | 30.47 | 11.42 |
| Akaike info criterion | -6.08 | -6.23 | -6.46 | -6.04 | -6.04 | -6.38 | -6.14 |
| Schwarz criterion | -6.00 | -6.15 | -6.39 | -5.97 | -5.96 | -6.31 | -6.07 |
| Hannan-Quinn criter. | -6.05 | -6.20 | -6.43 | -6.01 | -6.01 | -6.35 | -6.11 |

| **Panel C: Office** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | -0.001 | -0.009*** | -0.001 | 0.003*** | 0.002** | 0.006*** | 0.001** |
| RMRF | 0.038** | 0.03* | 0.032** | 0.042** | 0.038** | 0.025* | 0.038** |
| SMB | 0.066*** | 0.064*** | 0.069*** | 0.059*** | 0.064*** | 0.011 | 0.07*** |
| HML | 0.062** | 0.067*** | 0.067*** | 0.051** | 0.053** | 0.019 | 0.055** |
| UMD | 0.033* | 0.029 | 0.03* | 0.028 | 0.028 | 0.014 | 0.035* |
| LIQ | 0.029*** | 0.44*** | 0.548*** | -0.106*** | -0.149* | -0.298*** | 0.047*** |
| Adjusted R-squared | 0.06 | 0.17 | 0.31 | 0.08 | 0.05 | 0.36 | 0.18 |
| F-statistics | 5.06 | 13.32 | 27.22 | 6.17 | 4.36 | 34.17 | 14.20 |
| Akaike info criterion | -5.96 | -6.08 | -6.26 | -5.98 | -5.95 | -6.34 | -6.09 |
| Schwarz criterion | -5.89 | -6.01 | -6.18 | -5.90 | -5.87 | -6.26 | -6.02 |
| Hannan-Quinn criter. | -5.93 | -6.05 | -6.23 | -5.95 | -5.92 | -6.31 | -6.06 |

| Panel D: Industrial | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | 0.003*** | -0.004** | 0.000 | 0.002*** | 0.005*** | 0.006*** | 0.004*** |
| RMRF | 0.028* | 0.024 | 0.021* | 0.027* | 0.027* | 0.020 | 0.019 |
| SMB | 0.052*** | 0.057*** | 0.063*** | 0.055*** | 0.046** | 0.036* | 0.044** |
| HML | 0.037 | 0.038* | 0.027 | 0.037* | 0.030 | 0.023 | 0.035* |
| UMD | 0.017 | 0.020 | 0.010 | 0.017 | 0.013 | 0.009 | 0.014 |
| LIQ | -0.010 | 0.358*** | 0.656*** | 0.033*** | -0.282*** | -0.127*** | 0.088*** |
| Adjusted R-squared | 0.03 | 0.11 | 0.36 | 0.07 | 0.07 | 0.10 | 0.15 |
| F-statistics | 2.62 | 8.00 | 33.98 | 5.28 | 5.74 | 7.96 | 11.36 |
| Akaike info criterion | -6.19 | -6.27 | -6.60 | -6.23 | -6.24 | -6.27 | -6.32 |
| Schwarz criterion | -6.12 | -6.20 | -6.53 | -6.16 | -6.17 | -6.20 | -6.25 |
| Hannan-Quinn criter. | -6.16 | -6.24 | -6.57 | -6.20 | -6.21 | -6.24 | -6.29 |

Note: The LIQ coefficients for Volumes and PS measures have been multiplied by 1000 to make them comparable in size to coefficients estimated with other measures.

Exhibit 11: Estimated model (sample: 1996-2012).

| **Panel A: All Property** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | 0.000 | -0.007*** | -0.001 | 0.007*** | 0.005*** | 0.008*** | -0.003*** |
| RMRF | 0.059*** | 0.053*** | 0.04** | 0.055*** | 0.062*** | 0.041*** | 0.038*** |
| SMB | 0.049** | 0.048** | 0.062*** | 0.021 | 0.039* | -0.002 | 0.021 |
| HML | 0.038 | 0.031 | 0.037* | -0.005 | 0.024 | -0.018 | 0.006 |
| UMD | 0.025 | 0.020 | 0.013 | -0.002 | 0.019 | -0.005 | 0.010 |
| LIQ | 0.01* | 0.504*** | 0.813*** | -2.931*** | -0.279*** | -0.223*** | 0.034*** |
| Adjusted R-squared | 0.07 | 0.17 | 0.40 | 0.28 | 0.11 | 0.52 | 0.48 |
| F-statistics | 3.94 | 9.30 | 28.02 | 16.62 | 5.82 | 44.54 | 38.11 |
| Akaike info criterion | -6.13 | -6.25 | -6.57 | -6.39 | -6.18 | -6.79 | -6.71 |
| Schwarz criterion | -6.04 | -6.15 | -6.48 | -6.29 | -6.08 | -6.69 | -6.61 |
| Hannan-Quinn criter. | -6.09 | -6.21 | -6.53 | -6.35 | -6.14 | -6.75 | -6.67 |

