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Empirical analysis of the illiquidity premia of German real estate securities

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Abstract

In this study, we analyze illiquidity premia and their effect on the expected returns of German real estate securities. To this end, we use a unique data set that includes real estate stocks, real estate investment trusts (REITs), and open- and closed-end real estate funds for 2003–2017. We follow Amihud's (JFM 5:31–56, 2002) structural approach; specifically, we estimate Amihud's illiquidity factors, investigate the relationships between expected returns and illiquidity, and analyze the effects of expected and unexpected market illiquidity on future returns. We show that illiquidity plays an important role in expected returns for real estate stocks and investment trusts (REITs); however, it has less clear effects on open- and closed-end funds. We find that the adjusted *ILLIQ* includes appropriate correction factors for securities with low trading activity and is a useful improvement. We also find evidence of structural breaks in the relationship between returns and illiquidity.

Keywords Asset pricing · Real estate · REITs · Risk-factors · Illiquidity

JEL Classification G11 · G12 · G14

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1 Introduction

Both modern portfolio theory and asset pricing models imply a perfect capital market with boundless liquidity. Although economic theory incorporated the influence of liquidity for some time (e.g. Keynes 1930), capital market research has only about 30 years of data that incorporate liquidity in asset pricing within the scope of capital market models (Mishra 2008; Hibbert et al. 2009).[1] The global financial crisis of 2008 (GFC) indicated that prices react considerably to liquidity effects. This led to a clear increase in research activities on the one hand, but to more regulatory requirements for market participants on the other (see Tirole 2011).

Existing research concentrates primarily on the liquidity premia of stocks and bonds, and predominantly covers the North American markets (Hibbert et al. 2009; Rothböck et al. 2011). Few studies on the German stock market exist (Rothböck et al. 2011; Kempf et al. 2012; Paul et al. 2021). Moreover, a line of research on market microstructures focuses on the measurement of liquidity in market design (e.g., Schmidt and Iversen 1991; Küster-Simic 2001; Kindermann 2005). However, to the best of our knowledge, no study on liquidity premia for the German real estate market exists.

Nevertheless, the German real estate market is worth investigating for several reasons. First, real estate represents the largest asset class in the total wealth of German investors (Trübestein 2012). Second, several measures in recent decades aimed to expand the possibilities of indirect real estate acquisition through securitizations, such as the Real Estate Investment Trusts (REIT)-Act and the Investor Protection and Improvement Act (*"Anlegerschutz- und Verbesserungsgesetz"*). Third, the market recently endured significant illiquidity shocks (e.g., in open-end real estate funds [OEFs]).

For better comparability, we focus exclusively on securitized real estate investments in this study. We explicitly exclude direct investments from these analyses. We follow the prominent Amihud (2002) paper, extend our analyses with further illiquidity measures, and consider the relevant markets in a cross-sectional and time-series analysis. Thus, this study is the first to examine the liquidity premia for securities of the German real estate market.

The remainder of this paper proceeds as follows. In Sect. 2, we discuss the relevant aspects of illiquidity, its impact on security returns, and common illiquidity measures. Section 3 presents the research hypotheses. Section 4 outlines the data and methodology. In Sect. 5, we analyze the relationships between returns and illiquidity using a univariate portfolio analysis (Sect. 5.1) and cross-sectional analysis (Sect. 5.2). We provide a further analysis using the time-series regression analysis of expected and unexpected illiquidity in Sect. 5.3. Section 6 concludes.

[1] Such early works include Amihud and Mendelson (1986, 1989), Brennan and Subrahmanyam (1996).

2 Illiquidity in equity and real estate markets

According to Brunnermeier and Pedersen (2009), liquidity comprises market liquidity (the ease of trading an asset) and funding liquidity (the ease of obtaining funding). Market liquidity differs for the various classes of real estate property given their specific characteristics and market frictions. Research on market liquidity has significantly increased in the past decades, but is predominantly concerned with the US securities market, particularly the equity market thereof.[2] We contribute to this research by analyzing the German market for real estate securities for the first time.[3]

2.1 (Il)-liquidity and returns

Investors are compensated for less liquid assets with higher returns. Amihud and Mendelson (1986) predict a positive relationship between the bid-ask spread and expected returns. Amihud and Mendelson (1989) empirically test this prediction and find that the bid–ask spread has a positive cross-sectional relationship with future stock returns after controlling for other variables, such as market beta, market capitalization, and volatility. In perhaps the most cited article on the relationship between liquidity and expected returns, Amihud (2002) suggests a measure of stock illiquidity and shows that illiquidity is positively related to expected market returns, both in time series and cross-section.

While early studies on the determinants of liquidity focused on the cross-sectional dependency of specific asset characteristics, the more recent literature focuses on the time-series characteristics of liquidity. Chordia et al. (2000, 2011), Hasbrouck and Seppi (2001), and Huberman and Halka (2001) observe a significant common component of liquidity at both market and industry levels (Holden 2013). They conclude that this effect aggregates at the portfolio level, which indicates that it is not possible to diversify liquidity shocks at the portfolio level, and supports the assertion that an aggregate liquidity factor plays a strong role in asset pricing (Bali et al. 2016).

Recent works (e.g., Amihud and Mendelson 2015) also consider liquidity commonality in a global context. They find a commonality between illiquidity return premia across countries after controlling for other firm effects, which is not driven by and is distinct from variations in the level of global illiquidity.

Malkhozov et al. (2017) construct country-specific illiquidity indices from pricing deviations on government bonds, which demonstrate a high cross-correlation. Nevertheless, the measures show a pronounced idiosyncratic behavior, especially during country-specific political or economic events. Thus, the global measurement has been characterized by four major peaks in particular over the last 20 years (e.g. the crisis of the European Exchange Rate Mechanism, the Asian crisis, the dot-com bubble burst, and the GFC). Against this background, it seems appropriate to separately consider the German market.

[2] Hibbert et al. (2009) provided an overview of the estimates of liquidity premia across multiple asset classes.

[3] In addition to real estate shares, specific financial instruments such as open-ended and closed-end real estate funds exist in Germany. We provide a brief summary of the main characteristics of these securities in the Supplementary material.

2.2 Empirical Evidence of Illiquidity in real estate markets

Illiquidity risk is also priced in real estate markets (Lin and Vandell 2007; Bond et al. 2007; Kawaguchi et al. 2008; Krainer et al. 2010). One strand of the literature studies the determinants of real estate investment pricing depending on market liquidity. Since the real estate market has more far-reaching data series for private real estate investments, early research focused on housing prices; in this context, the impact of market liquidity and the expected time necessary to sell a property near its fair market value is referred to as "time-on-market" (Lippman and McCall 1986; Krainer 2001; Lin and Vandell 2007; Cheng et al. 2008). Another strand focuses on macroeconomic effects and macroprudential policy to mitigate credit and house price growth.[4] In our study, we focus on the differences in liquidity in securitized real estate investments and their impact on expected returns.

Though the percentage of real estate investments of the total assets in Germany represents an above-average proportion, there is hardly any empirical research on the returns and drivers of performance, in contrast to the US and UK markets, which have been studied extensively (Maurer et al. 2004b). This may also be because the share of listed real estate stocks in Germany is significantly lower than in the USA, both in percentage terms and even more so in absolute figures.[5] In Germany, alternative indirect real estate investments such as open-end funds (OEFs) or closed-end funds (CEFs) play a major role in securitized real estate investments (Maurer et al. 2004a). However, the state of research in these asset classes is nearly exclusively restricted to the OEF segment (Maurer et al. 2004a, b; Schweizer et al. 2013; Fecht and Wedow 2014). Fecht and Wedow (2014) examine German OEFs from December 2005 to June 2006, a period in which these investments experienced an unprecedented liquidity crisis. Their results showed that a segmentation of funds for different investor groups might help mitigate panic. If the liquidity crisis of German OEFs in 2005/2006 was non-fundamental, then the impact of the GFC was much stronger. In its aftermath, investors showed higher preference for liquidity and were afraid to tie up capital in the OEF market for an uncertain period (Schnejdar et al. 2019). As opposed to listed property companies, the prices of OEF shares depend on property appraisals and are not directly determined by demand and supply on the secondary market. Since the daily quoted price reflects experts' valuations of the properties, prices do not face financial volatility directly. As the valuation of a certain property

[4] Agnello and Schuknecht (2011) examined the characteristics and determinants of booms and busts in housing prices for a sample of 18 industrialized countries from 1980 to 2007. Chang (2011) found that the unexpected component of monetary policy is more important in REIT returns than the expected component of monetary policy. In particular, unexpected contractionary monetary policy has a significant negative impact on REIT returns and the negative effect in a bust market is stronger than it is in a boom market. Wiley (2017) shows for the US property market, credit policy through the lending channel also plays an important role in asset performance. Although this cycle cannot be fully explained, illiquidity in the real estate market leads to sluggish and prolonged price formation cycles.

[5] According to Trübestein (2012), the relative share of the market capitalization of REITs in the market value of all investable properties in Germany (3%) was less than half compared to North America (7%) in 2011. Niskanen and Falkenbach (2012) stated that the German REIT market in 2009 represented only 0.14% of the total value of the global REIT market.

takes place only once a year, the quoted price incorporates only a part of the market price of the underlying properties (Just and Maennig 2017). However, if share redemption is suspended, as observed in 2005/2006 and from 2008 in the context of the GFC, then the significance is not temporary, and the return–risk profiles of the OEFs will change considerably (Haß et al. 2012).

For international markets, various studies investigate securities-based REITs.[6] Early results on the differences between REIT and non-REIT stock liquidity are mixed. For example, whereas Ghosh and Miles (1996) find that REIT liquidity is not comparable to non-REIT liquidity, Nelling et al. (1995) and Bhasin et al. (1997) show the contrary. Subrahmanyam (2007) finds persistent liquidity spillovers running from non-REITs to REITs, and that non-REIT liquidity indicators Granger-cause those in the REIT market, which is economically relevant. This result suggests that asset allocation decisions in the stock market lead to investments in the substitute real estate market with a time lag. Cheung et al. (2015) examine the effects of stock liquidity on firm value in a REIT setting. Analyzing the US REIT market from 1988 to 2007, Cannon and Cole (2011) find improved liquidity, with the notable exception of 2007. They find high correlations between bid–ask spreads and the volatility of stock returns using microstructure-based measures (bid–ask spread) and price-impact measures, and a negative impact of trade volume and market capitalization. Cannon and Cole (2011) suggest that price-impact measures can replace more sophisticated price-impact information.

Many studies have identified positive correlations between returns and illiquidity for real estate investments (Benveniste et al. 2001; Zheng et al. 2015). In line with theoretical expectations, Ametefe et al. (2016) find liquidity risk to be generally lower for REITs than for other equities. In their analysis of a range of alternative asset class benchmarks, Pedersen et al. (2018) show that private real estate fund performance has significant exposure to the general equity market, a listed real estate factor: the Pástor and Stambaugh (2003) equity market-traded liquidity risk factor, nominal duration, and corporate bond yield spreads.

Recent studies have examined the causal relationships in the context of the GFC. Glascock and Lu-Andrews (2014) highlight the macroeconomic factors driving the funding liquidity of REITs and their links to market liquidity across business cycles. Hoesli et al. (2017) finds the US REITs market is not only driven by its original liquidity or the liquidity of the real estate market. They find that there are co-movements between the US REIT and equity markets, which are particularly impacted by the liquidity channel. They are particularly significant in market turmoil (Hoesli et al. 2017).

Downs and Zhu (2019) examine the transmission channels between securitized markets and underlying investment markets for the real estate market with

[6] With the introduction of REITs in 1960 in the US, and later in many other economies, the goal was to make transparent and fungible real estate investments available to the public. In the 1980s and 1990s, the global REIT market developed very slowly. At the turn of the millennium, there was a worldwide trend of REIT laws that had a significant impact on the importance of REIT investments, see Trübestein (2012). For descriptive overviews of listed REITs, see Corgel et al. (1995), Zietz et al. (2003), Feng et al. (2011).

reference to regional arrangement and other (firm-) specific factors. The authors find that the original liquidity of the regional real estate market and other firm-specific financial parameters significantly affect the liquidity of securitized assets, supporting the investment channel transmission proposition.

There are fewer studies on private real estate. Ametefe et al. (2016) present an overview of and Sieracki et al. (2008) provide a descriptive summary of public non-listed real estate investments for US funds. Brounen et al. (2009) offer a descriptive summary for US, UK, Australian, and Continental European funds. Prior studies therefore consider German assets to only a limited extent, and do not analyze them exclusively.

Overall, prior studies indicate that in the German real estate market, fund-based solutions are relatively dominant over the listed investment vehicles (Just and Maennig 2017). While the market segment of closed-end funds (CEFs) has scant existing research to date, the results for OEFs differ according to the data series up to 2008 and suspended funds after the GFC. Moreover, the market share of listed securities increased. Other studies reveal positive correlations between returns and illiquidity for international real estate markets. Thus, a cross-market analysis of returns and any potential illiquidity effects for the German real estate market is lacking. We aim to fill this gap with our study.

3 Research hypotheses

As stated above, the continuing ability to liquidate is an essential basic assumption in the relevant capital market models, and furthermore in the stated prices of assets. Hence, it is important for market participants to have a basis to calculate whether and to what extent income return expectations move with (temporary) changes in liquidity. Therefore, we aim to answer the following questions: First, can we observe liquidity premia in different segments of the German capital market for real estate securities? To answer this question, we consider financial instruments whose underlyings are German and international real estate. We examine the return characteristics of CEFs, OEFs, real estate companies (REOCs; hereafter simply referred to as stocks or equities), and REITs. These securities differ substantially in their investment strategy and regulatory requirements. In addition, they have different potential for trading and market microstructures. Following the literature described in Sect. 2, we formulate our first hypothesis as follows:

Hypothesis 1 Various segments of the German capital market for real estate investments will have significantly different return and illiquidity parameters.

Second, is there a relationship between returns and liquidity premia for the securities of interest? Amihud (2002) describes a strong cross-sectional relationship between expected stock returns as a function of stock illiquidity and other variables. This question leads to the next hypothesis:

Hypothesis 2 Investors consider the existing illiquidity of securities in their investment decisions. They expect a higher return on illiquid securities, which we can measure in the capital market; that is, "illiquidity is priced".

Third, how do fluctuations in liquidity affect returns? As studies by Amihud (2002), Acharya and Pedersen (2005), and Acerbi and Scandolo (2008) show, fluctuations in liquidity play a major role in asset pricing. Therefore, in a further step, we distinguish between expected and unexpected illiquidity. While expected illiquidity should be positively associated with returns, unexpected illiquidity should be negatively correlated. Therefore, we propose our last hypothesis:

Hypothesis 3 Ex ante security return is an increasing function of expected illiquidity, and unexpected illiquidity has a negative effect on contemporaneous unexpected stock return.

4 Methodology and data

4.1 Illiquidity measures

Liquidity is a broad concept and cannot be observed directly (Amihud 2002). Rather, it results from many individual factors that are largely easy to identify and quantify. There is a consensus in the literature that there are various aspects of liquidity that determine its different manifestations, although it is not conclusively defined (Díaz and Escribano 2020). According to Sarr and Lybek (2002) and Bervas (2006), a liquid market has five different dimensions: breadth, depth, immediacy, resilience, and tightness. Several liquidity measures have therefore been proposed to capture different aspects of liquidity. These include measures of bid-ask spread (Amihud and Mendelson 1986), turnover and volume (Brennan et al. 1998), price impact (Amihud 2002), and zero return (Lesmond et al. 1999; Bekaert et al. 2007). In various studies, the different factors and their impact on the dimensions of liquidity were analyzed in greater detail (see Aitken and Winn 1997; Aitken and Comerton-Forde 2003; Goyenko et al. 2009; Chai et al. 2010; Ametefe et al. 2016; Díaz and Escribano 2020). However, not all measures are suitable for all capital markets or capital market instruments. To address the different illiquidity effects as much as possible, we used illiquidity measures that capture different dimensions.[7] The data requirements vary for each measure. For example, transaction-cost-based metrics typically require detailed information about the order book for each security at each

[7] To cover the dimension of *resilience*, it is typically necessary to use consecutive trading quotes, which are often not available in our sample. Therefore, we use neither Pástor and Stambaugh's (2003) *Gamma* nor the Roll (1984)-estimator.

observation. In addition, we must consider the different trading practices and market microstructures. Often, the necessary data are no longer available. In the following, we present the measures we employ in our empirical analysis.

