1 Introduction

The benefits of including real estate in a portfolio have been extensively documented in the literature (MacKinnon and Al Zaman 2009; Brounen, Porras Prado and Verbeek 2010). Given some of the characteristics of real estate assets (e.g., their high unit value and illiquidity), many investors hold real estate securities in order to be exposed to the asset class. Ciochetti, Craft and Shilling (2002), for instance, show that institutional investors take larger positions in REIT stocks, as compared with private real estate, because of liquidity considerations. Yet, real estate stocks are not necessarily immune to liquidity risk in the sense of Pástor and Stambaugh (2003), and Acharya and Pedersen (2005). Liquidity risk differs from the average level of liquidity of an asset. Indeed, liquidity risk pertains to the fact that liquidity varies over time and displays commonality across securities (Chordia, Roll and Subrahmanyam 2000), whereas the liquidity level is an asset-specific characteristic.

Theoretical and empirical research has shown that liquidity risk is a priced risk factor in several markets. For instance, Acharya and Pedersen (2005) propose an asset pricing model in which liquidity risk has three dimensions: commonality in liquidity, the covariance of asset returns with market liquidity, and the covariance of asset liquidity with market returns. Their empirical analysis of the U.S. stock market provides support for their model. In contrast, little is known about the potential liquidity risk premium related to securitized real estate returns, although Subrahmanyam (2007) shows that current liquidity shocks forecast higher future returns in the U.S. market. However, he does not investigate liquidity risk per se.

In this paper, we seek to expand our knowledge of the liquidity risk of U.S. Real Estate Investment Trusts (REITs) by focusing on one of its components, i.e., the liquidity commonality. Generally speaking, commonality in liquidity is defined as the level of comovement between a security's liquidity and that of the overall market. This feature precludes investors from forming optimal portfolios where liquidity risk would be diversified away (i.e., systematic liquidity risk). Investors seek to hold assets that allow them to exit positions at a minimum cost when most needed, that is, during market downturns or liquidity dry-ups. Securitized real estate positions can be exited quite easily, and certainly more easily than is the case for direct real estate positions, but such investments could display a strong liquidity correlation causing adverse effects in crisis periods. Consequently, one would expect a compensation for holding an asset whose liquidity covaries with market liquidity (especially in bad market conditions).

The hybrid nature of real estate securities allows us to look at two other dimensions of commonality in liquidity. First, given that securitized real estate investments are listed on stock exchanges, it is reasonable to assume that the liquidity of the overall equity market could also affect the liquidity of real estate securities. Though quite scarce, the empirical literature has shown some evidence of commonality in liquidity across different asset classes.[1]

[1] See for instance Chordia, Sarkar and Subrahmanyam (2005) who find that innovations to stock and bond market liquidity are correlated.

We refer to this as *cross-asset commonality in liquidity* which differs from the commonality in liquidity within a market as discussed above. Thus, the risk that a real estate security's liquidity comoves with that of the common stock market could give rise to a premium for the investor undergoing this risk. We maintain that this cross-asset perspective is important to consider since investors usually hold mixed-asset portfolios and therefore make decisions at the mixed-asset level.

Second, real estate companies own assets for which there are benchmarking and trading activity indicators at the aggregate level, which is not the case for most other types of companies. Taking the commercial real estate market as a proxy for the assets held by real estate companies, we are thus able to analyze the commonality in liquidity with the underlying asset. Thus, we also test whether this type of commonality has an influence on REIT prices. This analysis will shed light on the benefits of investing in REITs from a liquidity perspective. More specifically, we address the important question of whether real estate stocks retain liquidity when the liquidity of the underlying market is decreasing. Real estate securities thus offer an interesting laboratory for testing whether commonality in liquidity is multi-faceted.

We use U.S. REIT data for our empirical investigations. A multi-factor approach is adopted for our pricing tests as we control for the effects of market return, value and size, momentum, credit conditions, investor sentiment, and market volatility. The asset returns' sensitivity to innovations in aggregate market liquidity is also controlled for (Pástor and Stambaugh 2003). We use firm-specific data and a panel model with switching regimes (Panel Threshold Regression model) developed by Hansen (1999) for the pricing test. This nonlinear regime-switching specification allows the pricing of liquidity risk to be conditional on the state of the economy (i.e., time-varying liquidity risk). With the exceptions of the papers by Watanabe and Watanabe (2008), and Acharya, Amihud and Bharath (2013), studies usually adopt an unconditional approach for analyzing the liquidity patterns. Yet, it has been well documented that liquidity behaves differently under a normal state of the economy in comparison with a more stressful period (Hameed, Kang and Viswanathan 2010).

We further seek to identify the sources of the within- and cross-asset commonality in liquidity.[2] We employ a time-series Threshold Regression (TR) model (Tsay 1989) for the analysis of the determinants of liquidity commonality (as averaged at the market level) over time, which should better reflect market dynamics. We test both supply-side and demand-side determinants of liquidity as in Karolyi, Lee and van Dijk (2012). The theoretical underpinning for the supply-side explanation of liquidity is based on the relation between market participants' funding constraints (i.e., funding liquidity) and asset liquidity (Brunnermeier and Pedersen 2009). Their theory predicts that commonality in liquidity results from the fact that the ability to obtain funding for leveraged market participants (e.g., financial intermediaries) holding various securities is impaired in times of large market declines or high volatility

[2] The potential drivers of the commonality in liquidity with the underlying asset are still not well established in the theoretical literature. Hence, we leave this point for future research and focus on the factors explaining the within- and cross-asset commonality.

(funding liquidity shock). This forces them to liquidate positions across several securities (reduction of the provision of liquidity), which increases the commonality in liquidity. Brunnermeier and Pedersen also show that a decrease of market liquidity further tightens funding liquidity creating a liquidity spiral that increases the commonality in liquidity even further. Thus, financial intermediaries fail to provide liquidity to the market in bad environments. In sum, the supply-side hypothesis stipulates that commonality in liquidity is negatively linked to credit conditions and is higher when markets decline.[3]

As regards the demand-side explanation, we rely on two potential sources: correlated trading activity and investor sentiment. The first hypothesis argues that if investors tend to trade in concert, this leads to common buying or selling pressures (i.e., trade imbalances) that reinforce the degree of comovement between securities' liquidity. This argument stems from the idea that investors with similar trading patterns should face the same shocks in liquidity or changes in the information available and would therefore trade in the same way in response to those shocks (Chordia, Roll and Subrahmanyam 2000). We expect therefore a positive impact of correlated trading activity (as proxied by the commonality in turnover) on commonality in liquidity. The second source is in the wake of the growing behavioral finance literature that stresses the role of noise traders and investor sentiment in the price formation and return comovements (Baker and Wurgler 2006; Kumar and Lee 2006). Similar effects on liquidity commonality are expected as shown by Huberman and Halka (2001).[4] The investor sentiment hypothesis does not offer clear theoretical predictions regarding the sign of the relationship between investor sentiment and commonality in liquidity (Karolyi, Lee and van Dijk 2012). We conjecture that within our two-regime framework a higher optimism should impact commonality in the normal regime, whereas a higher pessimism should impact it in the crisis regime.

Our main results are as follows. First, while insignificant in a low-volatility regime, the within-asset commonality in liquidity becomes a priced risk factor in a high-volatility regime. In contrast, the commonality in liquidity with the stock market has a significant impact on REIT prices only in the first regime. We also find that the level of liquidity correlation between REITs and the underlying property market constitutes a priced risk factor but again only during market downturns. Thus, the liquidity advantages of REITs should be nuanced. We further uncover that REIT prices are sensitive to shocks in REIT and stock market liquidity but that they are relatively immune to those in the private real estate market. Finally, our results favor a demand-side explanation of commonality in liquidity.

Our study contributes to the literature on liquidity risk by showing that different types of commonality in liquidity could have an impact on asset prices. We also contribute to the real estate literature by examining an asset whose higher liquidity represents a key characteristic

[3]Other important models that demonstrate the effects of financial intermediaries' financing constraints on market liquidity include, among others, Kyle and Xiong (2001), and Gromb and Vayanos (2002).

[4]Hameed, Kang and Viswanathan (2010), and Karolyi, Lee and van Dijk (2012) also find some evidence of sentiment-based commonality in liquidity.

in real estate investment decision-making but whose liquidity risk is not fully comprehended. Finally, the asset pricing literature has mainly studied the sensitivity of asset returns to market liquidity shocks, whereas commonality in liquidity has received much less attention and then only within an unconditional framework. Thus, by adopting a conditional approach, our research contributes to the literature by more thoroughly analyzing this specific dimension of liquidity risk.

The paper is structured as follows. We first review the extant empirical literature. Then, we develop our empirical strategy, before describing the data. We then turn to a discussion of our results. Given the nature of private real estate data, the analysis of the commonality in liquidity between REITs and direct real estate is contained in a separate section. A final section concludes.

2 Empirical Literature

The bulk of the literature on liquidity risk has focused on the stock market. Pástor and Stambaugh (2003), by means of a four-factor model with liquidity risk, show that U.S. stocks with higher sensitivity to innovations in market liquidity exhibit higher expected returns. Acharya and Pedersen (2005) develop a liquidity-adjusted capital asset pricing model (LCAPM), where liquidity risk has three distinct dimensions (commonality in liquidity, the covariance of a security's return with market liquidity, and the covariance of a security's liquidity with market return). In an analysis of the U.S. stock market, their empirical findings strongly support the LCAPM. In particular, they find that investors require a return premium for a security whose liquidity largely depends on that of the whole market. Lee (2011) extends the previous work by applying the LCAPM in an international context; his findings are in line with Acharya and Pedersen's theory. Emerging markets have also been considered as markets potentially sensitive to liquidity risk. Bekaert, Harvey and Lundblad (2007) examine liquidity risk in 18 emerging countries and find that such a risk is even more important than market risk.

The evidence of a priced liquidity risk has been extended recently to other types of assets. Li et al. (2009) and Acharya, Amihud and Bharath (2013) study the exposure of U.S. bond returns to liquidity shocks, whereas Mancini, Ranaldo and Wrampelmeyer (2013) analyze liquidity risk in the foreign exchange markets. Hedge funds (Sadka 2010; Gibson Brandon and Wang 2013), credit derivatives (Longstaff, Mithal and Neis 2005; Bongaerts, de Jong and Driessen 2010) and private equity (Franzoni, Nowak and Phalippou 2012) have also been investigated. All of these studies show that liquidity risk is a significant risk factor.

Another branch of the literature has looked at the relationship between the liquidity of a firm's security and the liquidity of the assets owned by that firm. Gopalan, Kadan and Pevzner (2012) find that asset liquidity significantly impacts stock liquidity. They also document that an increase in asset liquidity leads to a higher firm value. In a REIT context, Benveniste, Capozza and Seguin (2001) show that creating liquid claims on illiquid real estate assets increases the value of these claims. Thus, the underlying assets' liquidity can influence both the liquidity and the price of a security, which further motivates our hypothesis that the commonality in liquidity with the underlying real estate market could be a priced risk factor in the REIT market.