| **Panel B: Retail** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | -0.001 | -0.01*** | -0.001 | 0.007*** | 0.004*** | 0.008*** | 0.002* |
| RMRF | 0.064*** | 0.052*** | 0.042** | 0.064*** | 0.069*** | 0.044*** | 0.06*** |
| SMB | 0.051** | 0.05** | 0.066*** | 0.028 | 0.039 | -0.011 | 0.035 |
| HML | 0.042 | 0.037 | 0.035 | 0.010 | 0.025 | -0.010 | 0.022 |
| UMD | 0.030 | 0.021 | 0.011 | 0.011 | 0.022 | 0.008 | 0.022 |
| LIQ | 0.03** | 0.653*** | 0.838*** | -1.29*** | -0.253*** | -0.227*** | 0.029*** |
| Adjusted R-squared | 0.08 | 0.23 | 0.35 | 0.19 | 0.09 | 0.50 | 0.15 |
| F-statistics | 4.44 | 13.22 | 22.59 | 10.70 | 4.85 | 42.05 | 8.34 |
| Akaike info criterion | -5.98 | -6.16 | -6.32 | -6.11 | -5.98 | -6.59 | -6.06 |
| Schwarz criterion | -5.88 | -6.06 | -6.22 | -6.01 | -5.89 | -6.50 | -5.96 |
| Hannan-Quinn criter. | -5.94 | -6.12 | -6.28 | -6.07 | -5.95 | -6.55 | -6.02 |

| **Panel C: Office** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | 0.002 | -0.008*** | 0.000 | 0.007*** | 0.004*** | 0.008*** | 0.003*** |
| RMRF | 0.057*** | 0.048** | 0.047*** | 0.053*** | 0.059*** | 0.034** | 0.057*** |
| SMB | 0.052** | 0.042* | 0.061*** | 0.022 | 0.044* | -0.021 | 0.056** |
| HML | 0.043 | 0.051** | 0.055** | 0.015 | 0.032 | -0.008 | 0.039* |
| UMD | 0.027 | 0.023 | 0.026 | 0.009 | 0.021 | 0.005 | 0.03* |
| LIQ | 0.007 | 0.433*** | 0.544*** | -1.299*** | -0.235*** | -0.323*** | 0.042*** |
| Adjusted R-squared | 0.05 | 0.17 | 0.35 | 0.24 | 0.09 | 0.56 | 0.24 |
| F-statistics | 3.22 | 9.09 | 22.72 | 13.72 | 5.21 | 51.75 | 13.71 |
| Akaike info criterion | -6.08 | -6.21 | -6.46 | -6.30 | -6.13 | -6.84 | -6.30 |
| Schwarz criterion | -5.99 | -6.12 | -6.36 | -6.21 | -6.03 | -6.74 | -6.21 |
| Hannan-Quinn criter. | -6.05 | -6.17 | -6.42 | -6.26 | -6.09 | -6.80 | -6.26 |

| **Panel D: Industrial** | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS |
|---|---|---|---|---|---|---|---|
| C | 0.005*** | -0.003 | 0.000 | 0.007*** | 0.006*** | 0.009*** | 0.004*** |
| RMRF | 0.048*** | 0.043** | 0.034** | 0.047*** | 0.05*** | 0.031** | 0.037** |
| SMB | 0.041** | 0.042** | 0.044*** | 0.028 | 0.033* | -0.004 | 0.033* |
| HML | 0.026 | 0.027 | 0.007 | 0.000 | 0.014 | -0.022 | 0.025 |
| UMD | 0.015 | 0.014 | 0.000 | -0.002 | 0.009 | -0.014 | 0.012 |
| LIQ | -0.034 | 0.314*** | 0.701*** | -0.504*** | -0.36*** | -0.324*** | 0.076*** |
| Adjusted R-squared | 0.05 | 0.10 | 0.43 | 0.12 | 0.16 | 0.46 | 0.20 |
| F-statistics | 3.17 | 5.43 | 31.52 | 6.77 | 8.76 | 35.24 | 10.84 |
| Akaike info criterion | -6.37 | -6.42 | -6.88 | -6.45 | -6.49 | -6.93 | -6.54 |
| Schwarz criterion | -6.27 | -6.32 | -6.78 | -6.35 | -6.40 | -6.83 | -6.44 |
| Hannan-Quinn criter. | -6.33 | -6.38 | -6.84 | -6.41 | -6.45 | -6.89 | -6.50 |