4.1.1 Amihud's illiquidity ratio

First, we use the Amihud (2002) measure,[8] which is one of the most utilized measurements for illiquidity and which covers at least three main dimensions: *depth*, *breadth,* and *tightness*.[9] Lou and Shu (2017) argue that the Amihud measure has three important advantages over other indicators. First, it is based on a simple construction that compares the absolute daily price changes of the observed securities relative to the trading volume. Second, the data are typically available on a daily basis for long time series, which allows a more thorough analysis than with high-frequency data; that is, intra-day-based studies. Finally, numerous empirical studies demonstrated the close, positive interaction between *ILLIQ* and expected returns (e.g., Amihud 2002; Chordia et al. 2009). This positive return contribution is an illiquidity premium that compensates for price effects.

Amihud's standard *ILLIQ* is the ratio of the absolute price change and the corresponding trading volume (Amihud 2002):

$$ILLIQ_{A_{im}} = \frac{1}{D_{im}} \sum_{t=1}^{D_{im}} \frac{|R_{imd}|}{DVol_{imd}}, \tag{1}$$

where R_{imd} is the return of security i on day d of month m and $DVOL_{imd}$ is the relevant trading volume (in EUR) of security i on day d of month m. D_{im} is the number of days with available trading activities for security i in month m. In line with the literature, we control for outliers by winsorizing the measures at 0.5% and 99.5%.

The average market illiquidity across the subsegments in each month is

$$AILLIQ_m = \frac{1}{N_\mathrm{m}} \sum_{t=1}^{N_\mathrm{m}} ILLIQ_{A_{im}}, \tag{2}$$

where N_m is the number of stocks in month m of our sample. Since the monthly *ILLIQ* measures vary considerably, Amihud (2002) replaces *ILLIQ* with a standardized measure *ILLIQMA*, calculated as follows:

$$ILLIQMA_{im} = ILLIQ_{A_{im}} / AILLIQ_m \tag{3}$$

[8] Amihud himself does not consider it to be the most accurate illiquid measure (Amihud 2002, p. 32). However, these "finer and more accurate" methods require a large amount of microstructure data, which are often not available. This is also evident, for example, in our sample.

[9] Díaz and Escribano (2020) emphasized the following: "However, there is no unequivocal classification of measures that may measure regarding to which dimension is assessed by each one." On the one hand, they stated that Amihud's (2002) *ILLIQ* can be assigned to the dimensions of *depth*, *immediacy*, and *tightness* (p. 5). On the other hand, they assigned Amihud's (2002) measure in Table 2 to the dimensions *breadth* and *depth*. Ametefe et al. (2016) classified *ILLIQ* to the dimensions of *depth* and *resilience*.

Other studies on illiquidity use these measures and their variants. Amihud and Noh (2018) refer to Brennan et al. (1998), who find that *DVOL* has a negative effect on expected returns. Trading volume and price changes are positively correlated (for a survey of the evidence, see Karpoff 1987). Datar et al. (1998) and Chordia et al. (2001) show that stock turnover negatively affects expected returns.

4.1.2 Turnover ratio

The Amihud (2002) illiquidity measure responds to changes in both the numerator and denominator. Lou and Shu (2017) present variations of this measure in a study that decomposes it and examines what affects its price.[10] For example, a higher trading volume leads to a lower illiquidity measure ceteris paribus. This relationship is very strong because the trading volume component has much larger cross-sectional fluctuations than the return component. Consequently, Amihud's *ILLIQ* does not consider the relative proportion of potential trading volume, for example, related to shares issued or shares in free float. Such a turnover ratio, which relates trading volume in a period to shares outstanding, reflects the average holding period of assets. The higher the turnover, the lower the average holding period. Thus, turnover is a liquidity measure, as lower holding periods are associated with lower spreads (Amihud and Mendelson 1986). The turnover price–impact ratio implemented by Florackis et al. (2011) and Brennan et al. (2013) is independent of the size of the firm and is an unbiased measure. Since we analyze very different large financial instruments, we find the ratio of the Turnover, $ILLIQ_{AT}$, useful:

$$ILLIQ_{AT_{im}} = \frac{1}{D_{im}} \sum_{t=1}^{D_{im}} \frac{|R_{imd}|}{TO_{imd}}, \tag{4}$$

where TO_{imd} is the turnover of security i on day d of month m, calculated as the daily trading volume (in units) divided by the number of outstanding shares. For CEFs, we measure the number of shares issued as the issued nominal capital in 1 EUR shares. The other variables correspond to those in Eq. (1). Similarly to the Amihud *ILLIQ*, it represents several dimensions of illiquidity (at least *depth*, *immediacy,* and *tightness*), but overcomes the ability to measure liquidity because it is unbiased by size and is unambiguous to construct and interpret.

4.1.3 Zero-return measure

Lesmond et al. (1999) introduce a low-frequency proxy for illiquidity by observing days with zero returns. This is owing to the absence of trading based on new price-relevant information because of relatively high transaction costs. Moreover, stocks

[10] With the *ILLIQ* variants, Lou and Shu (2017) aimed to subdivide the illiquidity effect into price and trading volume components. Amihud and Noh (2018) commented on these statements and noted that this decomposition is correct only under certain assumptions. In our study, we used the *ILLIQ* alternatives exclusively to indicate the significance of the different numerators and denominators.

with lower liquidity are more likely to have zero-volume days and thus more likely to have zero-return days. Bekaert et al. (2007) and Goyenko et al. (2009) develop this approach to include a more direct consideration of days without trading volume as an indicator for illiquidity: "*ZEROs2*":

$$ZEROs2_{im} = \frac{ZeroVol_{im}}{TD_m}, \tag{5}$$

where $ZEROs2_{im}$ is the portion of days with zero-volume trading of stock i in month m ($ZeroVol_{im}$) to all trading days of this month (TD_m). Though this measure has a different economic basis than zero returns, it is closely correlated (Kang and Zhang 2014). Higher transaction costs are related to lower liquidity if investors reduce their demand and concentrate their activities on a few transactions to avoid higher costs. Therefore, the bid–ask prices are a good assessment measure for the *tightness* of the market. Similarly, *ZEROs2* covers the *depth* of the market over whose potential trading volume these transaction costs are spread at the equilibrium price.

4.1.4 Liu's measure

Another illiquidity measure that integrates non-trading days in a two-factor approach is Liu's (2006) *LMx*. It is a standardized turnover adjusted by the number of zero daily trading volume days over the prior x months ($x = 1,\ 6,\ 12$):

$$LMx_{im} = \left[NZVx_{im} + \frac{{}^{1}\!/\!(x - \text{month turnover})}{Deflator} \right] \times \frac{21x}{NoTD} \tag{6}$$

where $NZVx_{im}$ is the number of zero daily volume days in the prior x months for security i, x-month turnover is the sum of daily turnover over the prior x months; daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day; and *NoTD* is the total number of trading days in the market over the prior x months. The *Deflator* is chosen such that

$$0 < \frac{{}^{1}\!/\!(x - \text{month turnover})}{Deflator} < 1 \tag{7}$$

for all securities of the sample. For $x = 12$ the *Deflator* is set to 11.000, as suggested in Liu (2006).

This measure focuses on zero trading days over prior months, an essential sign of illiquidity. Thus, particular emphasis is placed on trading speed (*immediacy*), which existing research largely ignores. In the second step, turnover ratios are used to fine-tune the liquidity of different securities, accounting for both *breadth* and *tightness* (Liu 2006; Díaz and Escribano 2020).

4.1.5 Adjusted ILLIQ

An increasing number of studies have examined whether the proxies proposed for developed securities markets can also be applied to emerging markets, in which high-frequency data are often not available and the number of non-trading days is comparably high (Kang and Zhang 2014). The authors propose an adjustment of the Amihud measure by zero-volume days to compensate for these limitations:

$$ZHANG_{im} = \left[\ln\left(\frac{1}{D_{im}}\sum_{t=1}^{D_{im}}\frac{|R_{imd}|}{Vol_{imd}}\right)\right] \times \left(1 + ZeroVol_{im}\right). \tag{8}$$

This measure connects the considered dimensions of illiquidity of Amihud's *ILLIQ* and the *ZEROs2*. Consequently, the dimensions of *tightness* and *depth* are accentuated.

4.2 Data

Our dataset includes daily transactions for OEFs, REOCs, CEFs, and REITs traded on the German stock exchanges, Fondsbörse Deutschland and Deutsche Zweitmarkt AG, between July 1, 2002 and June 30, 2017. Transaction data are available for shares starting in July 2002, for OEFs from August 2002, and for CEFs from April 2007. Since some parameters are determined based on rolling periods, analyses with this dataset are possible from July 2003 and July 2007, respectively: 168 months for stocks (including REITs) and OEFs and 120 months for CEFs. For REITs and individual stocks, we chose the companies listed in the German real estate equity index DIMAX.[11] All securities predominantly represent real estate as assets. For CEFs, we use a unique dataset that includes all real estate fund transactions on the German secondary market exchanges that have "European" real estate as their investment target. Most of these are German office properties. European commercial real estate and residential real estate play a subordinate role as investments.

For our analysis, we only consider individual securities if they fulfill the following criteria:

1. The asset has return and volume data for more than 12 days during month *m*. Closed-end funds regularly show significantly lower trading activity. Therefore, we lower the criterion for this segment to 12 transactions per year. The securities nevertheless only became part of the sample if there was a trade in that month. This makes the estimated parameters more reliable.
2. The price is greater than EUR 1.00 at the end-of-month *m*.
3. A positive book-to-market ratio in month *m*. Because closed-end funds may have negative equity accounts owing to their construction, this restriction is necessary.

[11] The Deutsche Immobilienaktienindex (DIMAX) was launched by Bankhaus Ellwanger and Geiger in 1989.

Table 1 Sample summary

Sample				
Category	Number	Market cap. (June 2017)	Transactions	Trading volume
Real estate stocks	63	67,896,762,665 €	16,894,145	127,550,096,981 €
REITs	4	2,637,767,428 €	1,195,400	5,796,446,962 €
Open-end funds	23	79,855,544,547 €	795,928	13,820,877,040 €
Thereof temporarily "suspended" from trading	17	38,872,689,982 €	423,323	7,001,598,310 €
Closed-end funds	60	4,090,990,654 €	10,851	229,101,108 €
Total	150	154,481,065,294 €	18,896,324	147,396,522,091 €

This study examined four segments of the real estate market: real estate stocks, REITs, open-end real estate funds, and closed-end real estate funds. The second and third columns show the number of securities in the reporting periods and their market capitalization as of June 30, 2017. The analysis includes only the securities that satisfy the criteria set out in Sect. 3. Columns 4–5 show the number of trading transactions and the trading volume in the period from July 1, 2002 to June 30, 2017

After filtering the total sample of 1099 securities, our final sample comprises 150 securities, with approximately 18.9 million transactions and a trading volume of about EUR 147 billion.[12] Table 1 summarizes the details of the sample.

Out of the 23 retail-investable OEFs, 17 were temporarily suspended by the investment fund company. In these periods, investors had no alternative but to trade on the exchanges to buy or sell the shares of these funds. Initially, investors traded OEF fund shares on the Hamburg regional stock exchange to minimize transaction costs. Whereas the buyer must pay an upfront fee (usually approx. 5%) when buying shares from the fund company, the exchange calculates typical trading expenses, which are equivalent to a considerable reduction in the bid–ask spread.[13] From October 2008, the trading volume increased significantly and the share price of the suspended funds fell to an average of approximately 5% below the NAV (Haß et al. 2014). The share prices were no longer based on property appraisals by the fund companies and were rather determined by supply and demand. Thus, investors now trading on the secondary market of the Hamburg Stock Exchange accepted substantial discounts on the NAV (Schnejdar et al. 2019).

[12] The sample of OEFs and CEFs is based on the original dataset of all fund shares traded on German stock exchanges during this period that met the above selection criteria. With these 23 OEFs, the sample represents, on average, over 90% of the market capitalisation of the funds accessible to private investors in Germany (Benk et al. 2008). For the CEFs, the sample of 60 financial instruments covers about 4% of the total market (see Trübestein 2012). However, this is the most liquid sub-segment of closed-end real estate funds. It should also be noted that the size of the portfolio volume referred to there is regularly based on the invested equity of the funds at the time of issue and not on the current market capitalisation. The selection of real estate shares and REITs is based on the DIMAX index.

[13] Haß et al. (2014) show that prior to 2008, the trading price was less than 0.5% above the NAV of the fund.

We obtain the trading prices of the stocks, REITs, and OEFs directly from Deutsche Börse AG. For further analysis, we use closing prices only. We also collect market capitalization data, outstanding shares, and book-to-market ratios from Thomson Reuters Datastream. We retrieve information regarding corporate actions, such as dividends, from vwd Portfolio Manager.

For the analysis of the CEFs, we obtain the trading prices from Fondsbörse Deutschland and Deutsche Zweitmarkt AG, and the data on corporate actions, issued nominal capital, and the book value of the companies from their annual reports, available on eFonds24.

4.3 Illiquidity variables

Our first step is to analyze datasets for each category of securities following Amihud (2002) for the relationship between returns and illiquidity parameters. For this purpose, we apply a cross-section analysis of the effects of liquidity, risk, and other variables. Furthermore, we examine the effects of expected and unexpected market illiquidity on expected excess stock returns over time.

In Table 2, we present the descriptive statistics of the monthly returns and illiquidity measures for our sample of German real estate securities. It presents the time-series means for each cross-sectional value.

The monthly returns of real estate shares, at 1.75%, are higher than those of CEFs (0.66%) and OEFs (0.20%). In contrast, almost all illiquidity measures for the sample of closed-end funds show the highest average value. Only the Amihud *ILLIQ* on monthly data differ from this. The ranking of open-end funds depends on the illiquidity measure observed. For the measures that consider non-trading days (*ZEROs2*, *LIU*, *ZHANG*), this sample is classified as more liquid than the sample of stocks. This supports our hypotheses that there are different values of returns and illiquidity for the individual segments of securities. It seems obvious, however, that the illiquidity classification of the different security segments is not the only factor explaining the differences in returns.

Owing to the high skewness in the Amihud *ILLIQs* for all samples, we follow the literature and use logarithmized values. For example, *ILLIQ 12m* represents the natural logarithm of one plus the mean-adjusted firm-specific *ILLIQMA* over a 12-months rolling period, first multiplied by (10^6). We interpret this as the percentage price-impact of trading volume per EUR 1 Million (Bali et al. 2016).

For all three subsegments, the parameters of the illiquidity measures change only non-significantly from July 2007 to June 2017. There is a significant shift in the returns on stocks, which fell from 1.75 to 0.90% in monthly means. For open-end funds, the reduction in returns is 0.05% per month.[14]

[14] The data are presented in the Supplementary Material.