Several studies have sought to disentangle the dynamics of commonality in liquidity. Consistent with Brunnermeier and Pedersen's (2009) theory, Hameed, Kang and Viswanathan (2010) show that market liquidity dry-ups and commonality in liquidity in the U.S. stock market are more likely during market declines and times of tightness in the funding market. Although these results strongly support the supply-side explanation, the authors do acknowledge that factors related to the demand for liquidity may also influence their findings. In this spirit, Karolyi, Lee and van Dijk (2012) examine the sources of commonality in liquidity across 40 developed and emerging countries. Their results favor the demand-side determinants of liquidity and challenge therefore the ability of Brunnermeier and Pedersen's theory to fully explain commonality in liquidity. In a study of the impact of mutual funds' correlated trading on commonality in liquidity, Koch, Ruenzi and Starks (2010) also suggest an important role for demand-side factors.

3 Research Methodology

3.1 Liquidity Variables

In this section, we discuss the liquidity-related variables used for the within- and cross-asset commonality in liquidity analyses. We first specify the commonality in liquidity variable and then the market liquidity risk factor.

3.1.1 Commonality in Liquidity Variable

Liquidity is an elusive concept and no perfect measure exists that captures the different aspects of such a complex asset/market characteristic while having sufficient data to cover a large number of assets/markets for a long time period. We employ Amihud's (2002) illiquidity measure. As shown by Goyenko, Holden and Trzcinka (2009), this proxy is highly correlated with liquidity measures based on microstructure data (i.e., the bid-ask spread). Amihud's measure captures the market depth (price impact measure of liquidity) and is defined as:

$$ILLIQ^i_{t,d} = \frac{|r^i_{t,d}|}{VOLD^i_{t,d}} \tag{1}$$

with $r^i_{t,d}$ and $VOLD^i_{t,d}$, the daily return and volume on stock i on day d of month t, respectively. We apply a detrending factor to the above measure to control for the effects of inflation by multiplying $ILLIQ$ by the ratio between the total REIT market capitalization at time $t-1$ and that at the beginning of the sample period (Pástor and Stambaugh 2003;

Acharya and Pedersen 2005). To obtain a measure of liquidity (LIQ), we simply take the inverse of $ILLIQ$.

Karolyi, Lee and van Dijk (2012) utilize the R^2 of regressions as a measure of commonality in liquidity. More specifically, the R^2 of a regression of a security's liquidity on market liquidity (both contemporaneous and lagged) is estimated for each firm. Importantly, the market liquidity excludes the security analyzed to avoid any endogeneity issue and it is computed as the value-weighted average across the remaining securities' liquidity. We follow those authors and adopt the same approach for our measure of commonality in liquidity:

$$LIQ^i_{t,d} = \alpha^i_t + \beta^i_{1,t} LIQ^M_{t,d} + \beta^i_{2,t} LIQ^M_{t,d-1} + \upsilon^i_{t,d} \tag{2}$$

where $LIQ^i_{t,d}$ denotes the liquidity level of security i on day d within month t, and $LIQ^M_{t,d}$ the aggregate market liquidity. The market liquidity can be either that of securitized real estate (within-asset commonality in liquidity) or that of stocks (cross-asset commonality in liquidity). This regression is estimated each month t for each firm i which yields a time-series of commonality in liquidity ($R^2_{i,t}$) for all individuals that make up our sample. We require a minimum of 10 daily observations within a month for a given firm to estimate the R^2. We proceed identically for constructing the correlated trading activity variable which is proxied by the commonality in turnover ($Cturn_{i,t}$). The turnover, i.e., the ratio between the trading volume and the number of shares outstanding, is modeled instead of liquidity in Equation 2.

So far, we have discussed the computation of the liquidity and commonality in liquidity levels. We turn now to the construction of the commonality in liquidity risk factor to be used in the asset pricing model ($CLIQ$). We construct a commonality in liquidity factor at the aggregate level and return-based (traded liquidity factor). Hence, the construction of this risk factor follows the same rationale as, for example, the size factor in the Fama and French three-factor model (i.e., mimicking portfolios). Based on the levels of commonality in liquidity calculated previously, securities are ranked into P portfolios $p = 1, 2, \ldots, P$ and for each portfolio the value-weighted monthly return (r^p_t) is calculated. As commonality in liquidity risk factor, we take the return differential (that is, the risk premium) between the portfolio which exhibits the strongest commonality and the portfolio with the weakest commonality:

$$CLIQ_t = r^P_t - r^1_t. \tag{3}$$

The portfolios are formed according to the level of liquidity commonality during the previous month; the portfolios are therefore rebalanced every month. This return-based liquidity factor can be interpreted as the additional return required by investors for holding a real estate security whose liquidity comoves strongly with that of the overall securitized real estate market (or that of the stock market). If our hypothesis were to be verified, we would expect a positive coefficient on this variable, meaning that investors are compensated for systematic liquidity risk. In other words, the required rate of return should be therefore higher for securities whose liquidity covaries with market liquidity, all else being equal.

3.1.2 Market Liquidity Risk Factor

The market liquidity risk factor is tested as an additional liquidity-related risk factor in this study. This liquidity risk factor, initially suggested by Pástor and Stambaugh (2003), captures the sensitivity of asset returns to the aggregate market liquidity. Indeed, an investor could demand a premium when an asset's returns comove with market liquidity. We include this liquidity variable in order to be conservative in our conclusions with respect to the importance of commonality in liquidity in asset pricing. In the spirit of our liquidity commonality factor, we construct two market liquidity risk factors: one for the public real estate market and one for the stock market. Again, the security being tested is not included in the estimation of the market liquidity, which is calculated as the value-weighted average across the remaining securities' liquidity levels.

Given the persistence of market liquidity[5], only innovations (news) should drive returns. We obtain innovations in market liquidity by means of an autoregressive process of order one. This method of constructing innovations of liquidity is similar to that used by Pástor and Stambaugh (2003) and Acharya and Pedersen (2005). This non-traded liquidity risk factor (labeled $MLIQ$) is therefore integrated in the asset pricing model along with $CLIQ$. Realized returns are affected by liquidity shocks because expected returns are affected by expected liquidity (Amihud and Mendelson 1986). Thus, a negative shock to liquidity reduces future expected liquidity and raises the expected return, which in turn lowers prices today. This usually gives a positive liquidity beta. Therefore, we also expect a positive beta for the market liquidity risk factor.

3.2 Model Specification

In this section, we first specify the Panel Threshold Regression model of Hansen (1999) as utilized within our asset pricing framework and briefly discuss its characteristics. Then, we present the time-series Threshold Regression model that depicts the sources of commonality in liquidity within the public real estate market. Finally, the estimation method and linearity testing procedure of the PTR and TR models are discussed. Note that, in addition to the nonlinear models presented next, we also estimate their respective linear counterparts for comparison purposes.

3.2.1 Pricing Model

In our specific setting, the PTR model with two regimes which explains REIT excess returns over the 3-month T-bill rate can be written as:

[5] The serial correlation of the public real estate and stock market liquidity is 0.93 and 0.97, respectively.

$$
\begin{aligned}
r_{i,t} = & \mu_i + \left[\alpha_1 CLIQ_t + \beta_1 MLIQ_{i,t} + \delta_1' Z_t\right] \mathbb{1}_{(q_{i,t-1} \leq c)} \\
& + \left[\alpha_2 CLIQ_t + \beta_2 MLIQ_{i,t} + \delta_2' Z_t\right] \mathbb{1}_{(q_{i,t-1} > c)} + \varepsilon_{i,t}
\end{aligned}
\tag{4}
$$

where $r_{i,t}$ is the monthly excess return on the securitized real estate asset i for month t and $CLIQ_t$ the commonality in liquidity factor as estimated in Equation 3. $MLIQ_{i,t}$ is the asset-specific market liquidity risk factor.[6] Z_t is a vector of factors such as credit conditions, market return, Fama and French's (1993) factors, momentum, market volatility (Ang et al. 2006) and investor sentiment (Baker and Wurgler 2006), which reflect the state of the economic and financial outlook at the aggregate level and are consequently only time-varying. Finally, μ_i is an individual fixed effect and $\varepsilon_{i,t}$ is the remaining error term. When we examine cross-asset commonality in liquidity, $CLIQ_t$ and $MLIQ_{i,t}$ will stem from the analysis in which the securitized real estate market is replaced by the stock market.

Within this setup, the impact of a given factor on returns is not constant over time. Notably, we expect to find a differentiated impact of the various factors in a crisis regime compared to a normal one. The transition from one regime to the other is conducted by the observable transition variable $q_{i,t-1}$ (lagged by one month) through the indicator function $\mathbb{1}_{(\cdot)}$ which satisfies the condition in parentheses.[7] The threshold between the two regimes is defined by the parameter c: if $q_{i,t-1} \leq c$ we are in the first regime and if $q_{i,t-1} > c$ we are in the second regime. This threshold parameter is unknown and will be jointly estimated with the other parameters of the model. The marginal impact of a given variable, say $CLIQ_t$, is α_1 conditional on being in the first regime and α_2 in the second regime.

The choice of the observable transition variable is essential in threshold modeling. In general, this variable should reflect the business cycle variations. Economic and financial intuition could be used to choose an appropriate transition variable. In our case, REITs' realized volatility should be a convenient transition variable since it properly reflects fluctuations in the REIT market. The monthly realized volatility is measured by the standard deviation of daily returns within a month. The data show that periods of high REIT volatility correspond to bad general conditions in the economy such as during the 2008-2009 crisis or during the more recent debt crisis. Moreover, the realized volatility for each firm should reflect the firm's specific conditions which does not constrain the transition from a normal to a crisis regime to be common to all firms.

[6] The market liquidity risk factor is asset-specific because for each asset i tested, we do not consider its liquidity in the computation of the market liquidity.

[7] Given that the transition variable $q_{i,t}$ is defined at the firm level, the impact of a given factor is also not constant across firms.

3.2.2 Sources of Commonality in Liquidity

Let us now set up the time-series regime-switching model (i.e., TR model) which examines the economic sources of commonality in liquidity within the REIT market and the cross-asset commonality in liquidity. Thus, this specification allows the identification of a potential differentiated impact of the explanatory variables during crises and normal periods. More specifically, the R^2 measure of commonality in liquidity (Equation 2) averaged across firms, is regressed on the liquidity determinants discussed previously (i.e., supply-side and demand-side determinants) along with control variables that proxy for general market conditions. Given that the range of R^2 falls within the $[0; 1]$ interval, we apply the logit link function in order to obtain a dependent variable which potentially takes values in the total support of real numbers. The model estimated is as follows:

$$\log\left\{\bar{R}_t^2/\left(1-\bar{R}_t^2\right)\right\} = \theta_1' H_t\, \mathbb{1}_{(q_{t-1}\leq c)} + \theta_2' H_t\, \mathbb{1}_{(q_{t-1}>c)} + \omega_t \tag{5}$$

where $\bar{R}_t^2$ is the average of the commonality in liquidity measure across firms. The vector H_t includes the determinants of commonality in liquidity and the control variables. The average commonality in turnover within the public real estate market, the investor sentiment, the market volatility and various proxies of credit availability are chosen as potential factors explaining the commonality in liquidity as discussed in the introduction. The control variables include the market return, liquidity and turnover for both the REIT and stock markets. $\mathbb{1}_{(\cdot)}$ is the indicator function conducting the transition between regimes and the procedure for choosing the transition variable is similar to that of Equation 4. Given our market approach in studying the sources of commonality in liquidity, we use the VIX index as a measure of market volatility. As it measures the market's expectation about future stock market volatility, the VIX is a good indicator of market conditions. Indeed, the VIX exhibits spikes during periods of market distress and is low during normal times.