Note: The LIQ coefficients for Volumes and PS measures have been multiplied by 1000 to make them comparable in size to coefficients estimated with other measures.

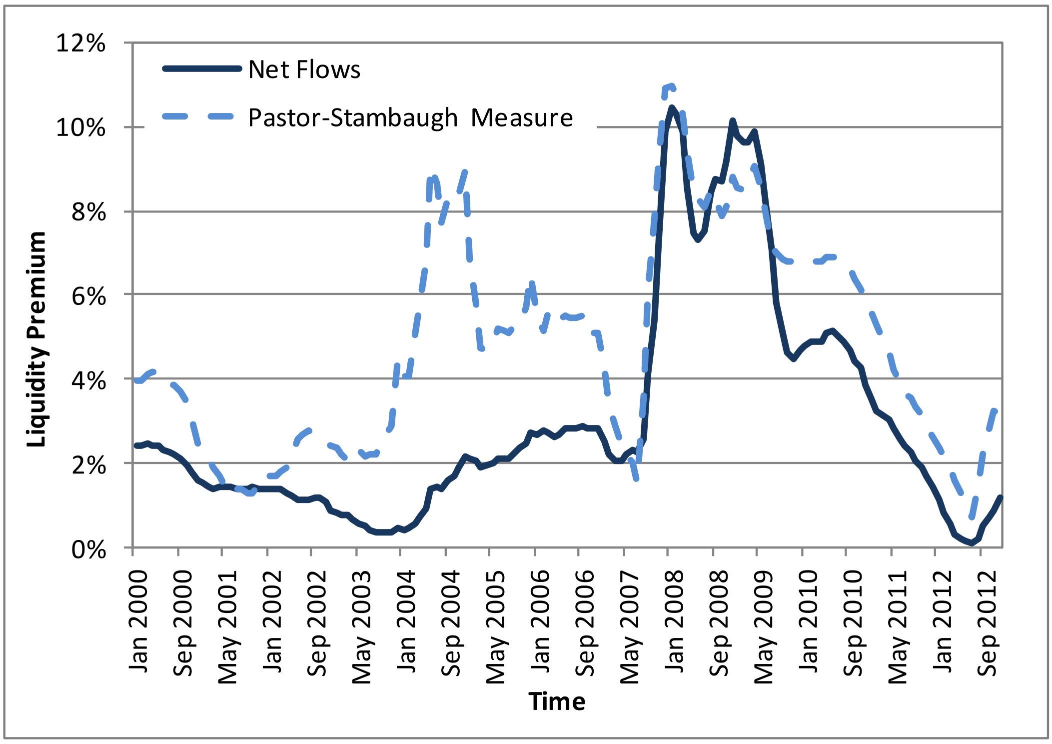
Exhibit 12: Estimated Annual Liquidity Premia.

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* | ***Average*** | ***Average (excl. Turnover)*** |
|---|---|---|---|---|---|---|---|---|---|
| **Sample 1988-2012** | | | | | | | | | |
| All Property | 3.19% | 11.95% | 4.08% | 0.88% | 1.77% | 4.61% | 5.01% | **4.50%** | **3.26%** |
| Retail | 4.06% | 14.91% | 3.67% | 1.19% | 1.57% | 4.84% | 4.36% | **4.94%** | **3.28%** |
| Office | 2.74% | 13.41% | 2.09% | 1.73% | 1.34% | 6.14% | 4.33% | **4.54%** | **3.06%** |
| Industrial | 0.42% | 8.71% | 4.19% | 1.25% | 2.54% | 2.76% | 4.61% | **3.50%** | **2.63%** |
| **Sample 1996-2012** | | | | | | | | | |
| All Property | 2.86% | 11.90% | 4.91% | 5.11% | 2.37% | 5.65% | 7.15% | **5.71%** | **4.67%** |
| Retail | 4.57% | 16.14% | 4.76% | 5.12% | 2.15% | 6.12% | 6.17% | **6.43%** | **4.81%** |
| Office | 0.87% | 12.83% | 2.94% | 5.40% | 2.18% | 5.74% | 5.89% | **5.12%** | **3.84%** |
| Industrial | 1.94% | 7.52% | 4.77% | 3.58% | 3.17% | 5.82% | 7.06% | **4.84%** | **4.39%** |