Table 2 Summary statistics of the illiquidity measures

Panel A: summary statistics: monthly measures of stocks and REITs

July 2003–June 2017	Monthly logarithmized measures						Monthly measures	
	Returns	*ILLIQ 12m*	*ILLIQ AT 12m*	*ILLIQ 1m*	*ILLIQ AT 1m*	*ZHANG*	*LIU*	*ZEROs2*
Mean	0.0175	11.2088	0.4458	10.7387	0.3850	1.8420	61.4826	0.1875
SD	0.1051	3.0625	0.5836	3.0942	0.6114	2.1700	62.7496	0.2167
Skew	0.84	−0.67	1.84	−0.28	2.37	1.44	0.97	1.17
Kurt	3.90	−0.23	3.53	−0.62	6.46	2.01	−0.05	0.30
Min	−0.1936	4.3897	0.0035	4.7834	0.0046	0.0029	6.1286	0.0238
5% Percentile	−0.1103	5.4614	0.0072	5.5208	0.0069	0.0065	6.1890	0.0238
25% Percentile	−0.0374	9.3505	0.0347	8.6132	0.0248	0.1746	8.6233	0.0247
Median	0.0036	11.8816	0.2211	11.1373	0.1162	1.0425	34.9242	0.0643
75% Percentile	0.0548	13.4451	0.5879	12.9962	0.4588	2.8401	103.5648	0.3227
95% Percentile	0.1861	15.0203	1.6816	15.1061	1.5794	5.8261	175.1654	0.5914
Max	0.3409	16.3320	2.3886	16.3613	2.5893	8.2861	207.0176	0.7143
n	5723.0	7196.0	7196.0	5723.0	5723.0	5723.0	5723.0	5723.0

Panel B: summary statistics: monthly measures of open-end funds

July 2003–June 2017	Monthly logarithmized measures						Monthly measures	
	Returns	*ILLIQ 12m*	*ILLIQ AT 12m*	*ILLIQ 1m*	*ILLIQ AT 1m*	*ZHANG*	*LIU*	*ZEROs2*
Mean	0.0020	12.1677	0.4836	11.9144	0.4728	0.4880	44.5462	0.1453
SD	0.0248	1.9086	0.5368	1.9983	0.5499	0.8200	48.2973	0.1707
Skew	0.13	−0.08	1.83	0.25	1.86	2.16	1.49	1.51
Kurt	3.20	−0.09	4.30	−0.27	4.08	4.87	1.88	1.68
Min	−0.0536	8.7140	0.0202	8.7019	0.0259	0.0064	6.7837	0.0249
5% Percentile	−0.0299	9.4664	0.0401	9.2098	0.0414	0.0116	7.1142	0.0251
25% Percentile	−0.0079	10.8457	0.1093	10.4386	0.1114	0.0388	10.5328	0.0294

Table 2 (continued)

Panel B: summary statistics: monthly measures of open-end funds

July 2003–June 2017	Monthly logarithmized measures						Monthly measures	
	Returns	*ILLIQ 12m*	*ILLIQ AT 12m*	*ILLIQ 1m*	*ILLIQ AT 1m*	*ZHANG*	*LIU*	*ZEROs2*
Median	0.0024	12.1114	0.3025	11.7682	0.2638	0.1391	25.0547	0.0673
75% Percentile	0.0119	13.4009	0.6514	13.2339	0.6150	0.5083	61.3993	0.1949
95% Percentile	0.0336	15.0651	1.3460	15.0791	1.4345	2.0514	131.2182	0.4635
Max	0.0565	15.7193	2.0679	15.8525	2.0682	2.9930	161.0844	0.5525
n	3103.0	3374.0	3374.0	3103.0	3103.0	3103.0	3103.0	3103.0

Panel C: summary statistics: monthly measures of closed-end funds

July 2007–June 2017	Monthly logarithmized measures						Monthly measures	
	Returns	*ILLIQ 12m*	*ILLIQ AT 12m*	*ILLIQ 1m*	*ILLIQ AT 1m*	*ZHANG*	*LIU*	*ZEROs2*
Mean	0.0066	12.2530	0.5418	11.0545	0.4924	2.6051	232.0405	0.8934
SD	0.1243	2.4895	0.4819	4.1315	0.5457	2.3197	12.0719	0.0713
Skew	0.46	−0.94	1.45	−1.55	1.57	1.07	−0.94	−1.41
Kurt	6.51	4.24	2.80	2.57	2.51	1.00	1.03	2.05
Min	−0.2473	5.2385	0.0165	1.2007	0.0045	0.0321	199.2761	0.6870
5% Percentile	−0.1313	8.2697	0.0572	2.1894	0.0102	0.0761	211.5569	0.7667
25% Percentile	−0.0306	11.4214	0.1812	10.0003	0.1036	0.8117	225.8157	0.8639
Median	0.0028	12.7017	0.3894	12.2643	0.3008	2.0607	234.4808	0.9146
75% Percentile	0.0302	13.7085	0.7717	13.4593	0.6778	3.8140	240.8319	0.9501
95% Percentile	0.1366	15.1658	1.4374	15.1003	1.5648	6.7484	246.1904	0.9540
Max	0.4422	16.0548	2.1289	16.0978	2.1185	8.7620	248.6877	0.9543
n	3724.0	5728.0	5728.0	3717.0	3717.0	3717.0	3717.0	3717.0

Table 2 (continued)

Panel A presents the summary statistics of the illiquidity measures for the stocks and REITs in the sample. The table presents the mean (*Mean*), standard deviation (*SD*), skewness (*Skew*), excess kurtosis (*Kurt*), minimum (*Min*), fifth percentile (*5%*), 25th percentile (*25%*), median (*Median*), 75th percentile (*75%*), 95th percentile (*95%*), and maximum (*Max*) values of the monthly firm data. Row "*n*" indicates the number of variables that are available for each segment during the observation period. Our sample contains ordinary shares with the investment focus "real estate" and Real Investment Trusts (REITs) listed on German Stock Exchanges. We estimate the illiquidity measures monthly for firms from July 2003 to June 2017. To examine the illiquidity effects, we followed Bali et al. (2016) and used the data on the relevant illiquidity measure up to and including month *m* (the month for which we calculated *ILLIQ*). We used this method for seven illiquidity measures. *ILLIQ 1m* and *ILLIQ 12m* were based on Amihud (2002) and were the mean-adjusted *ILLIQ* over rolling one resp. 12 months as calculated in Eq. (3) (see Sect. 4.1.1). *ILLIQ AT 1m* and *ILLIQ AT 12m* were the Turnover Ratios calculated by Eq. (4) (see Sect. 4.1.2), *ZHANG* was calculated by Eq. (8) (see Sect. 4.1.5), *LIU* was calculated by Eq. (6) (see Sect. 4.1.4) and *ZEROs2* was calculated by Eq. (5) (see Sect. 4.1.3). The logarithmized measures were the natural logarithm of the origin values, first multiplied by 10^6, added by one. The liquidity measures were winsorized at 0.5% and 99.5% in each cross-section.

In Panel B, we present the summary statistics for the open-end real estate funds in the sample. Accordingly, Panel C contains the data on closed-end funds. Since the German secondary market exchanges for closed-end funds did not begin trading until 2007, our observation starts in July 2007

4.4 Additional variables

Following Amihud (2002), we add further variables that appear to affect either returns or illiquidity to our regression model. Brennan et al. (1998) show that past stock returns affect their expected returns. We calculate *R100* for each stock as the return of stock i over the last 5 months (about 100 trading days). *R100YR* is the return of stock i over the rest of the period; that is, from the last 5–12 months. We calculate continuously compounded returns $\left(r_{\text{it}} = \ln \frac{P_{\text{it}}}{P_{\text{it}-1}}\right)$ for corporate actions. Owing to the very different characteristics of the individual stocks in size and market valuation, we analyze the book-to-market-ratio (*BMR*) to measure these effects.

$BETA_{iy}$ as a measure of risk calculated as the slope coefficient, estimated following the Scholes and Williams (1977) method and using the CDAX as the market index. The total risk of the asset is $VOLA_{im}$; that is, the standard deviation of the monthly returns on asset i over the last 12 months. *BMR* is the ratio of the book value and the market value. We use *SIZE* as the natural logarithm of the market capitalization of stock i during m. Both *BMR* and *SIZE* have significant explanatory effects for expected returns in many studies (Fama and French 1992, 1993).

5 Results and discussion

5.1 Illiquidity and stock returns

We begin our investigation of the cross-sectional relationship between illiquidity and expected returns with univariate portfolio analyses for all four real estate segments. We sort the assets at the end of each year into quintile portfolios by the ascending order of the chosen log-transformed *ILLIQ* variable. We then calculate the equally weighted returns of these portfolios each month and report the time-series averages of the portfolio returns. We also calculate the return spread between the top and the bottom quintiles, as well as the associated t-statistic based on the null hypothesis that the mean of the return spread is zero. Table 3 reports the results of the portfolio analysis with Amihud's (2002) *ILLIQ* as the sorting criterion for each subsegment.[15] Except for the OEF segment, all the categories have an illiquidity premium. However, this premium is only statistically significant (at least to the 5% level, using Newey and West-adjusted t-statistics) for the subsegments of shares or the entire sample. The illiquidity premium was not statistically significant for the CEFs. The raw return of the stocks and CEFs increased in most cases with rising illiquidity measures of the examined securities, which was economically significant.

At this point, we refer back to our first research question of whether we can observe liquidity premia in each segment of the German capital market for real estate securities and its associated hypothesis that each segment has significantly different return and illiquidity parameters. Based on the results presented in Table 3,

[15] We present the analyses with alternative illiquidity measures in the Supplementary Material (Table 3, Panels B–G).

Table 3 Continuous returns: portfolios sorted on illiquidity measures

Portfolios sorted on the original Amihud measure (*ILLIQ 12m*)—continuous returns

	Liquid	2	3	4	Illiquid	Illiq-Liq	*t*
Stocks and REITs return	0.26 (6.20)	1.05 (9.95)	0.28 (11.70)	1.25 (12.73)	1.57 (14.17)	1.31 (7.97)	(1.98)
Open-end REF return	0.05 (9.65)	0.06 (11.16)	0.13 (12.06)	0.44 (12.71)	−0.03 (14.24)	−0.09 (4.60)	(−0.28)
Open-end "susp." return	−0.20 (8.82)	0.30 (9.65)	−0.06 (11.04)	−0.30 (12.72)	−0.37 (14.30)	−0.38 (5.85)	(−0.37)
Closed-end REF return	−0.77 (11.75)	−0.36 (12.15)	−0.47 (12.48)	−0.18 (13.15)	−0.69 (14.31)	0.07 (2.56)	(0.08)
Total sample return	−0.11 (7.88)	0.25 (11.08)	0.43 (12.31)	0.06 (13.10)	1.25 (14.25)	1.36 (6.37)	(3.24)

This table presents the monthly returns (%) on portfolios sorted on the original Amihud Measure. *ILLIQ 12m* based on Amihud (2002) and was the mean-adjusted *ILLIQ* over rolling 12 months as calculated in Eq. (3) (see Sect. 4.1.1). At the beginning of each year from 2004 to 2017, we sort stocks into quintile portfolios according to the average *ILLIQ 12m* measure of the previous year. We then calculate the monthly equal-weighted portfolio returns for the quintile portfolios and report the time-series average portfolio returns. We also report the differences between the top and bottom quintiles with associated t-statistics. We calculate the open-end funds portfolios also from 2004 to 2017, and the closed-end funds portfolios from 2008 to 2017. We provide the average illiquidity values of the *ILLIQ 12m* in parentheses. In the last column we present the t-statistics of the spread portfolios against the null hypothesis that the mean is zero we conclude that the subsegments of our sample have different levels of illiquidity and returns. The spread portfolios based on illiquidity achieve higher statistically significant excess returns, except for those that consist exclusively of OEFs or CEFs. The excess returns of the spread portfolios sorted by Amihud's (2002) *ILLIQ* are 1.31% for the sample of stocks and REITs, 1.36% for the whole sample (both statistically significant) and 0.07% for the CEFs (statistically not significant). The alternative illiquidity measures (see Supplementary Material) generally confirm the results on the spread portfolios. However, using the turnover version of the *ILLIQ* reverses the sign of the spread portfolio for the CEFs, showing the importance of the return and trading volume components for the illiquidity effects on the subsegments. For the total sample, the spread portfolio fails to lose significance when Liu's measure and *ZEROs2* are used.

5.2 Cross-section relationship between illiquidity and returns

In this section, we examine the relationship between expected return, illiquidity, and other possible influencing factors. Following Amihud (2002), we start with a cross-sectional regression analysis of the subsegments over the sample period:

$$R_{\mathrm{im}} = k_{0m} + \sum_{j=1}^{J} k_{\mathrm{jm}} X_{ji\ m-l} + U_{\mathrm{imy}} . \tag{9}$$

In Eq. (9), R_{im} is the return on stock i in month m, with returns adjusted for delisted stocks to avoid survivorship bias. $X_{\mathrm{ji\ m}-l}$ is characteristic j of stock i estimated from data in month m minus l and known to investors at the beginning of the period in which they make their investment decisions. We integrate a time lag using variable l to analyze the persistence of the results. The coefficients k_{jm} measure the effect of stock characteristic j on the expected returns and U_{imy} are the residuals, k_{0m} is the monthly constant over all securities.

Table 4 provides the correlation coefficients between the cross-sectional means of the liquidity measures, *BMR*, *SIZE* (natural log of market capitalization), prior-period returns (*R100*), and standard deviation (*VOLA*, rolling 12 months). For all subsegments, we find low correlation coefficients between *ILLIQ* and the other factors, which indicates that the illiquidity component in the regression analysis serve as an additional explanatory variable. Only for stocks and REITs does *SIZE* have a strong negative correlation—*ILLIQ 1m* (−0.71), *ILLIQ 12m* (−0.70), and *ZHANG* (−0.59)—which corresponds to Bali et al. (2016) results. The past returns reveal low to negative correlation coefficients between −0.07 and 0.04 with the average illiquidity parameters of the same period.[16]

Constantinides and Scholes (1980) suggest that stocks with higher volatility should have lower expected returns. The correlations between *ILLIQs* and *VOLA* are

[16] The illiquidity measures of stocks and REITs are highly correlated. This coincides with Lou and Shu's (2017) findings concerning the US stock market. However, the correlations between *ILLIQs* and the corresponding "turnover" measures are weaker than those in Lou and Shu (2017) and range from 0.56 to 0.60.