3.2.3 Estimation Method and Linearity Testing Procedure

The parameters of Equations 4 and 5 are estimated by nonlinear least squares (NLS) which also accounts for a White correction for heteroskedasticity in the error term. Conditional on the value of the parameter c, both specifications are linear on the other coefficients which can be estimated by a standard least squares method. c is estimated using a grid search procedure which minimizes the residual sum of squares. The linear models are estimated by OLS with White-correction for heteroskedasticity.

A test to evaluate the accuracy of the regime-switching models, both in the time-series and in the panel framework, is also performed. Indeed, one should test the null hypothesis of a linear model against the alternative hypothesis of a two-regime specification. We use a likelihood ratio test whose distribution is non-standard because under the null hypothesis of a linear model the threshold parameter c is a nuisance parameter. This issue is solved by a bootstrap procedure to simulate the distribution of the test as suggested in Hansen (1999). A more detailed review of the estimation and testing procedures can be found in Tsay (1989), Chan (1993) and Hansen (1999).

4 Data

We focus on REIT data from the Center for Research in Security Prices/Ziman Real Estate Data Series. Prices, trading volume and shares outstanding (daily frequency) at the individual REIT level are collected to compute the returns, liquidity, commonality in liquidity and commonality in turnover (monthly frequency). The S&P 500 index is utilized as proxy for the U.S. stock market for the computation of the cross-asset commonality in liquidity. Daily prices, trading volume and shares outstanding are collected from Thomson Reuters Datastream for each constituent of the index to construct the aggregate stock market liquidity.[8] The market return, size, book-to-market and momentum factors, used in the asset pricing model as controls, are obtained from Kenneth French's website.[9] In the model, we further include the credit spread (difference between Moody's Baa corporate bond and 10-year U.S. government bond yields) and the term spread (difference between 10-year and 1-year U.S. government bond yields) as business cycle proxies. The VIX index is chosen as proxy for the stock market volatility. These data are obtained from Bloomberg.

We use the University of Michigan consumer confidence index (sourced from Bloomberg) as the investor sentiment variable. This index is based on surveys that poll U.S. households on their current financial situation and their expectations about the future of the U.S. economy. However, this raw investor sentiment indicator may reflect to some extent economic fundamentals (Lemmon and Portniaguina 2006). Therefore, we orthogonalize it with respect to various macroeconomic variables in order to obtain a 'pure' sentiment index in the spirit of noise trader theories. These macroeconomic variables include: growth in industrial production, growth in durable, nondurable and services consumption, growth in employment, inflation, and an NBER recession indicator. This filtered sentiment variable is used both in the pricing test and in the analysis of the economic sources of commonality in liquidity (i.e, the demand-side determinants).

As funding liquidity variables in the investigation of the determinants of liquidity commonality (i.e, the supply-side determinants), we use the variations in the TED spread, the variations in the difference between the 3-month commercial paper rate and the 3-month Treasury bill rate (commercial paper spread), and the variations in the spread between the 30-year conventional mortgage rate and the 3-month Treasury bill rate (mortgage spread). Increased spreads imply higher borrowing costs, that is a narrowing of the funding liquidity. The extant literature has shown that those indirect measures of aggregate supply of funding

[8]Since several REITs are included in the S&P 500 index, these firms are removed from this index in order to avoid any endogeneity issue and any confusion with the within-asset commonality in liquidity.

[9]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

are relevant. The data needed to construct those variables are also collected from Bloomberg. The time period for our analyses goes from January 1, 1999 through December 31, 2012. For this period, CRSP reports data for 366 REITs. However, we restrict our sample to firms having a minimum of two years of observations, yielding a sample of 295 REITs.

5 Estimation Results

We present in this section the empirical results from the analyses of the within- and cross-asset commonality in liquidity. First, we discuss their patterns and present some related statistics. Descriptive statistics for the main variables used in this study are also presented. Second, the results of the asset pricing model estimation which aims to test whether or not the commonality in liquidity is priced in REIT returns are discussed. Finally, the sources of commonality in liquidity within the REIT market and with the stock market are investigated.

5.1 Commonality in Liquidity: Statistics & Characteristics

This section aims to provide a detailed picture of the commonality in liquidity involving the U.S. public real estate market. Summary statistics are reported and various features of the liquidity commonality are examined, such as its evolution over time as well as its level with respect to firm size and liquidity level. Table 1 provides some summary statistics for the commonality in liquidity variables estimated (see Equations 2 and 3) as well as for the main variables utilized in the various analyses.

[Table 1 about here]

The average levels of the within- and cross-asset commonality in liquidity (i.e., R^2) during the 1999-2012 period are 11.4% and 12.6%, respectively, with a standard deviation of about 11%. The highest R^2 (for both variables) exceeds 70%. These figures are calculated from over 14,000 monthly firm-level observations stemming from 278 REITs[10] with varying numbers of observations. Taking the cross-sectional average level of commonality in liquidity does not lead to significant changes in those numbers. These levels of commonality are quite high and broadly in line with the levels found for the U.S. stock market by Karolyi, Lee and van Dijk 2012.[11] These values tell us that the phenomenon of commonality in liquidity exists within the U.S. REIT market, which warrants for further analysis of this phenomenon.

[10] Some firms do not have any commonality in liquidity observations due to the constraints for the estimation (e.g., a minimum number of liquidity levels observed within a month), which reduces the sample from 295 REITs to 278.

[11] These authors report an average R^2 of about 23%, but they include in their regressions for the commonality in liquidity (see Equation 2) the market liquidity in $t+1$. We do not include this variable because it seems doubtful that a variable in the future would influence another variable in the past. However, we ran our regressions with this additional variable for comparison purposes and found an average commonality in liquidity level of about 18%, which clearly shows some similarities between the two markets.

Figures 1 and 2 show the evolution, over the period 1999-2012, of the average levels across firms of the within- and cross-asset commonality in liquidity, respectively. It appears from Figure 1 that there is no trend over our sample period. Indeed, the level of liquidity commonality has been quite constant since 1999, even though some spikes emerge in early 2000, in 2006 and in 2012. Notably, the commonality in liquidity did not increase during the recent financial crisis. On the other hand, the cross-asset commonality in liquidity shows a positive trend and a much higher level during the 2007-2009 financial crisis compared to its average level. Thus, one can observe an increasing connection between REIT and stock markets' liquidity, which is particularly pronounced in stressful periods. This finding provides tentative support for Brunnermeier and Pedersen's (2009) theory.

[Figures 1 and 2 about here]

It is commonly recognized that liquidity is positively correlated with firm size. It seems therefore reasonable to expect the same relationship between commonality in liquidity and firm size. Figure 3 depicts bar graphs of the levels of liquidity commonality sorted according to firms' average market capitalization. As can be seen, there is no striking tendency between commonality in liquidity and firm size (for both types of commonality in liquidity). Therefore, the explanatory power of commonality in liquidity in the cross-section of REIT returns should be unrelated to firm size. We also analyze how commonality in liquidity varies cross-sectionally according to firms' liquidity level (Figure 4). Sorting firms from low to high liquidity does not uncover any relationship with commonality in liquidity.

[Figures 3 - 4 about here]

Turning now to our commonality in liquidity risk factors[12] ($CLIQ$) to be tested in the asset pricing model, we can see from Figures 5 (within-asset commonality) and 6 (cross-asset commonality) their evolution over our sample period. Both risk factors show some high levels after the dot-com bubble and during the recent financial crisis, emphasizing the importance of these risk factors in crisis periods. It is important to note that the cross-asset commonality in liquidity risk factor reaches however a very low level at the peak of the crisis. Also, although the levels of the within-asset commonality in liquidity did not increase during the 2007-2009 financial crisis, we observe here that $CLIQ$ did nevertheless increase. We explain this by the fact that in crisis periods, investors ask for a higher premium for the same level of commonality in liquidity. This feature clearly suggests that a regime-switching approach is suitable for the subsequent analyses. Over our sample period, $CLIQ$ exhibits an average return of 0.06% with a standard deviation of 0.97%, whereas *cross-asset* $CLIQ$ has an average return of 0.08% with a standard deviation of 1.14%. These results suggest that securities with a higher commonality in liquidity have, on average, a higher return one month later.

[12]For computing this return-based risk factor, we group the firms into five portfolios according to their level of commonality in liquidity and take the value-weighted return differential between the portfolio with the strongest commonality and the portfolio with the weakest commonality (i.e., "5-1" spread).

[Figures 5 and 6 about here]

Table 1 also reports the summary statistics of the other variables used in this study. To reduce the impact of outliers, the returns used in this study are winsorized at the 1% and 99% quantiles. The average monthly return is about 0.36% with a standard deviation of 8.27% based on nearly 30,000 firm-level observations. Interestingly, the levels of the within- and cross-asset commonality in turnover (i.e., R^2) are on average higher than their liquidity counterparts. The commonality in turnover is on average 20.7% within the REIT market and 17.9% for the stock market. In line with the results reported previously for the commonality in liquidity, a REIT's turnover comoves quite strongly with that of the overall market and with that of the stock market. In general, the remaining variables have characteristics that are consistent with the extant literature. Finally, all series are stationary[13] (test results not reported) except the credit and term spreads. To make them stationary, we take the first difference of these variables.

5.2 Pricing Model

In order to disentangle the pricing of commonality in liquidity, we estimate a linear model as well as a nonlinear model where REIT excess returns are regressed on our return-based commonality in liquidity factor (Equation 3) and a set of control variables. The estimation results of the asset pricing model which includes the within-asset commonality in liquidity factor and the REIT market liquidity risk are shown in Table 2. The table reports the estimation results of the linear asset pricing model at the security level (i.e., the linear panel data model) as well as those of the PTR model.

The estimation results for the linear model show that most of the factor loadings (i.e., λ in Tables 2) are highly significant based on t-statistics calculated from robust standard errors. Of primary interest to this paper, the coefficient on $CLIQ$ is significantly negative, indicating that investors are not compensated for bearing such a risk; they are even willing to pay for commonality in liquidity. This result is the opposite of what is predicted by theory. We explain this result as follows: the negative beta may be driven by periods during which markets are dominated by high liquidity and investors are looking for such a characteristic. Indeed, when market liquidity is high, one would like to buy a security whose liquidity is also high. On the other hand, evidence of innovations in REIT market liquidity being a significant priced factor is found. Hence, a negative shock to market liquidity lowers REIT prices (and increases expected returns). In short, REIT market liquidity risk is the only priced liquidity risk factor when a linear approach is adopted. The other factor loadings exhibit relatively consistent patterns with the extant empirical asset pricing literature.

[Table 2 about here]

[13] Several unit root tests are used for testing stationarity: the Phillips-Perron and Dickey-Fuller tests are used for the time series variables, while the Levin-Lin-Chu and Pesaran panel unit root tests are used for the variables in panel data.

Turning now to the estimation results for the PTR model, we first examine the adequacy of using a regime-switching model by testing the null hypothesis of a linear model against the alternative hypothesis of a two-regime specification. We use firms' realized volatility for detecting the regimes. The F-statistic strongly rejects the hypothesis of linearity, which supports the use of a two-regime modeling for examining REIT pricing. Based on the estimation of the location parameter c, we investigate the number of firms in the high-volatility regime (i.e., if $q_{i,t-1} > c$) for each month and present summary statistics for each year in Table 3. We find the highest percentages of firms in the high-volatility regime in 2008 and 2009 (approximatively 40% of the sample). Furthermore, we find that almost all REITs (i.e., 93%) included in the sample in November 2008 were in the high-volatility regime, consistent with what happened in the financial markets during that time. Thus, our transition variable does a good job in characterizing the different states of the economy.

