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Liquidity and conditional market returns: Evidence from German exchange traded funds

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A B S T R A C T

In the spirit of Merton (1973), we assert that temporary aggregate market illiquidity is compensated for in the form of higher conditional market returns. In order to test this hypothesis, we use two available liquidity proxies, namely versions of the Amihud illiquidity measure and a measure based on exchange traded fund prices. Our investigation is based on vector autoregressive models for the German stock market between July 2006 and June 2010. The fund-based illiquidity proxy dominates in capturing consistent results for the determination of time-varying market returns. Temporary illiquidity is indeed compensated for by higher market returns. We confirm a bidirectional relation between illiquidity and market returns, i.e. current returns depend on lagged illiquidity and current illiquidity can be determined by a combination of past returns as well as past illiquidity. The relation shows that illiquidity is persistent and driven by market declines.

1. Introduction

In their seminal paper, Amihud and Mendelson (1986) point out that liquidity has a significant impact on asset prices. Periods of market stress repeatedly exhibit that liquidity dries up and therefore stock markets overall do no longer provide the characteristics of stable turnover, balanced spreads, and smooth adjustments of price.[1] Any form of temporary illiquidity increase in stock markets is therefore an important signal to market participants. It is of particular interest to study the characteristics and determinants of aggregate market liquidity as well as its impact on aggregate asset prices.[2]

The present paper investigates temporary aggregate stock market illiquidity premia in the form of higher conditional expected market returns. We consider how liquidity affects market returns and, in turn, whether liquidity is determined by past returns. Part of our investigation of market liquidity concerns the availability of alternative measures, which can be used as illiquidity proxies. Our paper provides a contribution in this area, since few studies deal with these aspects so far.[3] In our study, liquidity is captured by two different proxies that are applied in two versions, respectively. First is the established Amihud (2002) illiquidity proxy, ILLIQ, which measures the price-impact of a one-dollar trading volume. Our first version follows Amihud and calculates absolute returns based on closing quotes. The second version, calculates absolute returns based on opening and closing quotes. Second is an illiquidity proxy as proposed by Chacko et al. (2010). It captures illiquidity based on the price difference between an index and an exchange traded fund (ETF) that designed to replicate the index. This fund-based illiquidity measure is also applied in two versions, namely as the general version as well as a transformed measure, which is denoted as EILLIQ. The object of our investigation is the German stock market, where a set of several ETFs based on the DAX index is available.

We use vector autoregressive (VAR) models in order to investigate the multivariate relation between market returns and illiquidity. We estimate the models for the German stock market index DAX during the period from July 2006 to June 2010. Our results confirm a significant

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[1] Sarr and Lybek (2002) and Ourir and Snoussi (2012) consider market liquidity under stress, where liquidity proxies may tend to provide unreliable results as the normally positive relation of volumes and volatility does not hold; see e.g. Marsh and Wagner (2000). Claessens et al. (2011) argue that financial markets are cyclic and that stress periods hence evolve at regular intervals. Market liquidity appears to be related to the development of the business cycle; see e.g. Næs et al. (2011) and Apergis et al. (2015).

[2] For example, Hasbrouck and Seppi (2001) fail in detecting a significant relationship between liquidity and returns. Amihud (2002) finds a positive relationship between expected illiquidity and returns, whereas unexpected illiquidity causes prices to decline. Bekaert et al. (2007) show that the local risk of variations in liquidity has the largest positive impact on expected returns, even assuming that markets are globally integrated. Wagner (2008) shows that lagged illiquidity relates to expected stock market returns and that illiquidity shocks in the U.S. are followed by illiquidity reactions in other developed markets. Uddin (2009) examines relative market liquidity and confirms a negative relation between stock returns and liquidity. Hameed et al. (2010) find that market drops decrease stock liquidity and that, following such drops, significant returns to supplying liquidity are obtainable. Bank et al. (2010) detect a compensation for illiquidity in the form of increased individual stock returns.

[3] Chacko et al. (2010) indicate that liquidity measures applied thus far may capture risks rather than illiquidity. Goyenko et al. (2009) find evidence for different liquidity measures capturing the same fundamental liquidity aspects. Muscarella and Piwowar (2001) and Bank et al. (2010) obtain results that confirm that applied liquidity measures indeed capture liquidity.

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and positive compensation of illiquidity in the form of higher conditional returns. We find that the results differ for the applied illiquidity measures. The findings for the Amihud illiquidity measure ILLIQ, confirm that current market illiquidity is persistent and Granger-caused by lagged market drops. The illiquidity measure ELLIQ dominates the Amihud measure in capturing the illiquidity–return relation and thereby yields consistent and significant overall results. These underline a positive illiquidity premium as part of a bidirectional relationship between illiquidity and returns, i.e. current returns depend on lagged illiquidity and current illiquidity depends on past returns as well as illiquidity. This bidirectional relationship is not found for the model based on the ILLIQ proxy.