Exhibit 13: Liquidity Premia Estimated with Rolling Windows (60 months).

| | Volumes | Turnover | Net flows | Amihud | Roll | Ret/Turn | PS | **Average** | **Average (excl. Volumes, Turnover)** |
|---|---|---|---|---|---|---|---|---|---|
| **All Property** | | | | | | | | | |
| Average | 11.27% | 15.80% | 3.03% | 4.69% | 4.45% | 6.30% | 3.87% | **7.06%** | **4.47%** |
| St.Dev. | 9.68% | 9.01% | 2.33% | 2.83% | 4.01% | 4.25% | 2.45% | **4.94%** | **3.17%** |
| Dec 2006 | 5.08% | 6.14% | 2.85% | 5.45% | 4.50% | 6.67% | 5.08% | **5.11%** | **4.91%** |
| Dec 2008 | 28.83% | 36.25% | 10.13% | 7.56% | 13.37% | 11.42% | 8.79% | **16.62%** | **10.25%** |
| Dec 2012 | 2.62% | 4.96% | 0.56% | 9.56% | 0.09% | 12.49% | 3.21% | **4.78%** | **5.18%** |
| **Retail** | | | | | | | | | |
| Average | 13.13% | 14.77% | 3.14% | 5.26% | 4.21% | 6.59% | 3.32% | **7.20%** | **4.50%** |
| St.Dev. | 10.71% | 9.94% | 2.18% | 3.01% | 3.99% | 4.31% | 1.87% | **5.14%** | **3.07%** |
| Dec 2006 | 2.04% | 2.60% | 1.00% | 5.05% | 3.01% | 5.02% | 2.04% | **2.97%** | **3.23%** |
| Dec 2008 | 22.09% | 20.72% | 8.31% | 9.48% | 13.28% | 12.36% | 7.48% | **13.39%** | **10.18%** |
| Dec 2012 | 21.13% | 24.92% | 2.24% | 9.26% | 1.59% | 11.81% | 4.61% | **10.79%** | **5.90%** |
| **Office** | | | | | | | | | |
| Average | 10.17% | 13.43% | 2.46% | 4.89% | 4.98% | 6.63% | 3.62% | **6.60%** | **4.52%** |
| St.Dev. | 6.60% | 7.29% | 2.08% | 3.61% | 4.87% | 4.87% | 1.81% | **4.45%** | **3.45%** |
| Dec 2006 | 8.91% | 10.39% | 3.79% | 1.30% | 3.03% | 6.25% | 6.51% | **5.74%** | **4.18%** |
| Dec 2008 | 11.92% | 25.80% | 9.32% | 8.54% | 14.94% | 11.38% | 6.63% | **12.65%** | **10.16%** |
| Dec 2012 | 5.11% | 7.34% | 2.84% | 8.77% | 0.06% | 10.47% | 3.90% | **5.50%** | **5.21%** |
| **Industrial** | | | | | | | | | |
| Average | 3.95% | 5.91% | 2.42% | 4.61% | 4.13% | 5.15% | 3.08% | **4.18%** | **3.88%** |
| St.Dev. | 3.00% | 4.17% | 2.10% | 3.45% | 3.12% | 4.83% | 2.16% | **3.26%** | **3.13%** |
| Dec 2006 | 2.58% | 1.53% | 2.46% | 4.78% | 1.61% | 3.84% | 2.58% | **2.77%** | **3.06%** |
| Dec 2008 | 2.41% | 9.45% | 9.46% | 11.43% | 11.75% | 12.55% | 7.51% | **9.22%** | **10.54%** |
| Dec 2012 | 7.63% | 1.76% | 2.00% | 9.08% | 2.50% | 12.33% | 4.00% | **5.61%** | **5.98%** |