[Table 3 about here]

The factor loadings in the low-volatility regime (i.e., λ_1 in Table 2) are relatively close to those of the linear model. In particular, we find that the REIT market liquidity risk remains significantly positive (based on t-statistics corrected for heteroskedasticity). The commonality in liquidity risk factor is, on the other hand, no longer significant. We also find that several factor betas significantly vary between the normal regime and the crisis regime (i.e., $\lambda_2 - \lambda_1$), which shows the inability of a linear model to correctly capture the various impacts on REIT prices in stressful times. Importantly, we find that both the commonality in liquidity and REIT market liquidity risk betas significantly increase in the second regime. The coefficient on $CLIQ$ becomes positive, suggesting that this risk factor is priced. Thus, part of the REIT excess returns in a high-volatility regime is explained by commonality in liquidity. Our liquidity risk factors become therefore clearly more important in bad market conditions. In other words, investors do not ask for the same compensation with respect to liquidity risk depending on the state of the economy, consistent with recent evidence of conditional liquidity risk in the literature (Watanabe and Watanabe, 2008; Acharya, Amihud and Bharath, 2013).

The estimation results of the asset pricing model which includes the cross-asset commonality in liquidity factor and the stock market liquidity risk are shown in Table 4. The estimates of the linear model (i.e., λ in Table 4) reveal that cross-asset commonality in liquidity is a significant factor in explaining REIT returns. Our hypothesis is therefore verified, which stresses the importance of also taking a cross-asset perspective when investigating liquidity risk. On the other hand, the stock market liquidity risk does not represent a significant risk factor. Again, the linearity hypothesis (i.e., F-test) is strongly rejected in favor of a two-regime specification. The estimation of the nonlinear model[14] provides values for the parameters in the

[14] Counting the number of firms in the high-volatility regime (results not reported) leads to similar results as those reported in Table 3. This is explained by the fact that the estimated location parameters c of both specifications are very close.

first regime (λ_1) very close to those reported for the linear model. The cross-asset commonality in liquidity factor remains the only significant liquidity variable. However, these dynamics significantly change when the economy switches to the high-risk state (λ_2). The effect of *cross-*$CLIQ$ becomes insignificant, whereas the effect of $MLIQ$ becomes significantly positive. In this latter case, the difference between regimes is highly significant. The results of the cross-asset commonality in liquidity therefore indicate a different story than those for within-asset commonality: although this risk factor gives rise to a premium in the low-volatility regime, this premium disappears in the high-volatility regime. Also, REIT prices turn to be sensitive to stock market liquidity in crisis periods, meaning that REIT prices fall when stock market liquidity dries up in inopportune moments. Hence, adopting a nonlinear approach shows that the dynamics are regime-dependent, which provides a more complete picture of the effects of liquidity on REIT prices.

[Table 4 about here]

In sum, both within- and cross-asset commonality in liquidity are relevant for REIT pricing and their impacts are robust to market liquidity risk, noise trader sentiment and standard systematic risks. We also find that our liquidity variables are in general much more important in a high-volatility regime, showing that liquidity risk is time-varying. These findings contribute thus to the debate on the REIT premium puzzle by showing the significant role of liquidity risk in REIT pricing. Given these results, an additional analysis, critical to fully understanding the commonality in liquidity phenomenon, is to examine its determinants. This is the purpose of the following section.

5.3 Sources of Commonality in Liquidity

As determinants of commonality in liquidity, we consider two supply-side variables, credit availability and market volatility, and two demand-side variables, commonality in turnover and investor sentiment. In addition to these factors, a set of control variables is also included in the analysis. Again, we estimate a linear as well as a nonlinear model since the impact of the above variables could be regime-dependent. Three models are estimated, each time with a different proxy for funding liquidity (i.e., Models 1-3). These proxies are the TED spread, the commercial paper spread (CP spread) and the mortgage spread. We take the changes in these variables for our tests.

We first discuss the results of the linear model which investigates the within-asset commonality in liquidity (Table 5). The results show that commonality in turnover (i.e., $Cturn$), our proxy for correlated trading activity, represents a significant economic source of commonality in liquidity. The coefficient on this variable being positive, it is therefore in line with the theory. This finding is robust to the funding liquidity proxy used. Thus, investors who tend to trade in concert the same assets influence positively their level of comovement in liquidity

(Koch, Ruenzi and Starks 2010). On the other hand, investor sentiment does not have a significant impact on the within-asset commonality in liquidity.

[Table 5 about here]

In contrast to the recent literature stressing the importance of funding liquidity in explaining commonality in liquidity, our empirical results strongly reject this hypothesis. Indeed, the impact of funding liquidity is not significantly different from zero and this finding is robust across various proxies of credit availability. The commonality in liquidity within the public real estate market is also not driven by market volatility (i.e., VIX), consistent with the fact that this commonality did not increase during the recent financial crisis (see Figure 1). In sum, no factor related to Brunnermeier and Pedersen's (2009) theory is significant when using a linear approach for investigating the within-asset commonality in liquidity.[15] Since the risk that liquidity suppliers will face funding constraints is much higher during pervasive market declines, the funding hypothesis could still be verified within a regime-switching framework. However, the F-statistics[16] show that the null hypothesis of linearity is never rejected. Thus, the findings for the linear model should reflect how the various factors studied influence the level of commonality in liquidity within the REIT market regardless of the state of the economy.

Table 6 displays the results of the linear model that analyzes the cross-asset commonality in liquidity. *Cturn* appears again as an important driver of commonality in liquidity. We further find that investor sentiment contributes to explaining the linkages between REIT liquidity and stock market liquidity. The parameter on sentiment is negative and significant across the different models. This indicates that more pessimistic investor sentiment increases the cross-asset commonality in liquidity level. This finding shows the need to take into account behavioral biases when analyzing the functioning of financial markets in line with the behavioral finance literature. Again, no support for the funding liquidity hypothesis is found. Although we find that cross-asset commonality in liquidity is higher in crisis periods (see Figure 2), we do not find a formal support for the impact of stock market volatility on this liquidity commonality. We test again if a nonlinear approach would be more adequate in explaining the sources of commonality in liquidity. The F-statistics (not reported) show that the null hypothesis of linearity is rejected only in one case, i.e., when the mortgage spread is used as funding variable.

[Table 6 about here]

The estimation of a Threshold Regression model that includes the mortgage spread yields a number of interesting results (Table 7). First, several factors become important in the

[15] Partial evidence supportive of the supply-side hypothesis would be the negative coefficient on the stock market returns, showing that liquidity commonality increases when the stock market declines. However, this relation could also be explained by demand-side factors (e.g., shifts in investor sentiment). Thus, this significant result does not represent sufficient evidence in favor of the supply-side explanation.

[16] The results of these tests are not reported but can be obtained upon request

second regime (i.e., θ_2) with statistically significant differences between the results for both regimes (i.e., $\theta_2 - \theta_1$). However, the TR model does not provide more support to the funding hypothesis since the mortgage spread is either negative or insignificant. On the other hand, market volatility appears to become a key variable in explaining the level of comovement between REIT liquidity and stock market liquidity when the economy switches to the high-risk regime. In addition, the increased impact is highly significant. We find that sentiment is not an important source in the normal regime but becomes a major determinant in the crisis regime. The significantly negative impact of sentiment within the unconditional approach coupled with the insignificant impact found in the low-risk regime tell us that the first result was primarily driven by the role of sentiment in stressful times. This finding is consistent with the extant literature that stresses the increased behavioral biases during bad market conditions. We also find that investors' correlated trading behavior increases liquidity commonality but only in the low-volatility regime. The demand-side determinants remain therefore relatively important within a two-regime framework, even though we observe an increasing role played by supply-side factors.

[Table 7 about here]

Overall, our findings are more in favor of demand-side determinants of liquidity and are thus in line with recent empirical works such as those by Karolyi, Lee and van Dijk (2012), and Koch, Ruenzi and Starks (2010). Our empirical setup thus shows the limited scope of Brunnermeier and Pedersen's theory in explaining commonality in liquidity. Furthermore, we uncover that most of the effects on liquidity commonality do not vary according to the state of the economy.

6 Commonality in Liquidity with the Underlying Asset

In this section, we extend our work by analyzing the commonality in liquidity between REITs and the underlying real estate market. More specifically, we test whether the covariation between REITs' liquidity and the private market liquidity affects REIT returns. Several papers have analyzed the relationship between REIT prices, and more broadly closed-end fund share prices, and the value of the assets owned by these funds. Deviations from Net Asset Value (NAV) have been attributed to investor irrationality (Lee, Shleifer and Thaler 1991), but also to the differences between the liquidity of the assets held by the funds and the liquidity of their shares (Cherkes, Sagi and Stanton 2009). This latter theory conjectures thus some linkages between REIT liquidity and the direct real estate market liquidity. Consistently, Benveniste, Capozza and Seguin (2001) show that the liquidity of the underlying real estate market has a significant influence on liquidity and price changes in the REIT market. Thereby, the commonality in liquidity between REITs and the private real estate market may give raise to a premium since real estate investors generally shift their holdings to the public market for liquidity purposes.

Assessing the liquidity of the private real estate market is no trivial task. Due to the nature of the available data, we need to implement an alternative strategy as regards the liquidity proxy and the construction of the commonality in liquidity variable to that adopted for the other two analyses of commonality. We use the number of properties sold as our measure of liquidity in the private real estate market[17] as Amihud's (2002) measure is inapplicable for the private market. Transaction frequency represents a reliable liquidity indicator especially in a highly illiquid market (Ling, Naranjo and Scheick 2012). The data are sourced from Real Capital Analytics and are available at a monthly frequency for the period 2001-2012. As regards the measure of commonality in liquidity, our previous approach (i.e., R^2) is no longer adequate since it requires daily data. We choose to use copula modeling to overcome this issue. A copula is a function that joins or couples two or more marginal distribution functions and describes their dependence structure. We use a normal copula, whose unique parameter is the correlation level, to estimate the degree of comovement between a REIT's liquidity (i.e., the inverse of Amihud's measure) and that of the private real estate market. The bivariate normal copula $C_N(v_1, v_2)$ takes the following form in a static case:

$$C_N(v_1, v_2; \rho) = \int_{-\infty}^{\Phi^{-1}(v_1)} \int_{-\infty}^{\Phi^{-1}(v_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp \left[\frac{-(r^2 - 2\rho rs + s^2)}{2(1-\rho^2)} \right] drds \tag{6}$$

where ρ is the correlation parameter and Φ^{-1} the inverse of the standard normal cumulative distribution function (*cdf*). v_1 and v_2 are the marginal distribution functions of our two liquidity series defined on a unit rectangle (i.e., $0 \leq v \leq 1$). To allow the correlation parameter ρ to vary over time, we specify a conditional normal copula (Patton 2006). Formally, the following model (akin to an ARMA(1,10)) is estimated:[18]

$$\rho_t = \tilde{\Lambda} \left(\omega_\rho + \beta_\rho \rho_{t-1} + \alpha_\rho \frac{1}{10} \sum_{j=1}^{10} \Phi^{-1}(v_{1,t-j}) \Phi^{-1}(v_{2,t-j}) \right) \tag{7}$$

where $\tilde{\Lambda}(x) = (1 - e^{-x})(1 + e^{-x})^{-1}$ is the modified logistic transformation, which ensures that the correlation parameter ρ_t remains bounded between -1 and 1 at all times.