The remainder of this paper is organized as follows. Section 1 presents a brief theoretical view on liquidity and outlines our basic hypothesis. Section 2 contains the empirical investigation including the data, the illiquidity proxies and the model estimation results. Section 3 concludes.

1. Liquidity and returns

From a theoretical perspective, liquidity has an impact on asset pricing and variations in liquidity result in a variation of asset prices. In the cross-sectional setting, the models derive the implications of liquidity and liquidity risk in the capital asset pricing model context; see for example Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Wang and Chen (2012).

In the time-series setting, the level of liquidity varies over time, as shown by Amihud et al. (1990) and Amihud (2002). With the arguments used by Merton (1973) who derives a time-varying market risk premium, it follows that time-variation in aggregate market illiquidity should relate to a time-varying market illiquidity premium. Assume that $\sigma^2_{M,t}$ denotes the conditional variance of market returns and $\text{ILL}_{M,t}$ denotes the conditional aggregate market illiquidity. It then follows that not only one but several risk factors are priced on the market level. Investors that try to hedge against adverse changes in the investment opportunity set, will adjust their holdings in the risky asset (i.e. the market portfolio) based on their expectations of future risk as well as liquidity. The purest hypothesis we can derive is therefore that expected market returns conditional on time-t illiquidity information are given as

$$\mathbb{E}_t(R_{M,t+1}) - \mu = \lambda\,\text{ILL}_{M,t}, \tag{1}$$

where μ is a constant and we expect a positive illiquidity premium, $\lambda > 0$. As market liquidity is not directly observable it has to be captured by proxies. Obviously, there is no single measure that is able to capture all properties of liquidity. The Amihud (2002) proxy will—as all other liquidity proxies—generally suffer from drawbacks.[4] Nevertheless, ample of financial studies have found the measure to be helpful. We will use two measures as examples in order to test the hypothesis in Eq. (1): The fund-based illiquidity proxy by Chacko et al. (2010) as well as the well-established Amihud measure.

2. Empirical analysis

In this section we investigate how market returns are affected by aggregate illiquidity proxies. We take the German market as an example and use performance data for the DAX index as well as for several related DAX ETFs. The second subsection deals with the illiquidity measure proxies ILLIQ and EILLIQ. The calculation and interpretation of the illiquidity measures is presented in the third subsection. The last subsection investigates the multivariate relationship between returns and illiquidity within a VAR model setting.

2.1. Data

The empirical tests are based on daily returns of the DAX index. DAX index data including open quote, close quote and volume are collected from Thomson One Banker. The Deutsche Börse StatistiX data base provided DAX ETF information based on six ETF issues that were available, see Table 1 for details. All data is in Euro. The period of investigation includes four years with 1015 trading day observations, starting June 28, 2006 and ending on June 28, 2010. DAX index returns are continuously compounded. Market returns are not only derived by daily close prices, but also by daily open and close prices.

The DAX index reflects the performance of the German stock market. It is composed of the leading German listed companies and reinvests cash dividends as well as cash profits from subscription rights. In case main entry criteria match for several companies, inclusion in the index is solely based on the highest market capitalization of company free-float. The weight of each single stock in the index is determined by the market capitalization of free-float.

ETFs replicate stock market indices such as the DAX and promise intraday-liquidity to their holders. ETFs represent a fast-growing investment segment. Price differences between the ETF and the underlying index may arise due to transaction costs or due to differences between the index strategy and the replication strategy that is implemented by the manager. Frequently, index rebalancing due to changes in the index composition can be seen as a trigger for pricing errors. Tracking errors further arise due to differences in tax assumptions. In our study, a constant number of six different DAX ETFs as given in Table 1 is used to form a representative average daily ETF net asset value (NAV).

2.2. Illiquidity measures

2.2.1. ILLIQ and ILLIQ OC

Amihud (2002) derives the price-impact measure ILLIQ to capture the level of illiquidity and to determine the relationship between illiquidity and returns over time. ILLIQ tries to capture the percentage change in price that is impacted by a trading volume of one dollar of a particular asset on a particular day t, thus representing the level of illiquidity:

$$\text{ILLIQ}_t = \frac{\left|R_t^{CC}\right|}{VOLD_t}. \tag{2}$$

Here, R_t^{CC} represents the return on day t, calculated based on close to close prices. $VOLD_t$ stands for the respective traded dollar volume. In particular, it is derived by the number of shares multiplied by the respective day's closing price. The higher ILLIQ, the greater the measured level of illiquidity. The approach follows the idea of market depth as represented by Kyle's-λ, which defines the effect of order flow on price. It also follows the concept of thinness of a market by measuring the outstanding supply in relation to the absolute change of price. There is a relation to the so-called Amivest measure (see e.g. Khan and Baker (1993)).