Table 4 Correlations among illiquidity measures

Panel A: Monthly measures of stocks and REITs

Correlation	*ILLIQ 1m*	*ILLIQ AT 1m*	*LIU*	*ZEROs2*	*ZHANG*	*ILLIQ 12m*	*ILLIQ AT 12m*	*BETA*	*R100*	*R100YR*	*SIZE*	*BMR*	*VOLA*
ILLIQ 1m	1.00												
ILLIQ AT 1m	0.60	1.00											
LIU	0.57	0.39	1.00										
ZEROs2	0.61	0.44	0.78	1.00									
ZHANG	0.86	0.67	0.60	0.70	1.00								
ILLIQ 12m	0.92	0.45	0.58	0.59	0.74	1.00							
ILLIQ AT 12m	0.52	0.73	0.47	0.49	0.52	0.56	1.00						
BETA	−0.19	(−0.02)	−0.09	−0.06	−0.13	−0.16	(−0.01)	1.00					
R100	−0.05	(−0.03)	(0.03)	(−0.02)	−0.05	(0.04)	(0.02)	(0.02)	1.00				
R100YR	−0.07	(−0.02)	(−0.03)	(−0.01)	−0.06	(−0.02)	(−0.01)	(0.03)	0.19	1.00			
SIZE	−0.71	(0.00)	−0.35	−0.36	−0.57	−0.70	0.05	0.19	0.09	0.11	1.00		
BMR	−0.04	−0.106	−0.18	−0.15	(−0.02)	(0.03)	−0.06	(0.00)	−0.06	−0.07	−0.28	1.00	
VOLA	0.14	(−0.01)	(0.00)	(−0.02)	0.15	0.23	0.04	(0.01)	0.10	0.08	−0.47	0.30	1.00

Panel B: Monthly measures of open−end real estate funds

Correlation	*ILLIQ 1m*	*ILLIQ AT 1m*	*LIU*	*ZEROs2*	*ZHANG*	*ILLIQ 12m*	*ILLIQ AT 12m*	*BETA*	*R100*	*R100YR*	*SIZE*	*BMR*	*VOLA*
ILLIQ 1m	1.00												
ILLIQ AT 1m	0.69	1.00											
LIU	0.63	0.40	1.00										
ZEROs2	0.60	0.42	0.88	1.00									
ZHANG	0.84	0.70	0.65	0.64	1.00								
ILLIQ 12m	0.84	0.50	0.67	0.61	0.68	1.00							
ILLIQ AT 12m	0.50	0.70	0.48	0.47	0.46	0.65	1.00						
BETA	(0.04)	(0.00)	0.08	(0.06)	0.07	0.08	(0.02)	1.00					
R100	(0.03)	(0.01)	−0.07	−0.07	(0.01)	(−0.02)	(−0.06)	−0.09	1.00				
R100YR	(−0.02)	(−0.01)	−0.13	−0.10	(−0.05)	(−0.05)	(−0.03)	−0.17	0.17	1.00			
SIZE	−0.53	0.09	−0.48	−0.40	−0.46	−0.52	0.15	(−0.11)	0.11	0.18	1.00		
BMR	0.18	−0.141	0.05	0.06	0.20	0.18	−0.09	(0.08)	−0.23	−0.22	−0.42	1.00	

Table 4 (continued)

Panel B: Monthly measures of open− end real estate funds

Correlation	*ILLIQ 1m*	*ILLIQ AT 1m*	*LIU*	*ZEROs2*	*ZHANG*	*ILLIQ 12m*	*ILLIQ AT 12m*	*BETA*	*R100*	*R100YR*	*SIZE*	*BMR*	*VOLA*
VOLA	0.35	0.07	0.23	0.20	0.36	0.35	0.13	0.14	−0.15	−0.21	−0.41	0.49	1.00

Panel C: monthly measures of clossed− end real estate funds

Correlation	*ILLIQ 1m*	*ILLIQ AT 1m*	*LIU*	*ZEROs2*	*ZHANG*	*ILLIQ 12m*	*ILLIQ AT 12m*	*BETA*	*R100*	*R100YR*	*SIZE*	*BMR*	*VOLA*
ILLIQ 1m	1.00												
ILLIQ AT 1m	0.61	1.00											
LIU	−0.06	−0.08	1.00										
ZEROs2	−0.14	(−0.02)	0.54	1.00									
ZHANG	0.75	0.82	(0.04)	(0.03)	1.00								
ILLIQ 12m	0.37	0.42	(−0.03)	−0.05	0.60	1.00							
ILLIQ AT 12m	0.26	0.61	−0.13	−0.10	0.46	0.64	1.00						
BETA	(−0.03)	(0.03)	(−0.03)	(−0.01)	(−0.04)	(−0.05)	(0.02)	1.00					
R100	(−0.01)	−0.11	(−0.05)	−0.06	−0.11	(−0.01)	(−0.05)	0.05	1.00				
R100YR	(−0.04)	−0.11	−0.07	−0.06	−0.12	−0.08	−0.10	0.10	0.06	1.00			
SIZE	−0.13	0.09	−0.20	−0.12	−0.36	−0.37	0.12	(0.12)	0.06	0.07	1.00		
BMR	0.17	0.252	0.06	(0.03)	0.47	0.51	0.34	(−0.02)	−0.18	−0.19	−0.37	1.00	
VOLA	0.20	0.28	(0.01)	(−0.04)	0.41	0.58	0.49	−0.09	(0.08)	(0.01)	−0.28	0.31	1.00

Panel A presents the correlation coefficients between pairs of variables measuring illiquidity as well as *BETA*, *SIZE* (ln_marketcap), prior-period returns (*R100* and *R100YR*), and standard deviation (*VOLA*) measures. The illiquidity measures used are *ILLIQ 1m* and *ILLIQ 12m* based on Amihud (2002), the mean-adjusted *ILLIQ* over rolling one resp. 12 months as calculated in Eq. (3) (see Sect. 4.1.1), *ILLIQ AT 1m* and *ILLIQ AT 12m* were the Turnover Ratios calculated by Eq. (4) (see Sect. 4.1.2), *ZHANG* was calculated by Eq. (8) (see Sect. 4.1.5), *LIU* was calculated by Eq. (6) (see Sect. 4.1.4) and *ZEROs2* was calculated by Eq. (5) (see Sect. 4.1.3). The logarithmized measures were the natural logarithm of the origin values, first multiplied by 10^6, added by one. The liquidity measures were winsorized at 0.5% and 99.5% in each cross-section.

The firm-specific parameters of our sample are constructed monthly from July 2003 to June 2017. *BETA* is the monthly average of the stock-specific betas estimated by the Scholes and Williams (1977) method. The prior-period return *R100* is calculated for each stock as the return of stock *i* over the last 5 months (about 100 trading days). *R100YR* is the return of stock *i* over the rest of the period; that is, from the last 5 to 12 months. We calculate continuously compounded arithmetic returns for corporate actions. *SIZE* is the average mean of the log-transformed market capitalizations. The book-to-market ratio, *BMR* is the average of the firm-specific valuations.

Panel B and Panel C present the correlation coefficients on the monthly illiquidity measures of the open-end and closed-end real estate funds samples, respectively, constructed each month from July 2003 to June 2017. For clarity, we omit the t-statistics. All correlation coefficients that are not at least significantly different from zero at the 5% level are given in parentheses.

low for all subsegments (between 0.23 and 0.59). Theoretically, risk and illiquidity are positively related.

We examine the effect of illiquidity on stock return separately for each subsegment. We follow Fama and MacBeth's (1973) test procedure[17] and estimate a cross-sectional-model for each month $m = 1, 2, \ldots, 12$. We analyze the cross-sectional relationship for the illiquidity measures for the 1-factor (only the relevant *ILLIQ*), 4-factor (*ILLIQ* measure, *R100*, *R100YR*, and *BETA*), and 7-factor models (the 4-factor model plus *SIZE*, *BMR*, and *VOLA*). Table 5 presents the results for stocks and REITs.

The cross-sectional regression analysis of stock returns sorted on the *ILLIQs* shows that it has a statistically significant influence on the expected stock returns of our sample in the 1-factor model for all lags of 1–3 months. We find the strongest effect at lag 1. The further the illiquidity measure shifts into the past (lags 2–3), the weaker the illiquidity effects are, both in size and significance. For the sake of brevity, we only present the coefficients and t-statistics for the control variables for the regression analyses with the *ILLIQ 12m*. The results for other illiquidity measures only differ slightly and are available on request from the authors.

If we extend the model to a 4-factor regression, the effects of illiquidity weaken, both in coefficients and significance, compared to the 1-factor model. However, they remain significant at the 5% level, up to a lag of 2 months. *BETA* has no measurable influence in all regression analyses. In contrast, the past returns are statistically significant, although the effect of the previous months (*R100*) is stronger and more constant than that of the returns of earlier periods (at lag 2, the coefficient of *R100* of 0.04 is three times larger than that of *R100YR*). The adjusted-R2s are about 4 times as high as the 1-factor model.

When the model is extended by the factors *SIZE, VOLA*, and *BMR*, the effects above reduce further. *ILLIQ 12m* remains significant until lag 2, and *SIZE and VOLA* remain statistically insignificant across all lags. On the other hand, *BMR,* across all regression analyses, is positive and highly significant for the expected returns of the equity sample (t-statistics ranged from 5.81 in lag 1 to 4.67 in lag 3).[18] This result coincides with expectations based on Fama and French (1992; 1993). The adjusted-R2s continue to increase. For most of the models, the intercepts remain statistically insignificant across all lags.

To place this result in an economic context, we use, for example, the average coefficient of *ILLIQ 12m* from the 7-factor regression analysis with a lag of 2 months of

[17] Amihud (2002) states that he performs the cross-sectional regression analysis with the "usual Fama MacBeth (1973) method" (FMB). Although the FMB only applies market factors, Litzenberger and Ramaswamy (1979) and others also consider this procedure with firm-specific factors. In the literature, however, the latter is also often referred to as the FMB method, see Chordia et al. (2020) and Jegadeesh et al. (2019).

[18] Amihud (2002) described the cross-sectional regression analyses without the ratio of book-to-market equity (*BE/ME*), as Easley et al. (2002) and Loughran (1997) found no significant effects in the sample of NYSE shares they used in their studies. However, the result could be explained by the inclusion of market capitalization (*SIZE*) (Berk 1995). On the other hand, we found no relevance of the dividend yield (*DIVYLD*), which, in Amihud's studies, had significant negative effects on expected returns.

Table 5 Cross-sectional regression analyses of stocks and REITs returns on illiquidity and other stock characteristics

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
1-Factor	1	Adj. R2	0.024							
		Constant	−0.011							
		LIQ		1.901***	8.191*	1.686	0.076**	16.974*	0.393	−1.999
	2	Adj. R2	0.023							
		Constant	−0.011							
		LIQ		1.815***	7.566*	0.602	0.086****	16.161	0.294	1.267
	3	Adj. R2	0.024							
		Constant	−0.011							
		LIQ		1.792***	7.420*	1.810	0.086	23.258**	0.640	4.155
4-Factors	1	Adj. R2	0.095							
		Constant	−0.015							
		BETA	−0.003							
		R100	0.022**							
		R100YR	0.023**							
		LIQ		1.654**	8.895**	0.953	0.054	11.682	0.248	−2.938
	2	Adj. R2	0.090							
		Constant	−0.014							
		BETA	−0.001							
		R100	0.040**							
		R100YR	0.013**							
		LIQ		1.639**	7.973**	1.211	0.073*	15.125	0.746	3.184
	3	Adj. R2	0.092							
		Constant	−0.010							
		BETA	0.002							
		R100	0.038**							
		R100YR	0.018**							
		LIQ		1.211*	7.724*	1.777	0.067*	20.575*	0.673	4.808

Table 5 (continued)

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
7-Factors	1	Adj. R2	0.173							
		Constant	−0.086*							
		BETA	−0.001							
		R100	0.024*							
		R100YR	0.034***							
		SIZE	0.003							
		VOLA	0.012							
		BMR	0.020***							
		LIQ		2.002**	11.335***	0.338	0.086**	25.522**	−0.002	−1.854
	2	Adj. R2	0.161							
		Constant	−0.075							
		BETA	0.003							
		R100	0.041***							
		R100YR	0.019**							
		SIZE	0.002							
		VOLA	0.011							
		BMR	0.020***							
		LIQ		1.753**	8.438**	0.748	0.094**	18.270*	0.888	3.033

Table 5 (continued)

Factor	Lag	Variable	*ILLIQ 12m*	*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
	3	Adj. R2	0.165						
		Constant	−0.072*						
		BETA	−0.009						
		R100	0.046***						
		R100YR	0.023***						
		SIZE	0.002						
		VOLA	0.011						
		BMR	0.020***						
		LIQ	1.367	5.533	0.598	0.081**	22.101*	0.523	2.108

This table presents the means of the coefficients from the monthly cross-sectional regression of stock and REITs returns on the respective variables using seven illiquidity measures as described in the notes to Table 2. In each month *m* from July 2003 to June 2017, the returns of listed stocks and REITs are regressed cross-sectionally on stock characteristics calculated from data in month *m* minus lag *l*. This means that the investor makes the investment decision based on the available information in month *m* minus *l*, starting in month *m*. *LIQ* is the coefficient of the respective illiquidity measure (see Sect. 4.1). *BETA* is the slope coefficient from an annual time-series regression on monthly returns on one of five size portfolios on the market return (CDAX) weighted equally using the Scholes and Williams (1977) method. The stocks *BETA* is the beta of the size portfolio to which it belongs. *SIZE* is the logarithm of the market capitalization of the stock at the end of the considered month, *VOLA* is the monthly standard deviation of the stock during the last 12 months before portfolio decision, and *BMR* is the book-to-market-ratio by the end-of-month price. *R100* is the stock return over the last 5 months (about 100 days) and *R100YR* is the return during the period between months 12 and 5 before the investment decision. The data include 168 months over 14 years, July 2003–June 2017, and the stock characteristics are calculated from 2002 onwards. The sample stocks have more than 12 days of data for the calculation of the characteristics in month *m* and their share price exceeds 1 EUR. The illiquidity measures were winsorized at 0.5% and 99.5% in each cross-section. The t-statistics (in parentheses) are calculated using Petersen's (2008) method. The adjusted I-squared values (Adj. R2) are reported for every regression with the illiquidity measure *ILLIQ 12m*

Table 6 Cross-sectional regression analyses of the open-end funds returns on illiquidity and other stock characteristics

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
1-Factor	1	Adj. R2	0.035							
		Constant	0.001							
		LIQ		0.015	−1.840	2.434	−0.007	−6.130	0.108	−2.089
	2	Adj. R2	0.037							
		Constant	0.000							
		LIQ		0.069	−0.939	3.412*	0.028	6.842	0.844**	2.848*
	3	Adj. R2	0.033							
		Constant	0.000							
		LIQ		0.111	−1.098	1.428	0.022	6.577	0.376	0.681
4-Factors	1	Adj. R2	0.254							
		Constant	−0.001							
		BETA	0.001							
		R100	−0.017							
		R100YR	0.035*							
		LIQ		0.133	−1.052	1.713	−0.004	−5.361	0.034	−2.030
	2	Adj. R2	0.210							
		Constant	0.000							
		BETA	−0.007							
		R100	0.025							
		R100YR	0.030*							
		LIQ		−0.019	−0.908	1.934	0.014	0.623	0.437	2.232*
	3	Adj. R2	0.214							
		Constant	−0.003							
		BETA	0.018							
		R100	0.033							
		R100YR	0.016*							
		LIQ		0.122	−0.522	1.173	0.017	6.251	0.282	0.583

Table 6 (continued)

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
7-Factors	1	Adj. R2	0.411							
		Constant	−0.106***							
		BETA	−0.009							
		R100	0.012							
		R100YR	0.062***							
		SIZE	0.002							
		VOLA	−0.015							
		BMR	0.070***							
		LIQ		0.189	0.763	1.827	−0.006	1.906	0.851	−1.156
	2	Adj. R2	0.364							
		Constant	−0.045							
		BETA	−0.004							
		R100	0.003							
		R100YR	0.056***							
		SIZE	0.002**							
		VOLA	−0.054*							
		BMR	−0.003							
		LIQ		0.255	1.125	6.804**	0.037	−6.173	−1.116	2.270*

Table 6 (continued)

Factor	Lag	Variable	*ILLIQ 12m*	*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
	3	Adj. R2	0.332						
		Constant	−0.051						
		BETA	0.015						
		R100	0.060**						
		R100YR	0.016						
		SIZE	0.001						
		VOLA	−0.052*						
		BMR	0.019						
		LIQ	0.372	1.463	3.116	0.031	10.681	0.373	1.077

This table presents the means of the coefficients from the monthly cross-sectional regression of open-end funds returns on the respective variables using *ILLIQ 12m* and six other illiquidity measures. In each month m from July 2003 to June 2017, the returns of listed open-end funds are regressed cross-sectionally on stock characteristics calculated from data in month m minus lag l. For the other variables, please see the notes to Table 5

Table 7 Cross-sectional regression analyses of closed-end funds returns on illiquidity and other stock characteristics

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
1-Factors	1	Adj. R2	0.034							
		Constant	−0.039**							
		LIQ		2.708*	−5.303	0.550	−0.163	4.063	0.498	−11.526
	2	Adj. R2	0.038							
		Constant	−0.045**							
		LIQ		3.297***	−1.288	1.244	−0.113	−3.967	0.773	−1.818
	3	Adj. R2	0.037							
		Constant	−0.027**							
		LIQ		1.846	−3.869	1.433	0.116	−45.713	0.965	2.163
4-Factors	1	Adj. R2	0.085							
		Constant	−0.009							
		BETA	−0.001							
		R100	−0.021							
		R100YR	0.026							
		LIQ		0.382	−10.357	1.356	−0.167	−199.124	−0.381	−12.230
	2	Adj. R2	0.107							
		Constant	−0.005							
		BETA	0.002							
		R100	−0.008							
		R100YR	0.059							
		LIQ		0.312	−1.268	−0.417	0.337	−74.623	−0.811	−2.659
	3	Adj. R2	0.088							
		Constant	0.017							
		BETA	0.004							
		R100	0.029							
		R100YR	−0.001							
		LIQ		−1.443	−2.389	1.539	0.002	−58.881	1.512	7.257