Relying on a conditional copula allows us to have a monthly commonality in liquidity measure from monthly data. However, this approach has the disadvantage of restricting our analysis to firms with no missing values over the sample period. Thus, our tests are conducted on a sample of 95 REITs (instead of 295).[19] Equation 7 is estimated for each firm i included in our sample, which yields a monthly time-series of commonality in liquidity for each REIT (i.e.,

[17] We apply a detrending factor to this raw measure of liquidity to remove any time trend.

[18] In a first stage, we filter our series (i.e., liquidity measures) by an AR(1)-GJR-t-GARCH(1,1) and estimate the marginal distributions by means of an empirical *cdf* based on the standardized residuals coming from the filtering process.

[19] We estimated our asset pricing model with the within- and cross-asset commonality in liquidity using the same restricted sample and the results are economically similar, suggesting that our findings with respect to the commonality in liquidity with the private real estate market could also be generalized to the REITs that are not included in the sample.

$\rho_{i,t}$). The commonality in liquidity risk factor (i.e., the traded liquidity factor) that we use in the asset pricing model is constructed in the same way as for the within-asset commonality in liquidity (i.e., "5-1" spread). We also construct a real estate liquidity risk factor. Again, we use the residuals from an AR(1) applied to the detrended real estate market liquidity as indicator of shocks to market liquidity. Both types of liquidity risk factors are included in the asset pricing model together with a set of control variables. This model is estimated both within a linear and a regime-switching framework (Equation 4).

Figure 7 shows the evolution of the average commonality in liquidity with the private market over the 2001-2012 period. Although quite low (i.e., 6% on average; see Table 1), the correlations are always positive and show some interesting features. The correlations sharply increase during the subprime crisis period, then decline during the 2008-2009 period, and increase again afterwards. It seems therefore that REITs offer some liquidity diversification but not constantly, given the strong fluctuations in the correlation levels. Thus, commonality in liquidity could be a priced risk factor in the REIT market, especially in a context of high market volatility. Consistent with this intuition, the highest excess returns due to commonality in liquidity (i.e., the return-based risk factor) appear in 2008 (Figure 8). We further analyze the characteristics of the commonality in liquidity between REITs and the underlying real estate market by sorting the levels of liquidity correlation according to firm size and liquidity (Figure 9). We observe that larger and more liquid REITs tend to comove less with the private market as shown by the higher number of negative correlations on the right-hand side of the graphs. These findings suggest that large and liquid REITs provide better diversification in terms of liquidity (with respect to direct investments) than small and less liquid REITs. This is consistent with Benveniste, Capozza and Seguin (2001) who show that the liquidity gains of creating equity claims on illiquid property assets are significant only above a certain firm size.

[Figures 7-9 about here]

Table 8 reports the results of the asset pricing model estimation. In the linear model, the commonality in liquidity with the direct market ($DRECLIQ$) is not a priced risk factor since its coefficient is negative. Investors are even willing to receive a lower return if a REIT exhibits this feature. Also, shocks to the private market liquidity are found to increase REIT prices (negative coefficient). This finding suggests that investors place a greater value on the liquidity of REITs (i.e., they are willing to pay more) subsequent to a decrease in the underlying real estate market liquidity, and vice versa. In summary, no premium is associated with both types of liquidity risks in an unconditional framework.

[Table 8 about here]

The null hypothesis of linearity being rejected (i.e., F-test in Table 8), we turn now to the discussion of the regime-switching model estimation results. Interestingly, the coefficient on $DRECLIQ$ switches from negative in the first regime to positive in the second regime (significant at the 10% confidence level). Moreover, this change is highly significant, suggesting that the dynamics between the commonality in liquidity with the underlying asset and REIT returns are time-varying. Although REITs are a liquid alternative to a direct investment, the extent to which their liquidity is correlated with the private market liquidity during high return volatility periods commands a premium. In contrast, the real estate market liquidity risk factor does not have a significant impact on REIT prices in the second regime. When the private market liquidity decreases, investors do not therefore pay more for owning a liquid REIT in a high-volatility regime as opposed to in a low-volatility regime. This is likely due to the fact that the REIT's liquidity also declines (see the above discussion on the commonality in liquidity) and does not constitute a diversifying investment in terms of liquidity anymore. This is consistent with the general liquidity dry-up which was observed during the recent financial crisis.

7 Conclusion

Liquidity is a key element in investment decision-making, but several of its facets remain insufficiently explored. Our paper aims to contribute to the literature on liquidity by studying the liquidity risk embedded in U.S. securitized real estate investments. Such assets have a higher liquidity level than direct real estate investments but they are not necessarily immune to liquidity risk. We focus on one dimension of liquidity risk, i.e., the commonality in liquidity. Formally, commonality in liquidity is defined as the level of comovement between a security's liquidity and that of the overall market. Taking advantage of the hybrid nature of REITs, we also examine the pricing implications of two other dimensions of commonality in liquidity: the commonality with the stock market liquidity and the commonality with the underlying asset liquidity. To the best of our knowledge, these aspects have to date remained unexplored. We first analyze the patterns of commonality in liquidity. Then, we test whether commonality in liquidity represents a priced risk factor in REIT returns. Finally, we seek to identify the economic sources of commonality in liquidity, testing both supply-side and demand-side determinants of liquidity.

This paper adopts a conditional approach for investigating the liquidity commonality. In this framework, the impact of commonality in liquidity on REIT returns and of the factors explaining commonality in liquidity are hypothesized to vary according to the state of the economy. We find evidence that the three types of commonality in liquidity are priced in REIT returns but differently depending on market conditions. More specifically, the within-asset commonality in liquidity and the commonality with the underlying asset liquidity are significant risk factors only in a high-risk state of the economy, while the cross-asset commonality is significant only in a low-risk state. Investors are thus willing to pay more for REIT shares which allow them to exit positions at a relatively low cost when the liquidity of the overall REIT market, that of the stock market or that of the underlying real estate market declines. We also uncover that REIT prices are sensitive to shocks in REIT and stock market liquidity, but that they are relatively immune to those in the private real estate market. We conclude that the liquidity benefits of REITs are somewhat overstated.

In the analysis of the economic sources of commonality in liquidity, we find that agent's correlated trading activity and investor sentiment play a major role in explaining within- and cross-asset commonality in liquidity. Our evidence is therefore in favor of a demand-side explanation of commonality in liquidity. These results, in line with Karolyi, Lee and van Dijk (2012), and Koch, Ruenzi and Starks (2010), thus challenge the popular funding hypothesis of Brunnermeier and Pedersen (2009).

Our empirical findings offer interesting insights to real estate investors. Although more liquid than direct investments, real estate securities embed a particular risk as materialized by commonality in liquidity. Furthermore, we show that commonality in liquidity has several dimensions which also influence REIT prices. Our paper is the first one highlighting the importance of such risks. Investors should be aware of such risks and avoid making decisions based solely on the liquidity level of the assets; they would benefit from holding assets whose liquidities are not correlated, in particular during stressful periods. Bearing this in mind, an avenue for future research would be to assess the role of commonality in liquidity in portfolio construction.

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Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Minimum	Maximum
<u>DEPENDENT VARIABLE</u>					
REIT return	29,717	0.359	8.273	-57.75	52.34
<u>COMMONALITY IN LIQUIDITY VARIABLES</u>					
Commonality in liquidity	14,409	0.114	0.105	0.000	0.735
Cross-asset comm. in liq.	14,409	0.126	0.108	0.000	0.791
Comm. in liq. with DRE	13,585	0.061	0.200	-0.833	0.795
CLIQ	167	0.061	0.970	-6.112	3.165
Cross-CLIQ	167	0.078	1.138	-4.726	4.473
DRECLIQ	143	-0.105	0.886	-3.939	3.623
<u>OTHER VARIABLES</u>					
MLIQ (REIT)	167	0.000	19.74	-56.49	82.00
MLIQ (Stock)	167	-0.000	875.26	-2,320.5	2,722.2
MLIQ (Private RE)	143	0.000	498.90	-1,726.1	1,966.5
$R_M - R_f$	167	0.200	4.737	-17.23	11.34
SMB	167	0.038	3.766	-22.00	7.73
HML	167	0.627	3.546	-9.78	13.84
Momentum	167	0.289	6.149	-34.74	18.39
Credit spread	167	0.002	0.224	-1.000	1.450
Term spread	167	0.008	0.210	-0.620	0.770
VIX	167	22.04	8.289	10.42	59.89
Sentiment	167	-0.066	11.30	-28.09	26.58
Commonality in turnover	167	0.207	0.098	0.086	0.543
Cross-asset comm. in turn.	167	0.179	0.084	0.078	0.543

Note: The 'Commonality in liquidity' and 'Cross-asset comm. in liq.' variables are the R^2 of a regression in which the liquidity of each asset within a month is explained by the liquidity of the REIT market and of the stock market, respectively (see Equation 2). 'Comm. in liq. with DRE' is the liquidity correlation between REITs and the direct real estate market (see Equation 7). 'CLIQ', 'Cross-CLIQ' and 'DRECLIQ' are the return-based commonality in liquidity risk factors computed from the REIT market, the stock market and the direct real estate market, respectively, as given in Equation 3. 'MLIQ (REIT)', 'MLIQ (Stock)' and 'MLIQ (Private RE)' are the market liquidity risk factors. '$R_M - R_f$' is the spread between the market return and the 3-month T-bill rate. 'SMB', 'HML' and 'Momentum' are the Fama and French factors controlling for size, book-to-market and momentum. The 'Credit spread' is computed as the difference between Moody's Baa corporate bond and 10-year U.S. government bond yields. The 'Term spread' is the difference between the 10-year and 1-year U.S. government bond yields. 'VIX' stands for the Chicago Board of Options Exchange implied volatility index. As a proxy for investor sentiment, we use the University of Michigan consumer confidence index. 'Commonality in turnover' and 'Cross-asset comm. in turn.' are computed in the same manner as 'Commonality in liquidity' and 'Cross-asset comm. in liq.' from the REIT and stock market turnover (turnover denotes the ratio between the trading volume and the number of shares outstanding). All return-based variables are expressed as percentages.