Exhibit 14: Illiquidity Premium Over Time (Net Flows and Pastor-Stambaugh Measure)



## Appendix: Further tables

Exhibit A1: Correlation Coefficients of Liquidity Measures for Retail Properties

Panel A: Retail 1988-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.14 | 0.36 | -0.42 | 0.20 | 0.11 | 0.57 |
| *Turnover* | | 1.00 | 0.42 | -0.03 | 0.00 | -0.29 | 0.31 |
| *Net flows* | | | 1.00 | -0.12 | -0.06 | -0.19 | 0.57 |
| *Amihud* | | | | 1.00 | 0.09 | 0.31 | -0.24 |
| *Roll* | | | | | 1.00 | 0.47 | -0.16 |
| *Ret/Turn* | | | | | | 1.00 | -0.30 |
| *PS* | | | | | | | 1.00 |

Panel B: Retail 1996-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.25 | 0.43 | -0.22 | 0.27 | 0.09 | 0.51 |
| *Turnover* | | 1.00 | 0.54 | -0.03 | -0.14 | -0.31 | 0.40 |
| *Net flows* | | | 1.00 | -0.17 | -0.17 | -0.27 | 0.67 |
| *Amihud* | | | | 1.00 | 0.43 | 0.72 | -0.32 |
| *Roll* | | | | | 1.00 | 0.53 | -0.19 |
| *Ret/Turn* | | | | | | 1.00 | -0.37 |
| *PS* | | | | | | | 1.00 |

Exhibit A2: Correlation Coefficients of Liquidity Measures for Office Properties

Panel A: Office 1988-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.27 | 0.22 | -0.43 | 0.28 | 0.02 | 0.41 |
| *Turnover* | | 1.00 | 0.21 | -0.14 | -0.05 | -0.25 | 0.30 |
| *Net flows* | | | 1.00 | -0.10 | -0.18 | -0.15 | 0.57 |
| *Amihud* | | | | 1.00 | -0.05 | 0.45 | -0.25 |
| *Roll* | | | | | 1.00 | 0.36 | -0.23 |
| *Ret/Turn* | | | | | | 1.00 | -0.38 |
| *PS* | | | | | | | 1.00 |

Panel B: Office 1996-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.42 | 0.20 | -0.21 | 0.32 | 0.16 | 0.30 |
| *Turnover* | | 1.00 | 0.45 | -0.10 | -0.13 | -0.20 | 0.39 |
| *Net flows* | | | 1.00 | -0.15 | -0.33 | -0.20 | 0.66 |
| *Amihud* | | | | 1.00 | 0.38 | 0.71 | -0.39 |
| *Roll* | | | | | 1.00 | 0.48 | -0.27 |
| *Ret/Turn* | | | | | | 1.00 | -0.40 |
| *PS* | | | | | | | 1.00 |

Exhibit A3: Correlation Coefficients of Liquidity Measures for Industrial Properties

Panel A: Industrial 1988-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.22 | 0.18 | -0.41 | 0.24 | -0.02 | 0.46 |
| *Turnover* | | 1.00 | 0.55 | -0.06 | -0.05 | -0.26 | 0.26 |
| *Net flows* | | | 1.00 | -0.04 | -0.29 | -0.25 | 0.60 |
| *Amihud* | | | | 1.00 | 0.02 | 0.49 | -0.23 |
| *Roll* | | | | | 1.00 | 0.39 | -0.35 |
| *Ret/Turn* | | | | | | 1.00 | -0.45 |
| *PS* | | | | | | | 1.00 |

Panel B: Industrial 1996-2012

| | *Volumes* | *Turnover* | *Net flows* | *Amihud* | *Roll* | *Ret/Turn* | *PS* |
|---|---|---|---|---|---|---|---|
| *Volumes* | 1.00 | 0.38 | 0.22 | -0.13 | 0.36 | 0.24 | 0.31 |
| *Turnover* | | 1.00 | 0.58 | -0.02 | -0.13 | -0.21 | 0.38 |
| *Net flows* | | | 1.00 | -0.31 | -0.43 | -0.44 | 0.75 |
| *Amihud* | | | | 1.00 | 0.40 | 0.64 | -0.50 |
| *Roll* | | | | | 1.00 | 0.61 | -0.40 |
| *Ret/Turn* | | | | | | 1.00 | -0.59 |
| *PS* | | | | | | | 1.00 |