Table 7 (continued)

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
7-Factors	1	Adj. R2								
		Constant	0.136**							
		BETA	0.010							
		R100	−0.028							
		R100YR	0.016							
		SIZE	−0.006*							
		VOLA	−0.128							
		BMR	0.002							
		LIQ		−2.623	−8.818	0.577	−0.293	−186.495	−0.005	−11.696
	2	Adj. R2	0.173							
		Constant	0.018							
		BETA	−0.007							
		R100	0.005							
		R100YR	0.070**							
		SIZE	0.000							
		VOLA	−0.175**							
		BMR	0.006							
		LIQ		−1.555	−2.526	1.298	−0.273	−35.861	1.776	−16.848

Table 7 (continued)

Factor	Lag	Variable	*ILLIQ 12m*		*ILLIQ AT 12m*	*ZHANG*	*LIU*	*ZEROs2*	*ILLIQ 1m*	*ILLIQ AT 1m*
	3	Adj. R2	0.143							
		Constant	−0.005							
		BETA	−0.001							
		R100	0.048***							
		R100YR	0.031							
		SIZE	0.003							
		VOLA	−0.068							
		BMR	0.003							
		LIQ		−3.819*	−6.003	0.978	−0.098	−103.069	−2.883	0.331

This table presents the means of the coefficients from the monthly cross-sectional regression of closed-end funds returns on the respective variables using *ILLIQ 12m* and six other illiquidity measures. In each month m from July 2007 to June 2017, the returns of closed-end funds are regressed cross-sectionally on stock characteristics calculated from data in month m minus lag l. For the other variables, please see the notes to Table 5

0.001753[19] (1.753 for 1.000 EUR trading volume). We multiply this value by the cross-sectional standard deviation of *ILLIQ 12m* of 3.0625 (Table 2) and find that a one-standard deviation difference in *ILLIQ 12m* is equivalent with a difference in expected returns of 0.54% per month. To examine the difference in expected returns between stocks in the lowest and highest quintile portfolio sorted on *ILLIQ 12m*, we multiply the average coefficient of 0.001753 by the difference between the average values of *ILLIQ 12m* for these corner-portfolios of 7.97 (illiquidity value of portfolio "Illiquidity"; i.e., 14.17, minus the illiquidity value of portfolio "Liquidity"; i.e., 6.20; see Table 3). The results indicate that the expected return of the stocks in the most illiquid portfolio is about 1.40% ($0.001753 \times 7.97 = 0.00140$) per month higher than that of stocks in the lowest quintile portfolio. This is in line with our results of the portfolio sorting (see Table 3). Both results show that illiquidity is economically important in the pricing of stocks and REITs.

The correlations between *ILLIQ* and the other variables are not surprising. *BETA* is not statistically significant in any model. One reason for this may be that we use the CDAX as a proxy for the German stock market. The particular investment focus of these stocks will dilute the beta effect. Following the literature,[20] we can also determine the statistical significance of the relevance of the effect of the returns of the immediate previous periods on the expected return for our sample.

Turning to OEFs, Table 6 shows that the illiquidity ratios are not statistically significant in any model using Amihud's *ILLIQ*, regardless of the chosen time lag. This result corresponds to the analysis of the return premium after portfolio sorting by illiquidity ratios (Table 3). In the 4-factor model, only the return variables *R100* and *R100YR* have statistical significance. This effect is further enhanced by the 7-factor model. Furthermore, *BMR* is positively significant at a 1% level for all lags. Interestingly, the effect of volatility turns negative for OEFs. This reverse relationship between volatility and expected return, which is statistically significant for all lags, corresponds to the insights of Constantinides and Scholes (1980). The size effect (*SIZE*) is also positive for regressions up to lag 2. Both variables also serve as proxies for illiquidity and may explain the lesser importance of *ILLIQ* measures in this segment. The constant in our 7-factor models has a significant negative value in the model calculated with a time lag of one month, which indicates that there are other nominal influencing variables that are not yet represented in our models. The explanatory power, measured by the adjusted R2, are higher in all models in this market segment than in the equity sample.

Table 7 shows the results for the cross-sectional regression analyses for the CEF sample. The coefficients of the illiquidity parameters up to lag 3 are higher than for stocks and REITs, and substantially higher than for OEFs for all lags; but they are not statistically significant in any model. Analogous to the analyses of OEFs, the

[19] We multiplied the estimated coefficients of *ILLIQ* in Tables 5, 6, 7 by 10^3 to improve readability. For further calculations, we used the original values.

[20] See, for example, Carhart (1997) and Chordia et al. (2014). Chordia et al. found that increasing market liquidity reduces anomalies, such as the momentum effect. In the regression analyses presented above, highly significant illiquidity parameters accompanied these effects from previous periods. However, without further investigation, we cannot equate the effects from previous periods with momentum effects.

added variables only have relevance in the 7-factor model. Previous-period returns have a significant impact with a positive coefficient from lag 2 on, and *SIZE* (lag 1) and *VOLA* (lag 2) have a negative impact. These results correspond to the univariate portfolio analyses in Table 3.

For robustness, we analyze different illiquidity measures in comparison to *ILLIQ 12m*. The turnover variant (*ILLIQ AT 12m*) shows no additional power. Obviously, if the bid–ask spreads are too large, trading activity in (very) low-capitalized companies remains absent and there are no sharp price changes with regards to the turnover (cf. Sect. 4.1.2). This is confirmed by the high significance of Goyenko et al. (2009)'s *ZEROs2*, which represents the dimension of density. In contrast, *ILLIQ 1m* and *ILLIQ AT 1m* often show negative signs for short lags, implying that this represents unexpected illiquidity. Skewness and kurtosis (see Table 2) make stable regressions more difficult. The adjusted *ILLIQ* of Kang and Zhang (2014) accounts for non-trading days and thus exploits the positive effect of *ZEROs2* described above. However, since it is built on monthly *ILLIQ* data, we do not find significant results overall in our analyses.[21] Liu's (2006) *LMx* uses a turnover variable and is therefore similar in parts to the turnover *ILLIQ*. We use a version based on rolling 12-month data. It confirms the results of both *ILLIQ 12m* and *ILLIQ AT 12m* in almost all models. The impact of non-trading days can be seen in the slopes of the coefficients across time-lags, which are similar to those of the *ZEROs2*.

For the OEFs, *ILLIQ* and *ILLIQ AT* show better results on a monthly basis up to a lag of 2 months. This indicates rapid and pronounced effects that disappear after a short period. These results were confirmed by the turnover variant and ZHANG's adjusted *ILLIQ*. At a lag of one month, the coefficients on many measures were negative in several models, providing evidence of a negative effect of unexpected illiquidity, as described earlier for equities. OEFs are regularly traded on the stock market (the mean of *ZEROs2* is 0.1453, corresponding to a trading probability of about 85.5% per month). Therefore, considering the non-trading days with the measures *ZEROs2* and *LMx* does not provide any explanatory power. Consequently, the *immediacy* dimension does not matter in this sample.

While CEFs have a high number of non-trading days (mean of *ZEROs2* is 0.8934), this is a steady trend (standard deviation of 0.0713). Because neither *ZEROs2*, nor *ZHANG* or *LMx* measure significant effects on expected returns, this does not generate illiquidity shocks. Using the *ILLIQ AT 12m* produces results with a negative sign. For CEFs, because outstanding shares do not change during the term, *ILLIQ* and *ILLIQ AT* should move in the same direction for each security. The analysis result is based on a change in the sample. While trading volumes have increased over the period under consideration, turnover ratios have not remained stable. This implies that CEFs with larger market capitalization have traded more in the secondary market over time than those with smaller market capitalization.

[21] We ran cross-sectional analyses with a *ZHANG* measure based on rolling 12-month *ILLIQs*. Accordingly, illiquidity was significantly positively related to ex-ante returns in many models. Nevertheless, the results for our sample were not superior to those of the *ILLIQ 12m* (see the Supplementary material).

The robustness test shows that *ILLIQ* provides plausible results for all three subsegments. Depending on the security category, longer rollover periods provide more stable results for the cross-sectional analysis. The choice of illiquidity measure matters for all subsegments. The effects of illiquidity persist after adding other control variables for the stocks and REITs and OEF samples; however, their statistical significance drops below 10%. For the sample of CEFs, many coefficients for illiquidity are negative but also not significant.

The results in Tables 5, 6 and 7 provide an answer to our second key question of whether a relationship between returns and illiquidity premia exists for German real estate securities. For the sample of stocks and REITs, the estimated cross-sectional regression analyses strongly support the second hypothesis that illiquidity is priced. We can quantify this using many variations of our illiquidity measure. Furthermore, we can determine the significance of the other company-specific factors. In particular, previous-period returns (*R100* and *R100YR*) and *BMR* are significant, which confirms earlier findings. However, we must view the effect of illiquidity on OEFs and CEFs differently.

5.3 The effect of market illiquidity on expected excess returns over time

In this section, we focus on the effects of market liquidity over time on the returns of securities portfolios. We hypothesize that the expected market liquidity over time will have a positive effect on the expected excess return on securities (surplus securities in short-term EUR government bonds or 1-month EURIBOR money market interest rates). This conjecture is in line with the positive cross-sectional relationship between returns and illiquidity. If investors expect higher market liquidity, then they value assets accordingly to achieve a higher expected return. This behavior would suggest that the excess return on assets, traditionally interpreted as a "risk premium", includes a premium for illiquidity (Amihud 2002). Following the methodology of French et al. (1987) we estimate the expected illiquidity using an autoregessive model, and we use this estimate to test the common hypotheses that the ex-ante excess stock return is an increasing function of the expected illiquidity, and the unexpected illiquidity has a negative impact on the simultaneous unexpected stock return.

5.3.1 Estimating procedure

We use the Amihud (2002) procedure with monthly data. For better comparability of the different illiquidity parameters for the time-series analysis, we follow Bank et al. (2010) and construct a market illiquidity index. The index starts for the stock sample with a value of 100 at the end of June 2003 and is computed for the following months using Eq. (10). The monthly illiquidity characteristic changes of the individual securities ($\Delta\ LIQ_{sm}$) are arithmetically equally weighted in the index development. Therefore, N_{sm} in Eq. (11) is the number of securities of our sample s with observations in month m. The illiquidity indices of the other samples are calculated as of the end of June 2003 (open-end funds) and June 2007 (closed-end funds) relative to the index of the stock sample. For the following months, the index developments were based on Eqs. (10) and (11)

$$LIQX_{sm} = \frac{\Delta\ LIQ_{sm}}{\Delta\ LIQ_{sm-1}} \times LIQX_{sm-1}, \tag{10}$$

$$\Delta LIQ_{sm} = \frac{1}{N_{\text{sm}}} \sum_{i=1}^{N_{\text{sm}}} LIQ_{im}. \tag{11}$$

The cross-sectional regression analyses showed already that—depending on the subsegments—the use of averaged illiquidity measures is more robust. Therefore, we now average parameters over the periods of the preceding $M = 2, 3, \ldots 12$ months:

$$\overline{LIQ}_{sm}^{M} = \frac{1}{M} \sum_{a=1}^{M} LIQ_{sm-a}. \tag{12}$$

The ex-ante effect of market illiquidity on stock excess return is

$$E\left(RM_m - RF_m \,\middle|\ln LIQ_m^E\right) = f_0 + f_1 \ln LIQ_m^E, \tag{13}$$

where RM_m is the monthly market return and RF_m is the monthly risk-free return. The expected market illiquidity for month m based on information in the prior period, *m-l,* $\ln LIQ_m^E$ is—following Eq. (12)—for each subsegment and rolling period $\overline{LIQ}_{sm-l}^{M}$. We hypothesized that $f_1 > 0$. We assume that market illiquidity follows an autoregressive model:

$$\ln LIQ_m = c_0 + c_1 \ln LIQ_{m-l} + v_m \tag{14}$$

At the beginning of month *m,* investors determine the expected illiquidity for the coming period, $\ln LIQ_m^E$, based on information in month $m-l$:

$$\ln LIQ_m^E = c_0 + c_1 \ln LIQ_{m-l}. \tag{15}$$

Then, they set market prices at the beginning of the new period that will generate the expected return for the month m, according to the model:

$$(RM - RF)_m = f_0 + f_1 \ln LIQ_m^E + u_m = g_0 + g_1 \ln LIQ_{m-l} + u_m, \tag{16}$$

where $g_0 = f_0 + f_1\, c_0$ and $g_1 = f_1\, c_1$.

We denote unexpected excess returns by the residual u_m. We hypothesize that $g_1 > 0$; higher expected market illiquidity will lead to higher ex-ante stock excess return. Consequently, rising expected illiquidity must lead to price decreases at the time of observation (t_0), which corresponds to an effect of unexpected illiquidity at time t_{-1}. Both effects together generate the following model:

$$(RM - RF)_m = g_0 + g_1 \ln LIQ_{m-l} + g_2 \ln AILLIQ_m^U + w_m, \tag{17}$$

where $\ln LIQ^U_m$ is the unexpected illiquidity in month m, and $\ln AILLIQ^U_m = v_m$, the residual from Eq. (14). We test the two hypotheses in the following model:

H1: $g_1 > 0$, and

H2: $g_2 < 0$.

First, we calculate the residuals v_m from Eq. (14) after we adjust the coefficients using Kendall's (1954)-bias correction method.[22] Next, we use these residuals as $\ln LIQ^U_m$ in Eq. (17). RM_m is the arithmetic-weighted return of all assets in month m, which are part of our sample and fulfill the conditions described in Sect. 4.2 and RF is the 1-month EURIBOR interest rate of the relevant period.

Finally, we estimate the monthly returns of our samples adding $JANDUM_{\mathrm{m}}$, a January dummy, that accounts for the well-known January effect.

$$(RM - RF)_m = g_0 + g_1 \ln LIQ_{m-l} + g_2 \ln LIQ^U_m + g_3\, JANDUM_m + w_m, \quad (18)$$

5.3.2 Results

We regress the illiquidity measures described in Sect. 4.1 for all rolling periods and with lags of 1–3 months for our three samples. Table 8 provides the results of the time-series regression analyses.

We find that expected illiquidity measured with *ILLIQ* affects expected returns with increasing coefficients with longer rolling periods, as well as with longer lags from 1 month onward, in the equity sample (Panel A). Apart from short rolling periods, the parameters for the expected illiquidity were positively associated with the returns. The unexpected illiquidity has negative effects, but these were not statistically significant at the 10% level. The robustness test with *ILLIQ AT* and the *ZHANGs* measure confirm these results–in the latter case, with significant results for unexpected illiquidity. Liu's (2006) *LMx* shows decreasing coefficients for decreasing illiquidity, which are significant for short rolling periods. *LMx* by design already uses 12-months data. Further smoothing of the measure does not produce more stable results. The expected illiquidity measured by *ZEROs2* is (highly) significant with increasing sign. However, both *LMx* and *ZEROs2* have unexpected illiquidity with a positive sign.

The regression analyses yield autocorrelation effects, made evident by the Durbin-Watson (DW) test results of between 1.24 and 1.29. We therefore correct the results according to the Newey and West (1987) method. In addition, the *F*-tests return results below the critical threshold. The regression analyses of the *ILLIQ* are significantly less significant than those in Amihud (2002). The other measures partially report coefficients with reversed signs to our hypotheses. Obviously, the regression procedure in Amihud (2002) is not (yet) sufficiently specified for our

[22] The ordinary least squares analysis—when including the lagged dependent variables in the regression model with a small sample—leads to biased estimates, and this bias increases as the number of irrelevant variables increases. Therefore, we use Kendall's (1954) method to adjust the estimated coefficients in Eq. (15).