Table 2: Asset Pricing Model Estimation Results
Commonality within the REIT Market - Realized Volatility

	Linear model	PTR model		
	λ	λ_1	λ_2	$\lambda_2 - \lambda_1$
CLIQ	-0.162**	-0.066	1.504***	1.570***
	(-2.324)	(-1.364)	(3.288)	(3.414)
MLIQ (REIT)	$3{\cdot}10^{-4}$***	$2{\cdot}10^{-4}$***	$8{\cdot}10^{-4}$***	$5{\cdot}10^{-5}$*
	(8.275)	(10.826)	(2.406)	(1.691)
$R_M - R_f$	0.613***	0.451***	1.098***	0.647***
	(21.14)	(31.740)	(11.928)	(6.947)
SMB	0.493***	0.424***	0.717***	0.293**
	(20.85)	(32.077)	(4.894)	(1.985)
HML	0.757***	0.580***	0.918***	0.338**
	(21.47)	(34.758)	(6.596)	(2.420)
Momentum	-0.188***	-0.095***	-0.249***	-0.154**
	(-11.94)	(-10.642)	(-3.573)	(-2.187)
Credit spread	-0.367	1.660***	-1.200	-2.860*
	(-0.598)	(4.893)	(-0.823)	(-1.900)
Term spread	-2.133***	-0.767***	2.265	3.032
	(-4.957)	(-2.955)	(1.113)	(1.476)
VIX	$-1{\cdot}10^{-4}$	$-6{\cdot}10^{-4}$***	$-5{\cdot}10^{-4}$**	$1{\cdot}10^{-4}$
	(-1.160)	(-5.006)	(-2.498)	(0.775)
Sentiment	$1{\cdot}10^{-4}$**	$2{\cdot}10^{-4}$***	$-5{\cdot}10^{-4}$	$-7{\cdot}10^{-4}$
	(1.967)	(4.743)	(-0.967)	(-1.438)
c		0.0877 [0.0875, 0.0883]		
F-test		832.70 (0.000)		
R-squared	0.1413	0.1667		
Observations	29,717	29,510		

Note: This table contains the estimation results for the pricing model (PTR) given by the following equation: $r_{i,t} = \mu_i + [\alpha_1 CLIQ_t + \beta_1 MLIQ_{i,t} + \delta_1' Z_t]\, \mathbb{1}_{(q_{i,t-1} \leq c)} + [\alpha_2 CLIQ_t + \beta_2 MLIQ_{i,t} + \delta_2' Z_t]\, \mathbb{1}_{(q_{i,t-1} > c)} + \varepsilon_{i,t}$ where $r_{i,t}$ is the monthly excess return on the securitized real estate asset i for month t. $CLIQ_t$ is the commonality in liquidity risk factor and $MLIQ_{i,t}$ is the market liquidity risk factor. Z_t includes all the market-wide factors considered in this study. The transition variable $q_{i,t-1}$ is the one-month lagged realized volatility of each firm. We define $\lambda_k = [\alpha_k,\, \beta_k,\, \delta_k']',\ k = 1, 2$. The estimation method is Nonlinear Least Squares with the covariance matrix corrected for White heteroskedasticity (t-statistics in parentheses); the estimation results are presented in the last three columns. The estimation results of a standard panel linear model with fixed effects are displayed in the first column. The estimation method is OLS with White-corrected t-statistics presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% confidence levels, respectively. The brackets contain the 95%-confidence interval of the threshold parameter c. The F-test (p-value in parentheses) tests the null hypothesis of a linear model against the alternative of a two-regime specification. The credit spread and the term spread are taken in first difference in order to obtain stationary series.

Table 3: Percentage of Firms in the Crisis Regime based on the PTR Model

Year	Mean	Std. dev.	Minimum	Maximum
1999	7.16	4.62	3.08	18.56
2000	8.85	2.00	6.00	12.56
2001	9.19	3.17	4.52	16.41
2002	7.23	3.11	4.74	14.05
2003	4.25	1.48	2.17	6.49
2004	2.59	1.91	0.00	7.69
2005	2.88	1.64	1.01	6.53
2006	2.66	1.17	0.00	4.21
2007	10.54	8.83	1.16	32.74
2008	40.46	32.18	10.69	[a]92.76
2009	39.54	25.44	5.26	[b]85.52
2010	13.09	6.33	5.66	26.58
2011	12.99	12.83	2.48	40.76
2012	3.00	2.06	0.65	7.05

Note: In this table, we present summary statistics concerning the percentage of firms in the crisis regime for each month within a year, based on the PTR estimation results. We take the estimated location parameter from the PTR specification in Table 2 and compare it with the value of the transition variable for each month. If $\hat{c} > q_{i,t-1}$, then for month t, firm i is classified in a crisis regime. "Mean" is the average proportion of firms for each month within a year estimated to be in the crisis regime. "Std. dev", "Minimum", "Maximum" are respectively the standard deviation, the minimum and maximum percentage of firms to be classified in a crisis regime within a month. [a]November 2008, [b]February 2009.

Table 4: Asset Pricing Model Estimation Results
Commonality with the Stock Market - Realized Volatility

	Linear model	PTR model		
	λ	λ_1	λ_2	$\lambda_2 - \lambda_1$
Cross-CLIQ	0.527***	0.245***	0.511	0.267
	(5.851)	(5.203)	(1.255)	(0.650)
MLIQ (Stock)	$-2{\cdot}10^{-7}$	$-7{\cdot}10^{-7}$	$2{\cdot}10^{-5}$***	$2{\cdot}10^{-5}$***
	(-0.261)	(-1.309)	(3.732)	(3.833)
$R_M - R_f$	0.595***	0.455***	1.016***	0.562***
	(21.15)	(30.822)	(10.354)	(5.681)
SMB	0.503***	0.435***	0.629****	0.194
	(21.03)	(32.486)	(4.066)	(1.248)
HML	0.727***	0.572***	0.941***	0.369**
	(21.34)	(34.751)	(6.446)	(2.523)
Momentum	-0.169***	-0.086***	-0.258***	-0.171**
	(-11.28)	(-9.773)	(-3.865)	(-2.550)
Credit spread	-0.589	1.279***	1.972	0.694
	(-0.946)	(3.800)	(1.177)	(0.403)
Term spread	-1.947***	-0.839***	2.565	3.404*
	(-4.806)	(-3.247)	(1.268)	(1.671)
VIX	$-3{\cdot}10^{-4}$**	$-7{\cdot}10^{-4}$***	$-5{\cdot}10^{-4}$***	$2{\cdot}10^{-4}$
	(-2.520)	(-5.838)	(-2.692)	(1.163)
Sentiment	$4{\cdot}10^{-5}$	$2{\cdot}10^{-4}$***	$-9{\cdot}10^{-4}$*	-0.001**
	(0.491)	(3.157)	(-1.799)	(-2.107)
c			0.0880 [0.0875, 0.0883]	
F-test			779.636 (0.000)	
R-squared	0.1417		0.1659	
Observations	29,717		29,510	

Note: This table contains the estimation results for the pricing model given by the following equation: $r_{i,t} = \mu_i + [\alpha_1 \text{Cross-CLIQ}_t + \beta_1 \text{MLIQ}_{i,t} + \delta_1' Z_t]\, \mathbb{1}_{(q_{i,t-1} \leq c)} + [\alpha_2 \text{Cross-CLIQ}_t + \beta_2 \text{MLIQ}_{i,t} + \delta_2' Z_t]\, \mathbb{1}_{(q_{i,t-1} > c)} + \varepsilon_{i,t}$ where $r_{i,t}$ is the monthly excess return on the securitized real estate asset i for month t. Cross-CLIQ$_t$ is the commonality in liquidity risk factor and MLIQ$_{i,t}$ is the market liquidity risk factor, both stemming from the stock market. Z_t includes all the market-wide factors considered in this study. The transition variable $q_{i,t-1}$ is the one-month lagged realized volatility of each firm. We define $\lambda_k = [\alpha_k, \beta_k, \delta_k']'$, $k = 1, 2$. The estimation method is Nonlinear Least Squares with the covariance matrix corrected for White heteroskedasticity (t-statistics in parentheses); the estimation results are presented in the last three columns. The estimation results of a standard panel linear model with fixed effects are displayed in the first column. The estimation method is OLS with White-corrected t-statistics presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% confidence levels, respectively. The brackets contain the 95%-confidence interval of the threshold parameter c. The F-test (p-value in parentheses) tests the null hypothesis of a linear model against the alternative of a two-regime specification. The credit spread and the term spread are taken in first difference in order to obtain stationary series.

Table 5: Sources of Commonality in Liquidity: Within REIT Market - Linear Model

	Model 1	Model 2	Model 3
TED spread	-4.565		
	(-1.170)		
CP spread		-2.368	
		(-0.522)	
Mortgage spread			0.724
			(0.480)
Cturn	0.648***	0.628***	0.593***
	(2.822)	(2.693)	(2.615)
Sentiment	0.001	0.001	0.002
	(0.607)	(0.570)	(0.702)
VIX	0.001	0.001	$1 \cdot 10^{-4}$
	(0.123)	(0.125)	(0.034)
REIT market return	0.309	0.356	0.363
	(0.916)	(1.059)	(1.084)
Stock market return	-0.840*	-0.836*	-0.836*
	(-1.861)	(-1.840)	(-1.840)
REIT market liquidity	0.001	0.001	0.001
	(0.757)	(0.703)	(0.738)
Stock market liquidity	$-5 \cdot 10^{-6}$	$-4 \cdot 10^{-6}$	$-3 \cdot 10^{-6}$
	(-0.478)	(-0.350)	(-0.303)
REIT market turnover	$2 \cdot 10^{-4}$	-0.001	-0.002
	(0.037)	(-0.238)	(-0.387)
Stock market turnover	-12.829	-14.546	-14.527
	(-1.259)	(-1.420)	(-1.408)
Constant	-2.099***	-2.088***	-2.110***
	(-14.861)	(-14.772)	(-14.078)
R-squared	0.1073	0.1010	0.1008
Observations	167	167	167

Note: This table contains the estimation results for the sources of commonality in liquidity within the REIT market given by the equation: $\log\left\{\bar{R}_t^2/\left(1-\bar{R}_t^2\right)\right\} = \theta' H_t + \omega_t$ where $\bar{R}_t^2$ is the average of the commonality in liquidity measure across firms. The vector H_t involves supply- and demand-side determinants of commonality in liquidity, and a set of control variables. We use three alternative funding liquidity variables: 'Model 1' uses the TED spread, 'Model 2' uses the variations in the spread between the 3-month commercial paper rate and the 3-month Treasury bill rate, and 'Model 3' uses the variations in the spread between the 30-year conventional mortgage rate and the 3-month Treasury bill rate. The estimation method is OLS with White-corrected t-statistics presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% confidence levels, respectively.

Table 6: Sources of Commonality in Liquidity: With the Stock Market - Linear Model

	Model 1	Model 2	Model 3
TED spread	-3.350		
	(-0.726)		
CP spread		-0.130	
		(-0.024)	
Mortgage spread			-0.450
			(-0.257)
Cturn	0.642**	0.591**	0.587**
	(2.166)	(1.978)	(2.039)
Sentiment	-0.005**	-0.005**	-0.005**
	(-2.026)	(-2.008)	(-2.026)
VIX	0.001	0.001	0.002
	(0.190)	(0.255)	(0.329)
REIT market return	-0.350	-0.292	-0.283
	(-0.887)	(-0.747)	(-0.730)
Stock market return	-0.282	-0.274	-0.263
	(-0.533)	(-0.517)	(-0.495)
REIT market liquidity	0.001	0.001	$5 \cdot 10^{-4}$
	(0.552)	(0.523)	(0.495)
Stock market liquidity	$-2 \cdot 10^{-6}$	$-5 \cdot 10^{-7}$	$-2 \cdot 10^{-7}$
	(-0.176)	(-0.040)	(-0.017)
REIT market turnover	0.014**	0.013**	0.013**
	(2.422)	(2.238)	(2.326)
Stock market turnover	2.673	0.488	-0.493
	(0.225)	(0.041)	(-0.041)
Constant	-2.301***	-2.294***	-2.279***
	(-14.140)	(-14.098)	(-13.161)
R-squared	0.3709	0.3688	0.3691
Observations	167	167	167

Note: This table contains the estimation results for the sources of cross-asset commonality in liquidity given by the equation: $\log\left\{\bar{R}_t^2/\left(1-\bar{R}_t^2\right)\right\} = \theta' H_t + \omega_t$ where $\bar{R}_t^2$ is the average of the commonality in liquidity measure across firms. The vector H_t involves supply- and demand-side determinants of commonality in liquidity, and a set of control variables. We use three alternative funding liquidity variables: 'Model 1' uses the TED spread, 'Model 2' uses the variations in the spread between the 3-month commercial paper rate and the 3-month Treasury bill rate, and 'Model 3' uses the variations in the spread between the 30-year conventional mortgage rate and the 3-month Treasury bill rate. The estimation method is OLS with White-corrected t-statistics presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% confidence levels, respectively.