Table 8 The effect of expected and unexpected market illiquidity on the excess returns of stocks and REITs

Panel A: Excess returns of stocks and REITs regressed on *LIQX* over div. rolling periods and lags

Averaged across *M* months	Lag	*ILLIQ* $\overline{LIQX}^{M}_{m-l}$	*ILLIQ* $LIQX^{U}_{m}$	*ILLIQ AT* $\overline{LIQX}^{M}_{m-l}$	*ILLIQ AT* $LIQX^{U}_{m}$	*ZHANG* $\overline{LIQX}^{M}_{m-l}$	*ZHANG* $LIQX^{U}_{m}$	*LIU* $\overline{LIQX}^{M}_{m-l}$	*LIU* $LIQX^{U}_{m}$	*ZEROs2* $\overline{LIQX}^{M}_{m-l}$	*ZEROs2* $LIQX^{U}_{m}$
1	1	−0.868	−0.410	−0.306	−0.430	−2.240	−4.667*	5.139**	7.885***	1.900	3.278**
3	1	−0.553	−0.854	0.497	−0.571	−1.704	−16.786***	6.136**	16.303***	6.055**	3.181
6	1	−0.105	−2.027	0.784	−2.271	−0.859	−39.132***	5.692*	33.504***	8.310***	11.957
9	1	0.386	−2.510	1.254	−2.806	0.019	−54.030**	5.417*	37.717***	9.323***	2.093
12	1	0.625	−0.787	1.582	−2.334	1.016	−56.751**	5.675	60.596***	10.979***	−17.928
1	2	−0.398	−0.628	0.399	−0.560	−1.232	−5.836*	5.350**	6.759***	4.206**	2.815*
3	2	−0.043	−1.372	0.642	−0.255	−0.620	−12.341***	5.124*	12.515***	6.911***	2.436
6	2	0.274	−2.073	0.943	−1.006	0.379	−23.557**	4.660	18.187***	8.764***	5.737
9	2	0.740	−2.457	1.477	−1.471	1.485	−30.655**	4.500	19.030**	9.740***	0.445
12	2	0.935	−2.383	1.745	−0.994	2.414	−33.949**	4.354	29.190***	11.652***	−16.643
1	3	−0.020	−0.786	0.235	−0.578	−0.148	−6.596**	4.358*	7.608***	4.085***	2.756*
3	3	−0.050	−0.922	0.305	0.087	0.336	−9.853***	4.091	10.834***	7.263***	3.204
6	3	0.614	−1.779	1.024	−0.559	1.404	−17.424**	3.745	14.104***	7.631***	7.744
9	3	0.977	−1.880	1.492	−0.597	2.664	−22.175**	3.820	13.952**	9.682***	2.128
12	3	1.098	−1.736	1.701	−0.070	3.454	−23.167**	3.378	21.762***	11.936***	−9.515

Panel B: excess returns of open-end funds regressed on *LIQX* over div. rolling periods and lags

Averaged across *M* months	Lag	*ILLIQ* $\overline{LIQX}^{M}_{m-l}$	*ILLIQ* $LIQX^{U}_{m}$	*ILLIQ AT* $\overline{LIQX}^{M}_{m-l}$	*ILLIQ AT* $LIQX^{U}_{m}$	*ZHANG* $\overline{LIQX}^{M}_{m-l}$	*ZHANG* $LIQX^{U}_{m}$	*LIU* $\overline{LIQX}^{M}_{m-l}$	*LIU* $LIQX^{U}_{m}$	*ZEROs2* $\overline{LIQX}^{M}_{m-l}$	*ZEROs2* $LIQX^{U}_{m}$
1	1	0.063	−0.004	−0.060	−0.207	0.209	0.241	−0.089	1.172	−0.478**	0.815**
3	1	0.179	−0.372	−0.055	−0.224	0.557	−0.238	0.099	−2.629	−0.174	0.928
6	1	0.177	−1.180*	−0.043	−0.631*	0.723**	−2.279*	0.135	−1.697	0.012	1.322

Table 8 (continued)

Panel B: excess returns of open-end funds regressed on *LIQX* over div. rolling periods and lags

Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$
9	1	0.157	−0.798	−0.052	−0.428	0.798**	0.911	0.226	0.620	0.296	2.200
12	1	0.179	−1.677	−0.023	−0.947	0.805**	−2.349	0.089	−4.394	0.133	−8.871**
1	2	0.183	−0.070	−0.173*	−0.175	0.407	0.124	0.230	−0.350	0.088	0.471
3	2	0.204	−0.205	−0.095	−0.145	0.700**	−0.198	0.230	−2.494	0.146	−0.129
6	2	0.189	−0.533*	−0.084	−0.228	0.804**	−1.083	0.185	−3.413	0.293	−1.076
9	2	0.169	−0.340	−0.146	0.133	0.733**	1.240	0.201	−1.593	0.313	0.425
12	2	0.214	−1.031	−0.029	−0.379	0.873**	−1.601	0.135	−3.168	0.282	−7.226***
1	3	0.145	−0.040	−0.132	−0.188	0.432*	0.132	0.336	−0.776	0.110	0.465
3	3	0.099	0.021	−0.158	−0.119	0.524*	0.204	0.214	−1.189	0.071	0.023
6	3	0.170	−0.215	−0.077	−0.182	0.800**	−0.420	0.234	−2.235	0.408	−1.238
9	3	0.201	−0.387	−0.068	−0.108	0.794**	0.365	0.214	−0.082	0.287	0.555
12	3	0.236*	−0.709*	−0.007	−0.346	0.902***	−0.903	0.171	−1.343	0.383	−4.692**

Panel C: Excess returns of closed-end funds regressed on *LIQX* over div. rolling periods and lags

Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$
1	1	0.464	−0.163	0.309	0.202	2.880	−0.028	−14.199	−29.473	10.697	−16.463
3	1	0.690	−0.235	−0.123	−0.736	2.782	1.807	−14.137	−29.122	20.535	−67.472
6	1	1.411	−2.946	0.444	−3.489	4.182	−0.443	−14.293	158.534	28.639	−147.980
9	1	2.068	−4.223	0.921	−2.588	5.830	2.912	−19.459	330.178*	41.324	−122.755
12	1	2.448*	−6.533**	1.221	−2.646	6.569*	12.480	−26.501	429.055**	49.631	−133.301

Table 8 (continued)

Panel C: Excess returns of closed-end funds regressed on *LIQX* over div. rolling periods and lags

Averaged across M months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$
1	2	0.459	0.061	−0.308	0.517	2.285	0.840	−16.945	−30.054	10.958	−9.729
3	2	1.115	−0.042	0.561	−1.589	4.184*	1.478	−18.297	−3.462	24.016	−26.246
6	2	2.040	−2.233	1.067	−3.873	5.820*	−1.346	−24.386	118.824	35.940	−82.380
9	2	2.618**	−2.816	1.454	−4.526	7.237**	3.464	−33.782**	197.214**	45.968	−39.671
12	2	2.926**	−3.047	1.606	−3.488	7.751**	13.601	−42.915**	248.128**	52.953	−18.812
1	3	0.747	0.010	0.678	0.131	2.761	1.161	−19.605	−16.926	24.134	−16.465
3	3	1.359	0.188	1.156	−1.518	5.407**	2.332	−23.869	19.850	29.724	−21.044
6	3	2.503*	−1.763	1.717	−3.952	7.249**	−0.176	−33.227*	99.128	42.503	−67.459
9	3	3.013**	−2.351	1.973*	−4.349	8.154***	5.575	−43.818***	136.312**	51.028	−33.057
12	3	3.139**	−1.749	1.945	−3.261	8.326***	14.701	−53.930***	169.694**	53.790	5.557

Panel A shows the results over time of the time-series regression analyses of excess returns of the stocks and REITs sample as specified in Eq. (18). We use the residuals from the autoregressive process of the *LIQX*-measures as a parameter of unexpected illiquidity. $\overline{LIQX}^{M}_{m-l}$ is the lagged market illiquidity variable, which is averaged across the previous M months (see first column), serving as a proxy for expected illiquidity $LIQX^{U}_{m}$ represents the unexpected illiquidity, calculated as the residuals of the autoregressive process in Eq. (16). Additionally, we consider the variables with various lags (see column 2) on the respective excess returns. We used this method for several illiquidity measures. *ILLIQ* based on Amihud (2002) and is the mean-adjusted *ILLIQ* over rolling one resp. 12 months as calculated in Eq. (3) (see Sect. 4.1.1), *ILLIQ AT* was the Turnover Ratios calculated by Eq. (4) (see Sect. 4.1.2), *ZHANG* was calculated by Eq. (8) (see Sect. 4.1.5), *LIU* was calculated by Eq. (6) (see Sect. 4.1.4) and *ZEROs2* was calculated by Eq. (5) (see Sect. 4.1.3). This model adds *JANDUM*, a January dummy that accounts for the well-known January effect. The table shows the coefficients of the expected and unexpected illiquidity. ***, **, and * denote the test statistics of the coefficients at the 1%, 5% and 10% level. The sample spans 168 months, from July 2003 to June 2017.

Panel B presents the results for the regression analyses of the open-ended real estate funds. Time series from July 2003 to 2017 are used also for this sample

The results of the calculations for closed-end real estate funds are presented in Panel C for the period from July 2007 to June 2017 sample. Moreover, it is remarkable that the well-known January effect is not statistically significant.

As can be seen from Table 8 (Panel B), the results of the time-series regression analyses of the OEFs are similar to those of the stock sample. There are differences in the robustness test with the turnover ratio (*ILLIQ AT*), which generates negative signs in the coefficients of the expected illiquidity. This effect is already well-known from cross-sectional analysis. The regression analyses with *ZHANG's* measure show increasing effects of expected illiquidity with rising significance. Unexpected illiquidity is predominantly not statistically significant. The Durbin-Watson test fails to provide any indication of autocorrelation.

Table 8, Panel C presents the results for CEFs. The time regression analysis yields increasing effects of expected illiquidity for the "classical" *ILLIQs* as regressors. As in the previous analyses, the values of the coefficients of expected illiquidity have positive signs and are increasing with the lag length, which are statistically significant for longer rolling periods. This is in line with the results of the cross-sectional analysis. However, unexpected illiquidity shows decreasing magnitudes of coefficients over time, as in the analyses of the samples of equities and OEFs, and at longer roll periods, these values are also negative, as assumed. The turnover ratio confirms the results of *ILLIQ*. However, as in the other samples, they remain statistically at a significance level below 10%. Further, in this sample, the robustness test for the measure according to Kang and Zhang (2014) produces robust results. Expected illiquidity has an increasingly positive effect on excess returns and is increasingly (highly) statistically significant. The cross-sectional analysis confirms that owing to the high number of non-trading days, the measures *LMx* and *ZEROs2* cannot be reasonably applied to the sample of CEFs. Figure 1 reveals the nearly horizontal nature of the corresponding time series, and the constant of the regression becomes increasingly statistically significant.

Figure 1 illustrates considerable shifts in the time series surrounding or in the aftermath of the GFC. Therefore, in a further step, we examine whether the time-series regression analyses provide indications of structural breaks. We use the Quandt-Andrews breakpoint test for one or more unknown structural breaks (see Andrews 1993; Andrews and Ploberger 1994) to sequentially analyze whether the regression coefficients differ significantly in each subperiod. We apply three different test statistics: the maximum F statistic (Sup$F$), the exponential F statistic (Exp$F$), and the average F statistic (Ave$F$). For brevity, Table 9 only provides the Sup$F$-Test.[23] The p-values are based on Hansen (1997). In addition, the last column shows the times at which the limit value of the Sup$F$ statistics is exceeded. These are not necessarily the possible structural breaks, but they provide initial indications.

The Sup$F$ statistics have the greatest explanatory power and are highly significant for the sample of stocks and REITs across all lags (see Table 9, Panel A). The maximum F statistics are reached between May 2006 and January 2009. Only a few models based on *ZEROs2* show no evidence of structural breaks.

[23] The results for Exp$F$- and Ave$F$ are qualitatively similar to the Sup$F$ statistic and are available on request from the authors.

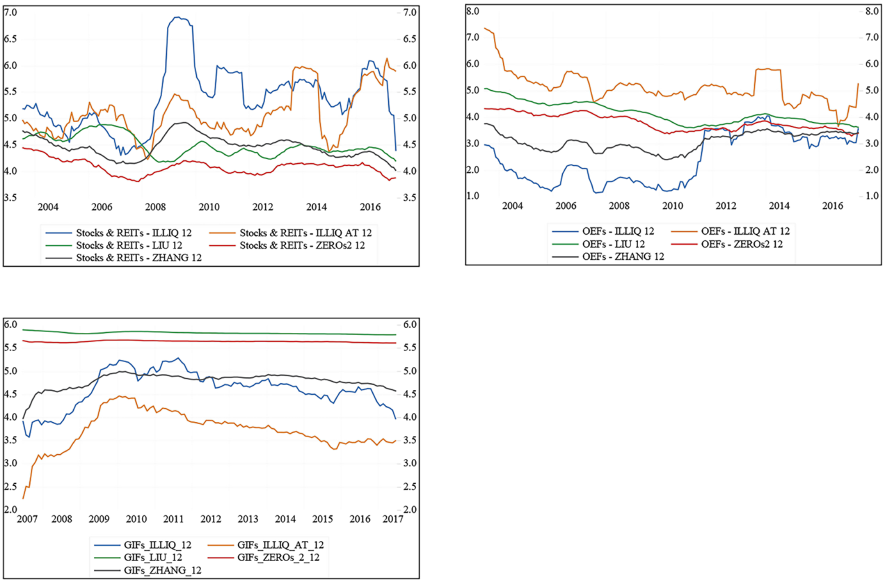

Fig. 1 Market illiquidity indices. This figure shows the development of the market indices for the illiquidity measures used, based on rolling 12-month data. We used this method for seven illiquidity measures. *ILLIQ 1m* and *ILLIQ 12m* were based on Amihud (2002) and were the mean-adjusted *ILLIQ* over rolling one resp. 12 months as calculated in Eq. (3) (see Sect. 4.1.1), *ILLIQ AT 1m* and *ILLIQ AT 12m* were the Turnover Ratios calculated by Eq. (4) (see Sect. 4.1.2), *ZHANG* was calculated by Eq. (8) (see Sect. 4.1.5), *LIU* was calculated by Eq. (6) (see Sect. 4.1.4) and *ZEROs2* was calculated by Eq. (5) (see Sect. 4.1.3). The indices are calculated as shown in Eq. (10) and Eq. (11). The illiquidity measures are normalized to 100 for the sample of stocks and REITs as of end of June 2003. The indices of the other samples reflect the relative position in June 2003 to the stock sample and their individual evolution in the subsequent periods

Panel B shows the results for the OEF sample. Except for the *ZHANG* measure, we found an indication of at least one structural break based on the maximum *F* statistics in nearly all models. The limit was exceeded in most models first in September 2013. However, as explained, this subsample included both the OEFs, which investors can trade at any time via the fund companies, and those whose units were at least temporarily suspended from issue and/or redemption by the fund company ("frozen" funds). This may have diluted the stronger effects of the "frozen" funds subgroup. For the subgroup of closed-end funds, the references to structural breaks were highly significant for all statistics and from February to April 2009 (see Panel C).

We determined the importance of effects from the GFC by adding the dummy variable *FinCrisD*, which equals 1 for the period of September 2008 to February 2009, and 0 otherwise, see Eq. (19).

$$(RM - RF)_m = g_0 + g_1 \ln LIQ_{m-l} + g_2 \ln LIQ_m^U + g_3\, JANDUM_m + g_4 FinCrisD_m + w_m, \tag{19}$$

Table 10, 11 and 12 present the results for the three subsegments. Unsurprisingly, we found that *FinCrisD* had a significant, negative effect on the stock returns and increased the effects of expected illiquidity for *ILLIQ* and Kang and Zhang's (2014) adjusted *ILLIQ* (see Table 10, Panel A). For the other measures, the results from Table 9 remained almost unchanged. This is plausible since during the GFC there was no significant reduction in trading activity.[24] Consequently, the *LMx* and *ZEROs2* measures do not provide any further information.

Apart from the expected effects of expected and unexpected illiquidity on expected returns, we should observe a second effect called "flight to liquidity" when examining the individual sub-portfolios. For this purpose, we divided the respective sample into portfolios based on market capitalization, whereby the smallest companies were assigned to portfolio P1. Owing to the small number of securities considered, only three portfolios were formed. Our analysis of this effect for the sample of stocks and REITs, which we present in Table 10 (Panel B), is contrary to that of Amihud (2002). He found that securities with lower (vs. higher) liquidity showed above-average lower returns in periods of market illiquidity, as investors sell these shares and prefer more liquid equities. Thus, we should expect that smaller, illiquid equities will have a stronger impact on market liquidity, whereas the effect should be weaker for more liquid equities. Only *ZEROs2* focusing on the *tightness* dimension yielded this effect described by Amihud (2002). For *ILLIQ*, we found that the excess returns of the P1 (small firms) and P3 (larger firms) portfolios were more sensitive to expected market illiquidity than those of medium-sized firms. This was also supported by other measures of illiquidity. The turnover ratio even showed that with increasing market capitalization the effect of illiquidity increases.

OEFs (see Table 11, Panel A) do not change substantially in the absolute values of the coefficients and retain the signs of the regression analyses without the GFC dummy. The values for *FinCrisD* were not as pronounced as in the case of equities and REITs; but this may also indicate that the relevant period for OEFs differs from that of the equity sample. Based on *ILLIQ*, OEFs show the expected size effect. This was also robust when using the other measures–except for the Turnover Ratio. As shown in Sect. 5.2, *ILLIQ AT* shows inverse effects of illiquidity on returns.

Table 12 shows the results of the regression analyses for CEFs. On the one hand, the results from Table 9 are validated and strengthened by the addition of the financial crisis dummy. Regarding unexpected illiquidity, on the other hand, there was no consistent pattern. Using the *ILLIQ* with a lag of one month, coefficients increased with increasing roll period, while a decreasing trend was expected. Using the *ZHANG* measure, unexpected illiquidity had a positive effect on returns. Note that the (il)liquidity index *LIQX* for this measure and sample rose steadily until the peak in 2010 and then showed a very consistent trend (see Fig. 1). Consequently, the economic effect of unexpected illiquidity as a residual

[24] In the period from September 1, 2008 to February 28, 2009, the mean value of *ZEROs2* for the stock sample was 0.2047 (September 1, 2009 to February 28, 2010: 0.1965), for OEFs 0.1443 (0.094), and for CEFs 0.9114 (0.9219).

Table 9 Expected and unexpected returns: robustness test for potential breaks

Panel A: Quandt–Andrews Test of stocks and REITs–*LIQX*-measures regressed over div. rolling periods and time-lags

Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs 2*	
		sup*F*-Test	*Max. Date*	sup*F*-Test	*Max. Date*	sup*F*-Test	*Max. Date*	sup*F*-Test	*Max. Date*	sup*F*-Test	*Max. Date*
1	1	8.5358***	2008M12	4.6504**	2006M05	5.2876***	2006M05	10.1005***	2008M12	4.4140**	2006M05
3	1	6.6129***	2008M12	5.1805**	2006M05	5.4094***	2006M04	10.6807***	2008M12	4.1380*	2006M05
6	1	7.1668***	2008M12	6.0076***	2006M05	5.9973***	2006M02	10.6858***	2008M12	3.9911*	2006M05
9	1	7.5791***	2008M12	6.4507***	2006M05	5.2645***	2006M05	10.0382***	2008M12	3.7430*	2006M05
12	1	7.2577***	2008M12	6.8219***	2006M05	6.7416***	2006M04	9.0621***	2008M12	4.1020*	2008M12
1	2	7.4068***	2008M12	5.0810**	2006M05	5.4331***	2006M05	10.7046***	2008M12	4.0484*	2009M01
3	2	6.0185***	2008M12	5.2925***	2006M05	4.8349**	2006M05	10.9279***	2008M12	3.8258*	2008M12
6	2	6.9746***	2008M12	5.8663***	2006M05	5.3435***	2006M03	10.5046***	2008M12	3.5244	2006M05
9	2	7.7699***	2008M12	6.7113***	2006M05	4.5899**	2006M05	10.1750***	2008M12	3.4741	2006M05
12	2	7.8610***	2008M12	6.6869***	2006M05	6.6031***	2006M03	9.3836***	2008M12	4.6553**	2008M12
1	3	7.3128***	2008M12	4.9203**	2006M05	5.1747**	2006M04	10.8208***	2008M12	3.7678*	2006M05
3	3	6.3198***	2008M12	5.6523***	2006M05	4.7444**	2006M05	10.6441***	2008M12	3.5295	2006M05
6	3	6.5330***	2008M12	6.2786***	2006M05	4.9195**	2008M12	10.4021***	2008M12	3.9060*	2006M05
9	3	6.8868***	2008M12	6.6995***	2006M05	4.5934**	2008M12	10.2016***	2008M12	3.4298	2006M05
12	3	8.0500***	2007M06	6.7767***	2006M05	6.3157***	2006M04	9.3010***	2008M12	4.3617**	2008M12

Panel B: quandt-Andrews-test of open-end funds–LIQX-measures regressed over div. rolling periods and time-lags

Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-Test	*Max. Date*
1	1	4.6845**	2013M09	4.2166**	2013M12	3.6633	2013M09	4.9571**	2013M09	4.5197**	2013M09
3	1	3.9937*	2013M09	4.0112*	2013M10	2.9931	2013M09	5.5625***	2013M09	5.0675**	2013M09
6	1	3.7686*	2013M09	4.3130**	2013M09	2.7064	2013M09	5.9384***	2012M05	5.2527***	2013M09

Table 9 (continued)

Panel B: quandt-Andrews-test of open-end funds–LIQX-measures regressed over div. rolling periods and time-lags											
Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-Test	*Max. Date*
9	1	4.8149**	2013M02	4.5781**	2013M04	2.5808	2013M04	5.6573***	2013M09	5.9377***	2013M09
12	1	3.7505*	2013M09	4.6372**	2013M09	2.6338	2012M01	5.4476***	2013M09	5.1239**	2013M09
1	2	3.8285*	2013M09	2.9668	2013M09	2.9526	2013M09	5.8245***	2013M09	6.3284***	2013M09
3	2	3.5523	2013M09	4.0469*	2013M12	3.1377	2011M12	6.0499***	2011M12	6.2839***	2013M09
6	2	3.7221*	2013M09	3.9855*	2013M09	2.6839	2013M09	6.5231***	2011M12	5.6065***	2013M09
9	2	4.0632*	2013M09	4.2016**	2013M04	2.5751	2013M12	5.3955***	2013M09	5.9214***	2013M09
12	2	3.3507	2013M09	4.7395**	2013M09	3.3489	2012M01	5.7209***	2013M09	5.6209***	2010M11
1	3	5.1175**	2013M03	3.1138	2013M09	2.9366	2013M09	6.1800***	2013M09	6.0547***	2013M09
3	3	4.6889**	2013M09	3.6019	2013M12	3.0842	2013M09	5.3208***	2011M12	5.0381**	2013M09
6	3	4.1641*	2013M09	3.9915*	2013M09	2.5863	2013M09	6.3164***	2011M12	5.6303***	2013M04
9	3	3.9760*	2013M09	3.9730*	2013M09	2.5291	2013M09	5.5605***	2013M09	5.5864***	2013M09
12	3	3.2405	2013M09	4.4701**	2013M09	3.1993	2011M10	6.5527***	2010M12	5.8339***	2010M11

Panel C: Quandt-Andrews-Test of closed-end funds–*LIQX*-measures regressed over div. rolling periods and time-lags											
Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*
1	1	17.5657***	2009M02	16.8587***	2009M02	14.5401***	2009M04	17.7555***	2009M04	12.5818***	2009M02
3	1	16.4762***	2009M02	23.8746***	2009M02	18.1836***	2009M02	22.2012***	2009M02	14.0617***	2009M04
6	1	19.0825***	2009M02	24.8698***	2009M02	18.5622***	2009M02	19.5139***	2009M02	15.1665***	2011M09
9	1	17.3736***	2009M02	22.8245***	2009M02	16.5054***	2009M02	15.8017***	2009M02	16.4019***	2011M09
12	1	16.0468***	2009M02	20.9105***	2009M02	15.5126***	2009M02	15.1326***	2009M02	16.2676***	2010M09

Table 9 (continued)

Panel C: Quandt-Andrews-Test of closed-end funds–*LIQX*-measures regressed over div. rolling periods and time-lags

Averaged across *M* months	Lag	*ILLIQ*		*ILLIQ AT*		*ZHANG*		*LIU*		*ZEROs2*	
		sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*	sup*F*-test	*Max. Date*
1	2	16.7847***	2009M04	25.7912***	2009M04	17.2959***	2009M04	19.6818***	2009M04	15.4550***	2009M02
3	2	17.8434***	2009M02	23.3396***	2009M02	17.5426***	2009M02	23.0617***	2009M01	17.2441***	2009M04
6	2	17.8680***	2009M02	21.0491***	2009M02	16.1584***	2009M02	17.9514***	2009M01	17.7028***	2011M09
9	2	16.4084***	2009M02	19.1531***	2009M02	13.9279***	2009M02	14.3059***	2009M02	18.2692***	2011M09
12	2	15.0821***	2009M02	18.8678***	2009M02	12.5005***	2009M02	13.2440***	2009M01	17.9273***	2010M10
1	3	17.7324***	2009M02	19.4576***	2009M02	21.1085***	2009M02	24.2465***	2009M02	15.4582***	2009M04
3	3	22.6297***	2009M02	20.6309***	2009M02	16.9138***	2009M02	24.7003***	2009M01	19.0609***	2009M02
6	3	18.5078***	2009M02	18.1972***	2009M02	14.5082***	2009M02	16.7410***	2009M02	18.1554***	2011M09
9	3	16.7126***	2009M02	17.4387***	2009M02	12.9003***	2009M02	14.8282***	2009M02	18.9254***	2011M09
12	3	15.5069***	2009M02	18.0617***	2009M02	11.5566***	2009M02	13.9371***	2009M01	18.1374***	2010M10

The regression analyses in Table 8 are subject to the well-known Quandt–Andrews breakpoint test for structural breaks. Panel A describes the results over time for the stocks and REITs sample. We report the statistics for the maximum *F* test with absolute values. ***, **, and * denote the asymptotic Hansen *p*-values (1997) at the 1%, 5%, and 10% levels. The Quandt–Andrews test does not provide an estimate of the times at which structural breaks occur, though the *Max. Date* column of the table shows the time at which the critical value in the test statistics was exceeded. Panel B describes the results for the comparable observations for the open-end fund sample (see Table 8, Panel B) and Panel C presents the results for the analysis of closed-end funds based on Table 8, Panel C

Table 10 Excess returns and illiquidity: the effects considering the 2008 Global Financial Crisis on stocks and REITs

Panel A: Excess returns of stocks and REITs regressed on *LIQX* over div. rolling periods and lags

Averaged across M months	Lag	ILLIQ			ILLIQ AT			ZHANG			LIU			ZEROs2		
		$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*
1	1	0.122	0.327	−12.618***	0.108	−0.099	−12.036***	0.850	−2.478	−11.985***	3.385*	7.315***	−10.796***	1.889	3.985*	−12.392***
3	1	0.819	0.791	−13.710***	1.033	−0.278	−12.452***	2.107	−11.833***	−12.351***	4.109**	16.114***	−10.919***	5.464***	5.753	−12.125***
6	1	1.170*	0.676	−13.669***	1.304	−1.672	−12.351***	2.706*	−26.682***	−11.827***	3.239	35.084***	−11.532***	7.488***	13.809	−11.837***
9	1	1.515**	1.670	−13.846***	1.611	−1.233	−12.189***	3.253*	−32.891**	−11.370***	2.480	40.507***	−11.811***	8.731***	3.428	−11.734***
12	1	1.607*	4.878	−14.355***	1.620	−0.228	−11.987***	4.078**	−20.694	−11.768***	2.229	63.423***	−12.050***	10.478***	1.186	−11.533***
1	2	0.478	0.187	−12.992***	0.722	−0.156	−12.248***	1.580	−3.282*	−11.994***	3.796**	5.802***	−10.624**	4.051***	3.496*	−12.264***
3	2	1.067*	0.276	−13.641***	1.153	0.108	−12.527***	2.778*	−7.387**	−12.201***	3.142	11.477***	−10.890***	5.977***	3.986	−11.839***
6	2	1.220*	0.420	−13.418***	1.380	−0.384	−12.331***	3.427**	−13.504**	−11.685***	2.101	18.270***	−11.533***	7.862***	6.585	−11.656***
9	2	1.501**	1.114	−13.584***	1.657	−0.052	−12.135***	4.067**	−15.461**	−11.251***	1.424	19.657***	−11.810***	9.063***	1.332	−11.668***
12	2	1.520*	2.864	−14.151***	1.583	0.721	−11.992***	4.559**	−10.486	−11.514***	0.844	28.953***	−11.930***	10.674***	−3.076	−11.137***
1	3	0.666*	0.129	−12.996***	0.626	−0.206	−12.249***	2.469*	−3.821**	−12.005***	2.576	6.876***	−10.847***	3.238**	3.603*	−12.030***
3	3	0.771	0.685	−13.686***	0.769	0.508	−12.464***	3.236**	−5.000	−12.100***	1.945	10.010***	−11.124***	6.076***	4.289	−11.686***
6	3	1.255**	0.460	−13.249***	1.392	0.048	−12.329***	3.987**	−8.989*	−11.597***	0.998	13.955***	−11.751***	6.725**	8.186*	−11.702***
9	3	1.384*	1.372	−13.672***	1.493	0.736	−12.191***	4.615**	−10.096*	−11.043***	0.582	13.994**	−11.940***	8.939***	2.848	−11.650***
12	3	1.302	2.969	−14.562***	1.341	1.484	−12.133***	4.874**	−5.702	−11.491***	−0.132	20.430***	−11.920***	10.588***	1.111	−11.146***

Panel B: Excess returns of diverse portfolios to *LIQX* with lag 3 months

#P	Averaged across M months	ILLIQ			ILLIQ AT			ZHANG			LIU			ZEROs2		
		$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*
All	1	0.666*	0.1290	−12.996***	0.626	−0.206	−12.249***	2.469*	−3.821**	−12.005***	2.576	6.876***	−10.847***	3.238**	3.603*	−12.030***
P1	1	0.433	0.0427	−11.868***	0.414	0.337	−11.665***	0.988	−4.908**	−10.336**	2.408	7.386***	−10.141**	2.837	2.666	−11.241***
P2	1	0.495	−0.4652	−12.317***	0.541	−0.628	−12.376***	2.363	−4.423**	−12.159***	3.636	9.594***	−10.742***	2.406	5.466***	−12.745***
P3	1	1.095**	0.6912	−15.031***	0.845*	−0.209	−13.091**	3.587**	−2.968	−13.455**	1.074	4.744**	−12.144**	4.230***	2.712	−12.511**

Table 10 (continued)

Panel B: Excess returns of diverse portfolios to *LIQX* with lag 3 months

#P	Averaged across *M* months	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*
All	12	1.302	2.9687	−14.562***	1.341	1.484	−12.133***	4.874**	−5.702	−11.491***	−0.132	20.430***	−11.920***	10.588***	1.111	−11.146***
P1	12	1.649*	3.2280	−14.077***	0.648	1.776	−11.597***	4.619*	−9.880	−9.998**	−1.222	20.561**	−11.534***	12.091***	−9.639	−9.672**
P2	12	0.916	1.3994	−13.606***	1.474	0.785	−12.313***	4.174*	−2.730	−12.316***	0.693	26.853***	−11.988***	11.129***	12.875	−12.142***
P3	12	1.834*	4.2018	−16.347***	2.014*	1.913	−12.845**	6.118**	−4.746	−12.512**	−1.634	16.037*	−13.146**	9.053**	1.558	−12.035**