Table 7: Sources of Commonality in Liquidity: With the Stock Market - TR Model

	θ_1	θ_2	$\theta_2 - \theta_1$
Mortgage spread	1.640	-16.960**	-18.600**
	(0.891)	(-2.278)	(-2.447)
Cturn	0.806**	-0.788*	-1.594***
	(2.163)	(-1.789)	(-2.717)
Sentiment	-0.001	-0.007**	-0.006
	(-0.477)	(-2.123)	(-1.501)
VIX	-0.009	0.044***	0.054***
	(-1.282)	(3.970)	(4.074)
REIT market return	-0.642	-1.028**	-0.386
	(-1.122)	(-1.984)	(-0.507)
Stock market return	-0.487	2.695***	3.183**
	(-0.578)	(2.789)	(2.465)
REIT market liquidity	$-7 \cdot 10^{-6}$	0.006*	0.006*
	(-0.007)	(1.907)	(1.847)
Stock market liquidity	$-3 \cdot 10^{-6}$	$2 \cdot 10^{-5}$	$3 \cdot 10^{-5}$
	(-0.155)	(1.125)	(1.008)
REIT market turnover	0.024**	0.017***	-0.007
	(2.259)	(2.798)	(-0.691)
Stock market turnover	15.090	-86.361***	-101.45***
	(0.941)	(-2.881)	(-3.094)
c		27.50 [24.95, 28.92]	
F-test		33.319 (0.020)	
R-squared		0.4745	
Observations		167	

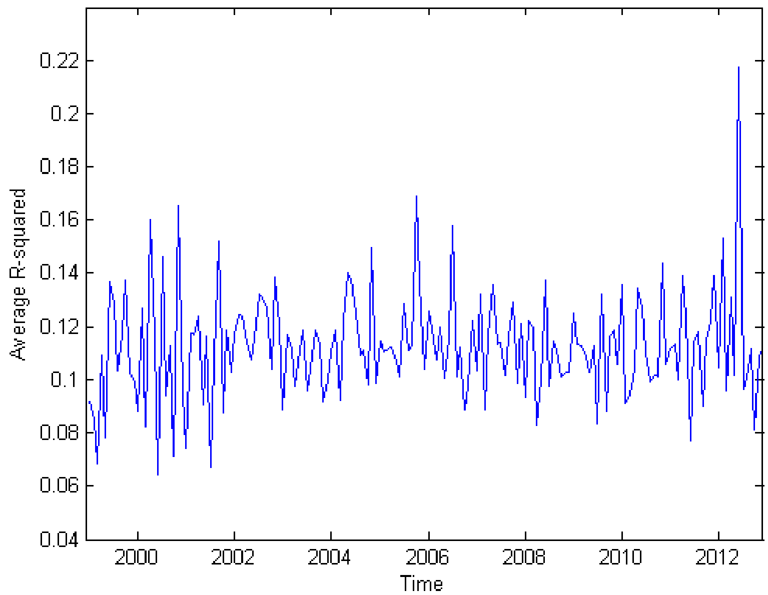
Note: This table contains the estimation results for the sources of cross-asset commonality in liquidity given by the equation: $\log\left\{\bar{R}_t^2/\left(1-\bar{R}_t^2\right)\right\} = \theta_1' H_t \mathbb{1}_{(q_{t-1}\leq c)} + \theta_2' H_t \mathbb{1}_{(q_{t-1}>c)} + \omega_t$ where $\bar{R}_t^2$ is the average of the commonality in liquidity measure across firms. The vector H_t involves supply- and demand-side determinants of commonality in liquidity, and a set of control variables. In this regression the variation in the spread between the 30-year conventional mortgage rate and the 3-month Treasury bill rate is used as funding liquidity variable. The estimation method is Nonlinear Least Squared with the covariance matrix corrected for White heteroskedasticity, t-statistics presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% confidence levels, respectively. The brackets contain the 95%-confidence interval of the threshold parameter c. The F-test (p-value in parentheses) tests the null hypothesis of a linear model against the alternative of two-regime specification.

Table 8: Asset Pricing Model Estimation Results
Commonality with the Private Real Estate Market - Realized Volatility

	Linear model	PTR model		
	λ	λ_1	λ_2	$\lambda_2 - \lambda_1$
DRECLIQ	-2.218***	-2.318***	1.312*	3.631***
	(-12.15)	(-18.194)	(1.796)	(4.894)
MLIQ (Private RE)	$-9{\cdot}10^{-6}$***	$-1{\cdot}10^{-5}$***	$2{\cdot}10^{-6}$	$1{\cdot}10^{-5}$
	(-5.849)	(-7.288)	(0.231)	(1.209)
$R_M - R_f$	0.500***	0.420***	1.167***	0.747***
	(11.62)	(16.743)	(7.550)	(4.799)
SMB	0.424***	0.362***	1.032***	0.670***
	(13.45)	(13.168)	(5.003)	(3.219)
HML	0.623***	0.399***	1.348***	0.949***
	(10.72)	(12.072)	(7.127)	(4.955)
Momentum	-0.0304*	0.042**	-0.105*	-0.148**
	(-1.729)	(2.102)	(-1.677)	(-2.232)
Credit spread	-0.511	-0.880*	-0.874	0.006
	(-1.242)	(-1.827)	(-0.612)	(0.004)
Term spread	-1.874***	-1.566***	-5.347**	-3.781*
	(-4.370)	(-4.344)	(-2.509)	(-1.757)
VIX	$-2{\cdot}10^{-4}$***	$-4{\cdot}10^{-4}$***	$-2{\cdot}10^{-4}$	$2{\cdot}10^{-4}$
	(-1.784)	(-3.182)	(-0.899)	(1.048)
Sentiment	$-2{\cdot}10^{-4}$***	$4{\cdot}10^{-4}$***	$-3{\cdot}10^{-4}$	$-7{\cdot}10^{-4}$
	(2.853)	(5.060)	(-0.515)	(-1.112)
c		0.0863 [0.0861, 0.0864]		
F-test		424.49 (0.000)		
R-squared	0.299	0.3215		
Observations	13,490	13,490		

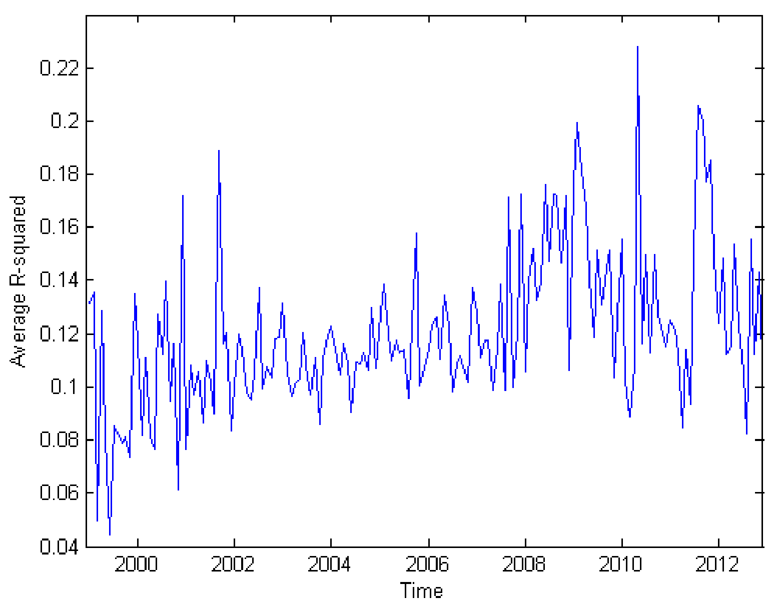
Note: This table contains the estimation results for the pricing model (PTR) given by the following equation: $r_{i,t} = \mu_i + [\alpha_1 DRECLIQ_t + \beta_1 MLIQ_{i,t} + \delta_1' Z_t]\ \mathbb{1}_{(q_{i,t-1} \leq c)} + [\alpha_2 DRECLIQ_t + \beta_2 MLIQ_{i,t} + \delta_2' Z_t]\ \mathbb{1}_{(q_{i,t-1} > c)} + \varepsilon_{i,t}$ where $r_{i,t}$ is the monthly excess return on the securitized real estate asset i for month t. $DRECLIQ_t$ is the commonality in liquidity risk factor and $MLIQ_{i,t}$ is the market liquidity risk factor. Z_t includes all the market-wide factors considered in this study. The transition variable $q_{i,t-1}$ is the one-month lagged realized volatility of each firm. We define $\lambda_k = [\alpha_k,\, \beta_k,\, \delta_k']'$, $k = 1, 2$. The estimation method is Nonlinear Least Squares with the covariance matrix corrected for White heteroskedasticity (t-statistics in parentheses); the estimation results are presented in the last three columns. The estimation results of a standard panel linear model with fixed effects are displayed in the first column. The estimation method is OLS with White-corrected t-statistics presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% confidence levels, respectively. The brackets contain the 95%-confidence interval of the threshold parameter c. The F-test (p-value in parentheses) tests the null hypothesis of a linear model against the alternative of a two-regime specification. The credit spread and the term spread are taken in first difference in order to obtain stationary series.

Figure 1: Cross-Sectional Average R^2 (Commonality in Liquidity)



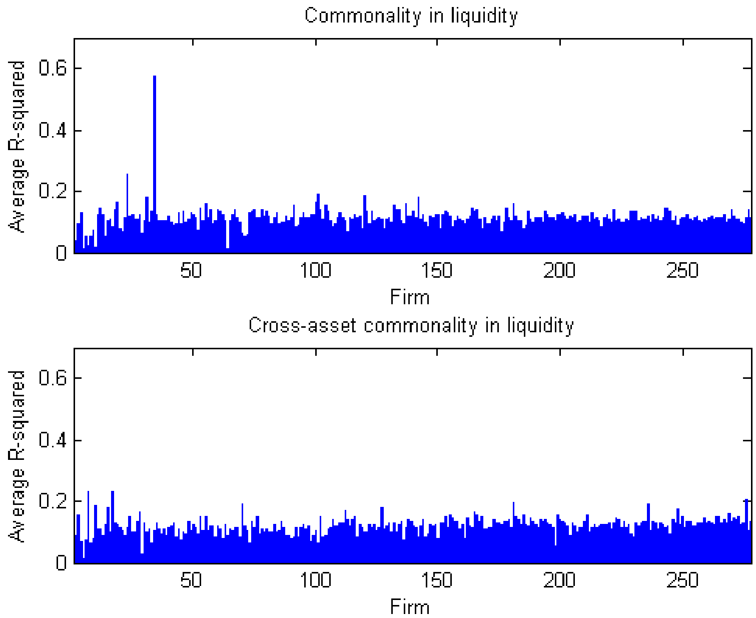
Note: This figure displays the cross-sectional average R^2 (commonality in liquidity) over time. The sample includes 278 firms which have at least one observation for the R^2.