Based on the evidence of potential structural breaks, we add a dummy *FinCrisD* for the phase of the Global Financial Crisis from September 2008 to February 2009. All other presentations correspond to those in Table 8. Panel A shows the results over time of the time-series regression analyses of the sample of stocks and REITs, which were analyzed from July 2003 to June 2017. Panel B gives the estimates of the coefficients and the corresponding t-statistics of our calculations related to three size-based portfolios (P1 represents stocks with small market capitalization, P3 aggregates stocks with higher market capitalization) and the total sample as a function of expected and the unexpected illiquidity

Table 11 Excess returns and illiquidity: The effects considering the 2008 Global Financial Crisis on open-end funds

Panel A: Excess returns of OEFs regressed on *LIQX* over div. rolling periods and lags

Averaged across M months	Lag	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*
1	1	0.054	−0.009	−0.565*	−0.051	−0.200	−0.525*	0.196	0.230	−0.534*	−0.070	1.176	−0.587**	−0.468**	0.817**	−0.565**
3	1	0.166	−0.379	−0.494	−0.044	−0.218	−0.569*	0.533	−0.250	−0.478	0.121	−2.627	−0.623**	−0.162	0.944	−0.605**
6	1	0.162	−1.186*	−0.472	−0.030	−0.624	−0.576**	0.695**	−2.305*	−0.462	0.156	−1.634	−0.615**	0.030	1.269	−0.565**
9	1	0.140	−0.824	−0.515	−0.042	−0.421	−0.582**	0.772**	0.813	−0.421	0.249	0.815	−0.631**	0.323	2.040	−0.577**
12	1	0.163	−1.700	−0.491*	−0.017	−0.930	−0.571*	0.778**	−2.451	−0.489*	0.114	−3.865	−0.565**	0.182	−9.223**	−0.794***
1	2	0.174	−0.074	−0.504*	−0.165	−0.167	−0.484	0.392	0.115	−0.499*	0.252	−0.351	−0.642**	0.103	0.472	−0.613**
3	2	0.191	−0.211	−0.475	−0.084	−0.138	−0.555*	0.677**	−0.210	−0.448	0.251	−2.480	−0.623***	0.160	−0.123	−0.608**
6	2	0.174	−0.540*	−0.473	−0.073	−0.220	−0.566*	0.778**	−1.098	−0.434	0.204	−3.359	−0.590**	0.322	−1.136	−0.686**
9	2	0.154	−0.361	−0.508	−0.138	0.145	−0.580**	0.711**	1.175	−0.408	0.220	−1.441	−0.600**	0.350	0.264	−0.643**
12	2	0.198	−1.059	−0.515*	−0.024	−0.366	−0.579*	0.848**	−1.702	−0.523*	0.153	−2.831	−0.534*	0.341	−7.457***	−0.849***
1	3	0.136	−0.045	−0.529*	−0.123	−0.180	−0.481	0.419	0.122	−0.497*	0.356	−0.769	−0.644**	0.116	0.470	−0.622**
3	3	0.086	0.013	−0.526*	−0.147	−0.111	−0.534*	0.502*	0.188	−0.473	0.233	−1.162	−0.601**	0.084	0.032	−0.603**
6	3	0.156	−0.226	−0.502*	−0.066	−0.1	−0.565*	0.775**	−0.446	−0.458	0.251	−2.177	−0.578**	0.440	−1.287	−0.721**
9	3	0.186	−0.409	−0.519*	−0.061	−0.096	−0.578**	0.773**	0.304	−0.446	0.231	0.069	−0.622**	0.330	0.409	−0.630**
12	3	0.221	−0.730*	−0.499*	−0.003	−0.331	−0.575*	0.879**	−0.977	−0.513*	0.187	−1.057	−0.565*	0.444	−4.840**	−0.826***

Panel B: Excess returns of diverse portfolios to *LIQX* with 3-month lag

#P	Averaged across M months	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*
All	1	0.136	−0.0453	−0.529*	−0.123	−0.180	−0.481	0.419	0.122	−0.497*	0.356	−0.769	−0.644**	0.116	0.470	−0.622**
P1	1	0.198	−0.3549	−0.454	−0.072	−0.359	−0.305	0.881	−0.249	−0.316	0.656	−2.285	−0.542*	0.099	0.801	−0.500*
P2	1	0.193*	0.1078	−0.608	−0.211*	−0.112	−0.628*	0.433*	0.431*	−0.616*	0.401	0.010	−0.819**	0.243	0.597*	−0.794**

Table 11 (continued)

Panel B: Excess returns of diverse portfolios to *LIQX* with 3-month lag

#P	Averaged across *M* months	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*
P3	1	0.022	0.0268	−0.505	−0.114	−0.117	−0.438	0.068	0.058	−0.506	0.170	−0.386	−0.550	0.073	0.086	−0.534
All	12	0.221	−0.7303*	−0.499*	−0.003	−0.331	−0.575*	0.879**	−977	−0.513*	0.187	−1.057	−0.565*	0.444	−4.840**	−0.826***
P1	12	0.373	−1.5110	−0.324	0.017	−0.515	−0.430	1.641**	−2.378	−0.334	0.374	−6.145	−0.231	0.960	−10.698*	−0.966***
P2	12	0.256*	−0.6713	−0.628*	0.035	−0.350	−0.736*	0.936***	−0.584	−0.645*	0.241	1.366	−0.830**	0.474	−3.430*	−0.951***
P3	12	0.071	−0.2299	−0.496	−0.042	−0.182	−0.512	0.283	−0.392	−0.504	0.065	0.570	−0.556	0.142	−2.195**	−0.619

Panel A shows the results over time of the time-series regression analyses of the sample of the open-end funds, for the period July 2003–June 2017. All presentations correspond to those in Table 10

Panel B gives the estimates of the coefficients and the corresponding t-statistics of our calculations related to three size-based portfolios (P1 represents stocks with small market capitalization, P3 aggregates stocks with higher market capitalization) and the total sample as a function of expected and the unexpected illiquidity

Table 12 Excess returns and illiquidity: The effects considering the 2008 Global Financial Crisis on closed-end funds

Panel A: excess returns of CEFs regressed on *LIQX* over div. rolling periods and lags

Averaged across *M* months	Lag	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*
1	1	0.427	−0.187	0.121	0.290	0.189	0.048	3.008	0.052	−0.162	−25.508	−40.433	1.014	8.488	−17.574	0.188
3	1	0.743	−0.206	−0.097	−0.578	−0.983	0.685	2.983	1.937	−0.183	−25.189	−57.576	0.980	24.035	−65.775	−0.219
6	1	2.025	−2.598	−0.833	0.368	−3.548	0.099	4.749	0.314	−0.449	−21.622	124.690	0.655	47.232	−142.597	−0.953
9	1	3.555**	−3.317	−1.804*	1.440	−2.096	−0.632	6.930	5.199	−0.805	−22.706	307.447	0.284	82.037*	−104.469	−1.819
12	1	4.539***	−4.499	−2.390**	2.192	−1.218	−1.122	8.069*	17.619	−1.040	−27.805	417.383*	0.112	108.542*	−85.195	−2.367*
1	2	0.426	0.036	0.104	−0.496	0.391	0.476	2.326	0.865	−0.052	−32.826**	−47.732	1.369	8.117	−11.345	0.237
3	2	1.334	0.094	−0.392	0.390	−1.682	0.250	4.651*	1.824	−0.419	−32.465**	−31.996	1.258	28.156	−24.007	−0.253
6	2	2.940**	−1.662	−1.224	1.311	−3.690	−0.321	6.620**	−0.313	−0.655	−32.324*	94.260	0.744	59.975	−75.062	−1.188
9	2	4.439***	−1.570	−2.203**	2.300	−3.708	−1.030	8.657**	6.170	−1.061*	−36.911**	182.658*	0.305	89.472*	−18.414	−1.901
12	2	5.205***	−0.508	−2.654***	2.842*	−1.582	−1.440	9.701***	19.940**	−1.415**	−44.018**	241.637**	0.109	112.749*	24.156	−2.390*
1	3	0.753	0.015	−0.023	0.729	0.166	−0.136	2.878	1.249	−0.154	−38.198**	−38.843	1.578	25.447	−15.671	−0.110
3	3	1.730	0.466	−0.679	1.270	−1.439	−0.171	6.207***	3.090	−0.739	−39.395**	−7.510	1.370	38.329	−16.577	−0.506
6	3	3.649***	−0.954	−1.577*	2.339*	−3.464	−0.819	8.356***	1.224	−0.926	−41.112**	78.885	0.756	76.382	−58.039	−1.614
9	3	5.111***	−0.748	−2.548***	3.160**	−3.147	−1.452	9.868***	8.756	−1.324**	−47.583***	122.355*	0.389	100.204*	−8.106	-2.121*
12	3	5.556***	1.394	−2.873***	3.474**	−0.985	−1.803	10.560***	21.455**	−1.724**	−55.914***	160.598*	0.211	115.026*	48.088	−2.436*

Panel B: Excess returns of diverse portfolios to *LIQX* with 3-month lag

#P	Averaged across *M* months	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*	$\overline{LIQX}^M_{m-l}$	$LIQX^U_m$	*FinCrisD*
All	1	0.753	0.0151	−0.023	0.729	0.166	−0.136	2.878	1.249	−0.154	−38.198**	−38.843	1.578	25.447	−15.671	−0.110
P1	1	1.149	−0.4938	0.464	0.946	−1.745	0.839	3.580	−1.057	0.412	−64.732**	−80.796	3.035**	43.589	−26.755	0.076
P2	1	0.665	0.2655	−1.078	0.712	0.014	−1.094	2.359	0.986	−1.078	−17.156	17.234	−0.327	9.560	−5.201	−0.854
P3	1	0.707	0.2144	0.673	0.393	1.733	0.310	2.508	4.582	0.409	−36.991*	−44.430	2.319	39.115	−12.594	0.269
All	12	5.556***	1.3937	−2.873***	3.474**	−0.985	−1.803	10.560***	21.455**	−1.724**	−55.914***	160.598*	0.211	115.026*	48.088	−2.436*
P1	12	7.744***	2.0853	−3.641**	4.474*	−2.872	−1.802	13.630***	22.808	−1.671	−90.489***	161.727	1.277	130.660	61.938	−2.322

Table 12 (continued)

Panel B: Excess returns of diverse portfolios to *LIQX* with 3-month lag

#P	Averaged across *M* months	*ILLIQ*			*ILLIQ AT*			*ZHANG*			*LIU*			*ZEROs2*		
		$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*	$\overline{LIQX}^{M}_{m-l}$	$LIQX^{U}_{m}$	*FinCrisD*
P2	12	4.337***	1.0787	−3.183***	3.024**	1.240	−2.687**	7.651***	13.431**	−2.108***	−29.377**	161.220**	−1.245*	106.276**	32.863	−3.218***
P3	12	6.198***	2.9958	−2.598*	4.082**	0.492	−1.552	12.456***	35.901***	−1.669**	−64.504***	201.397**	0.827	140.976*	104.536	−2.410

Panel A shows the results over time of the time-series regression analyses of the sample of the closed-end funds, for the period July 2007–June 2017. All columns correspond to those in Table 10

Panel B gives the estimates of the coefficients and the corresponding t-statistics of our calculations related to three size-based portfolios (P1 represents stocks with small market capitalization, P3 aggregates stocks with higher market capitalization) and the total sample as a function of expected and the unexpected illiquidity of the AR-process of illiquidity according to Eq. (14) was marginal and thus should not be overestimated, especially as it is usually non-significant.

The size effects at the portfolio level were in line with the findings we made when analyzing the stock sample. We demonstrated a highly significant portfolio effect on expected illiquidity and unexpected illiquidity for portfolio P3, each with a positive sign. This means that the securities with higher market capitalization reacted to unexpected market illiquidity with positive changes in returns. As trading activities are much less extensive overall than for equities, REITs, and open-ended funds, this may be equivalent to a kind of "flight to liquidity", as these securities generally also generate larger trading volumes.

Overall, we conclude that market liquidity influences the market returns of our sub-samples over the entire sample period. Contrary to Amihud's (2002) findings, these effects on the expected and unexpected illiquidity of the subsegments were not fully consistent in both significance and sign. Nevertheless, the time series and cross-section regression analyses showed that these were not robust results. Rather, our results suggest structural breaks effects for the GFC period, which require more intensive consideration. Thus, we can now answer our third key question of how fluctuations in liquidity affect returns. For all of our samples, we can accept the hypothesis that expected illiquidity has a positive effect. We also found a negative effect of unexpected illiquidity on future returns for our sample of stocks, REITs, and OEFs. In contrast, unexpected illiquidity had a positive effect on CEFs. We can furthermore state the importance of choosing the illiquidity measure regarding securities. While Amihud's (2002) *ILLIQ* generally serves well in both cross-sectional and time-series studies, the choice of averaged illiquidity data is advantageous, at least for the samples of stocks, REITs, and CEFs. Of the remaining measures, Kang and Zhang's (2014) adjusted *ILLIQ* sticks out, offering interesting advantages especially for the securities with lower trading activity. Liu's (2006) *LMx* and Goyenko et al.'s (2009) *ZEROs2* formally emphasizes non-trading days such that they are not useful for markets with low activity.

6 Conclusion

We empirically examined the illiquidity premia for the German real estate market. We followed Amihud (2002); however, we extended it with alternative measures of illiquidity that capture additional dimensions. First, we analyzed the cross-sectional relationship between illiquidity and expected returns. While prior studies proposed numerous measures of liquidity, we focused on the most commonly used measure suggested by Amihud (2002). We can generally state that the securities-based asset classes for German real estate investments differ significantly in their risk/return ratios. We demonstrated that, consistent with the findings throughout the empirical asset pricing literature, illiquidity has a strong positive cross-sectional relationship with the future returns of real estate stocks and REITs. However, integrating other firm-specific factors, such as the market-book value ratio or momentum, reduced these effects; although they remained significant. However, this illustrates that a more comprehensive analysis of firm-specific factors is relevant to make a well-founded investment decision.

For the other market segments, the results were less clear. In addition, the robustness test showed that selecting the illiquidity standard is important, especially for time-series effects. Owing to the varying growth in trading volumes and the outstanding shares in the individual market segments over time, we can derive different results. Therefore, an analysis of the different *ILLIQ* variations can provide valuable insights. Here, Kang and Zhang's (2014) measure, which extends Amihud's (2002) *ILLIQ* by a factor for non-trading days, seems a useful extension. In contrast, other measures further weighting non-trading days are not appropriate. Moreover, in many models averaged illiquidity data stabilized the results.

Second, our analysis of the impact of unexpected illiquidity on future returns resulted in diverse findings. While the results of earlier studies hold for the OEF segment, we can only partially confirm the results for the equity market.

Lastly, our analysis suggests the presence of a structural break in the relationship between real estate returns and market liquidity, which affects the importance of illiquidity significantly. In addition, we must consider other, special factors related to "suspended" OEFs, given that asset price reductions may lead to price changes, and correspondingly high *ILLIQs*. However, these do not necessarily result in higher returns after the unexpected event occurs.

Further studies on the special features of the market microstructure of the trading venues for CEFs and the effects of trading opportunities for OEFs, which investors can return to the issuer daily at net asset value under certain conditions, must be considered. In-depth research is required to determine whether structural breaks can be identified, as well as their effects on regression analyses.

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Data availability The authors will make the results of the analysis available on request. The raw data used require the approval of the Karlsruhe Institute of Technology, Fondsbörse Deutschland AG, and Deutsche Zweitmarkt AG.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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