Figure 2: Cross-Sectional Average R^2 (Cross-Asset Commonality in Liquidity)



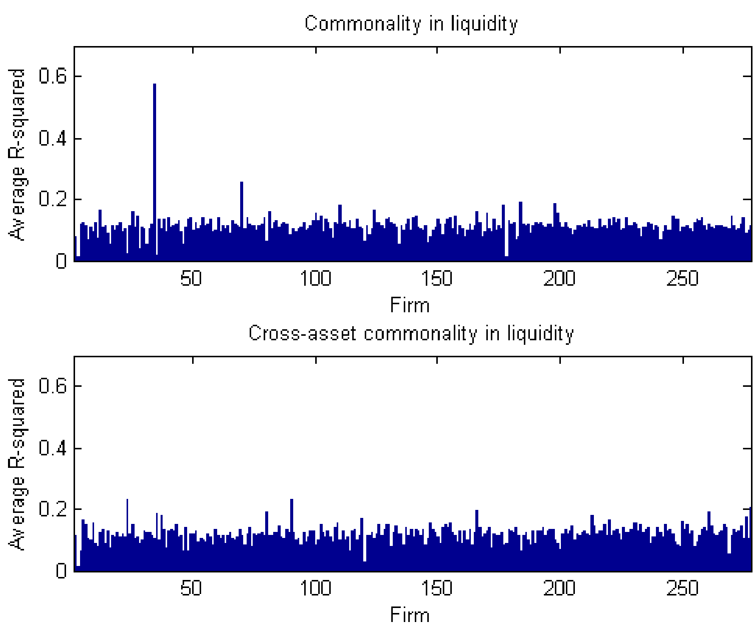
Note: This figure displays the cross-sectional average R^2 (cross-asset commonality in liquidity) over time. The sample includes 278 firms which have at least one observation for the R^2.

Figure 3: Average R^2 per Firm Ordered According to the Average Market Capitalization



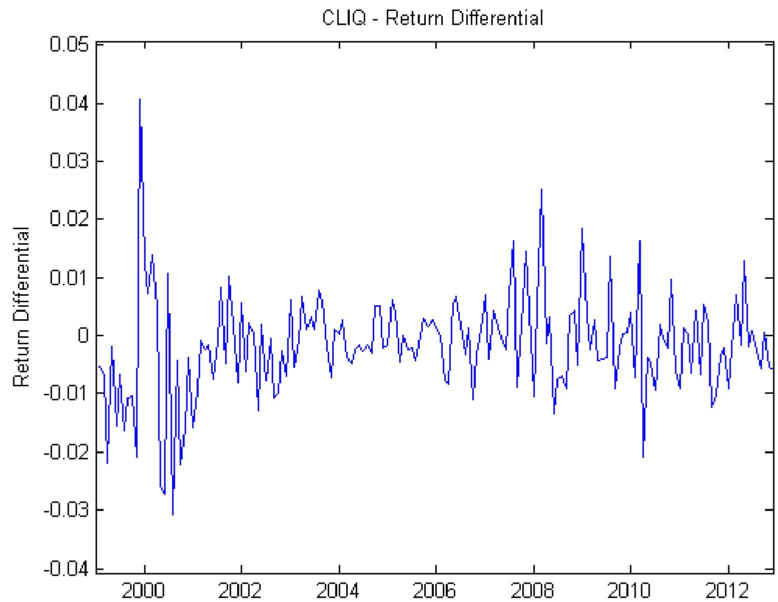
Note: These figures display the average within- and cross-asset commonality in liquidity by firm ordered by market capitalization. The sample includes 278 firms, those which have at least one observation for the firm size and for the R^2.

Figure 4: Average R^2 per Firm Ordered According to the Average Liquidity



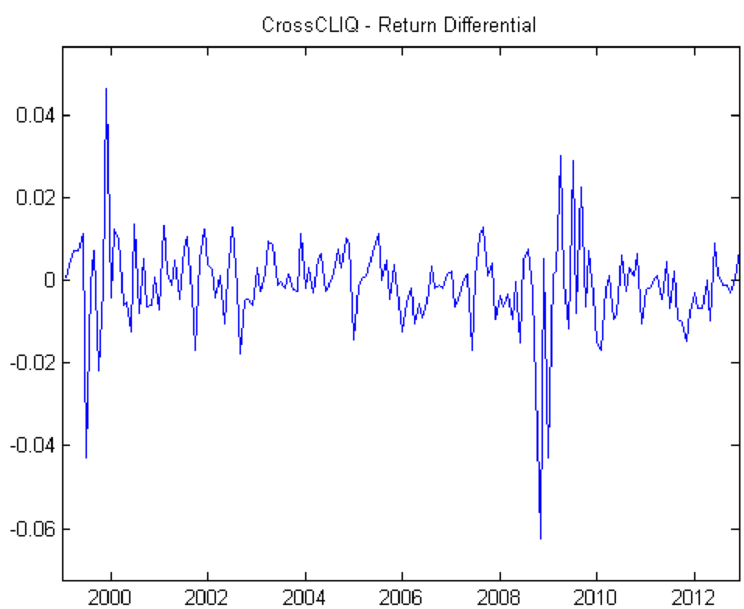
Note: These figures display the average within- and cross-asset commonality in liquidity by firm ordered by liquidity level. The sample includes 278 firms, those which have at least one observation for the liquidity level and for the R^2.

Figure 5: Commonality in Liquidity - Return Differential



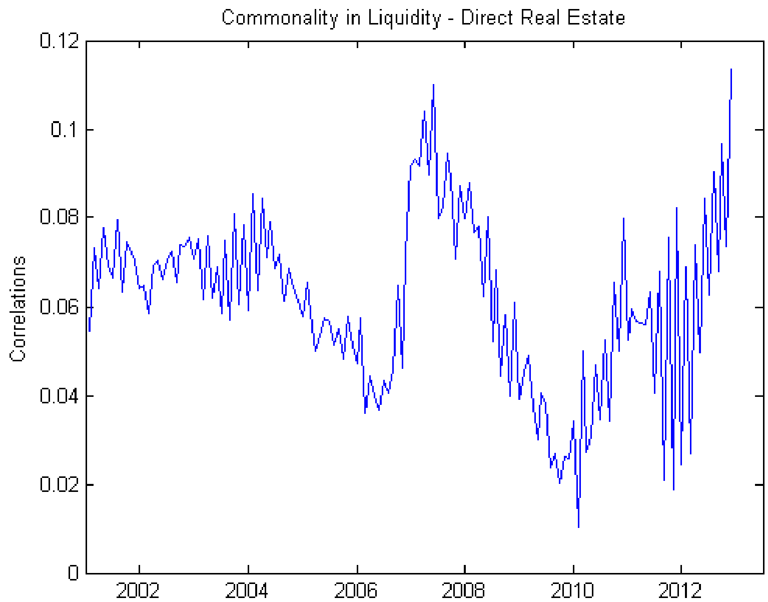
Note: This figure displays the commonality in liquidity risk factor given by the difference in returns between a portfolio with high R^2 and a portfolio with low R^2 ("5-1" spread).

Figure 6: Cross-Asset Commonality in Liquidity - Return Differential



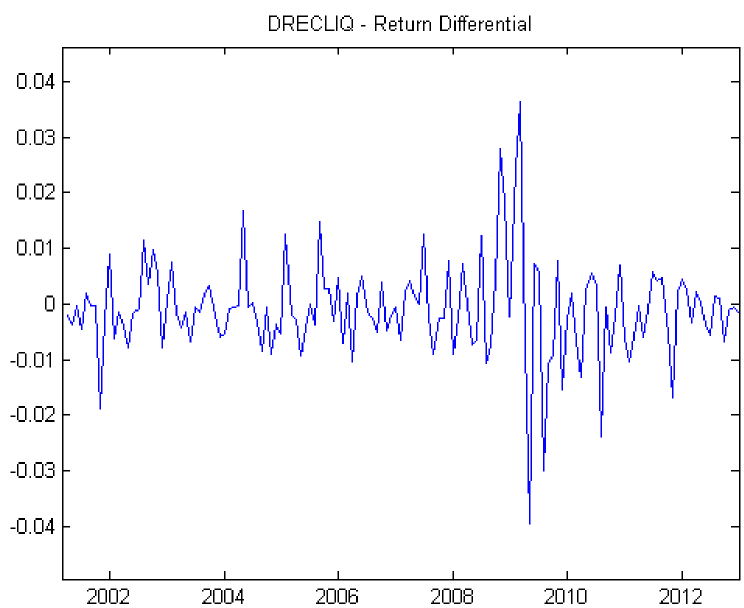
Note: This figure displays the cross-asset commonality in liquidity risk factor given by the difference in returns between a portfolio with high R^2 and a portfolio with low R^2 ("5-1" spread).

Figure 7: Cross-Sectional Average Correlation (Commonality in Liquidity with the Private Real Estate Market)



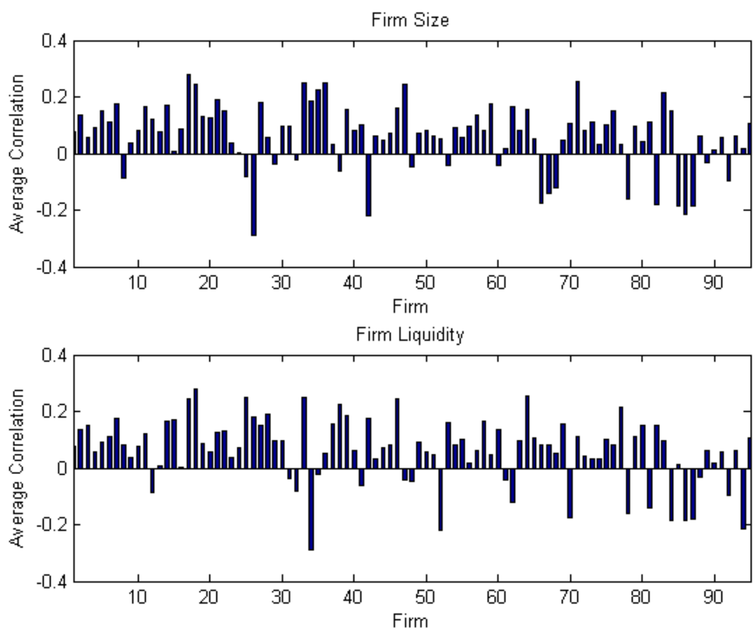
Note: This figure displays the cross-sectional average correlation (commonality in liquidity with the private real estate market) over time. The sample includes 95 firms which have no missing values over the entire sample period.

Figure 8: Commonality in Liquidity with the Private Real Estate Market - Return Differential



Note: This figure displays the commonality in liquidity risk factor given by the difference in returns between a portfolio with high liquidity *correlation* and a portfolio with low liquidity *correlation* ("5-1" spread).

Figure 9: Average Liquidity Correlation per Firm Ordered According to the Average Size and Liquidity



Note: These figures display the average commonality in liquidity with the private real estate market by firm ordered by size and liquidity level. The sample includes 95 firms.