We use the Amihud measure ILLIQ as well as a modified version. The standard measure is based on day t and day $t-1$ close quotes which yield close–close returns R_t^{CC} that are used in Eq. (2). Our modified proxy ILLIQ OC is based on day t open and day t close quotes, i.e. on intraday returns, R_t^{OC} in Eq. (2). ILLIQ OC is expected to provide better results as the denominator in Eq. (2), i.e. volume, solely considers trading within the intraday period, and therefore liquidity should only be affecting intraday price activity excluding overnight price changes. To our

[4] A drawback of the Amihud proxy includes the fact that the proxy measure cannot distinguish between price changes, which are due to unobservable common information events and those which are not. Information driven events increase the illiquidity measure but do not indicate illiquidity. A different issue considers market risk factors that may be associated with available illiquidity proxy measures; see e.g. Chordia et al. (2001) and Chacko et al. (2010).

Table 1
ETF data.

ETF	ISIN	Replication type	Start date	AuM Mio Euro
ComStage ETF DAX TR	LU0378438732	Swap-based	09/08/2008	609.10
db x-trackers DAX ETF	LU0274211480	Swap-based	01/22/2007	2910.58
Multi Units Lux. — Lyxor ETF DAX	LU0252633754	Swap-based	06/28/2006	865.60
ETFlab DAX	DE000ETFL011	Full replication	03/31/2008	581.16
DAX Source ETF	DE000A0X80V0	Full replication	02/18/2010	10.82
iShares DAX (DE)	DE0005933931	Full replication	01/02/2004	4491.09

The ETF benchmark index is the DAX index. Assets under management (AuM) are as of 01/31/2011. Each ETF delivers daily closing ETF net asset value (NAV) quotes as reported by the asset manager and ETF closing quotes as reported by Deutsche Börse stock exchange during the sample period June 28, 2006 to June 28, 2010. Information was retrieved from Deutsche Börse under: http://deutscheboerse.sh02.de/EN/index.aspx?pageID=123.

knowledge, the application of ILLIQ OC based on open–close prices has not been found in the literature so far.

2.2.2. ILLIQUIDITY and EILLIQ

Chacko et al. (2010) point out that liquidity proxies can have large errors as they may relate to other market risk factors. The authors analyze the correlations of several measures from different studies. They find low correlations and argue that liquidity measures that actually capture liquidity should result in a much higher correlation. For this reason, they introduce a new liquidity proxy on the basis of traded prices of two portfolios, which should have the same value. More precisely, they choose a portfolio that is long in ETFs that replicate a particular index and short in the respective underlying index. Thereby, market risk factors are eliminated. At the same time, higher liquidity of the ETFs as compared to the underlying results in a systematic price difference between the long and the short position. This price difference can be seen as emerging from either market inefficiencies, where differences would offer arbitrage possibilities, or due to liquidity differences. Assuming markets to be efficient, the difference is interpreted as a proxy for the level of illiquidity: the greater the difference, the greater the level of illiquidity. Based on ETF prices and ETF NAVs for day t, the authors define:

$$ILLIQUIDITY_t = \left| \frac{ETF_t}{NAV_t} - 1 \right|. \quad (3)$$

In order to allow for a comparison of bond market liquidity with stock market liquidity, a non-linearly transformed illiquidity measure is introduced by the authors. We use both versions for our empirical tests, ILLIQUIDITY and the transformed EILLIQ, which is defined as:

$$\text{EILLIQ}_t = -\ln\left[\frac{NAV_t}{NAV_t + |ETF_t - NAV_t|}\right]. \quad (4)$$

As an illustration, the illiquidity measures ILLIQ and EILLIQ as well as the DAX index levels are presented in Fig. 1. The picture exhibits the differing general behavior of both illiquidity measures during the sample period.

2.3. Preliminary analysis

In order to analyze the relationship between the respective illiquidity measures of the previous section and the index returns we use changes in aggregate market illiquidity. The respective relative illiquidity measure dILL is expressed as a logarithmic difference, dILLt = ln(ILLt) − ln(ILLt − 1), where illiquidity ILL can be measured by one of our for illiquidity proxies, namely ILLIQ, ILLIQ OC, ILLIQUIDITY or EILLIQ.

Table 2 shows the descriptive statistics for all applied variables. In order to test for stationarity we first apply the Phillips and Perron PP-test and reject the non-stationarity hypothesis for all variables. The results in Table 2 show that the standard deviations of the illiquidity measures (representing estimated liquidity risk) are higher for the Amihud proxies, whereas the standard deviations for the fund-based proxies are lower and closer to that of the market returns. All variables possess a positive sample skewness. The observed positive sample skewness of the illiquidity measures is lower than the one for the returns. The sample kurtosis for all variables clearly exceeds the value of three, which is an indication of the presence of fat-tails. For all included variables, the null of normality clearly has to be rejected.

Table 3 outlines the estimated contemporaneous correlations of the market returns and the illiquidity measures. Both fund-based measures are positively correlated with the close–close and open–close returns. The remaining correlation coefficients indicate that Amihud illiquidity is weakly correlated with the returns. It can also be observed that our two main alternative illiquidity measures are hardly associated. The Amihud and fund-based illiquidity measures show very low correlations which are below 5%. This observation suggests that the measures capture different illiquidity aspects and represent uncorrelated alternative illiquidity proxies.

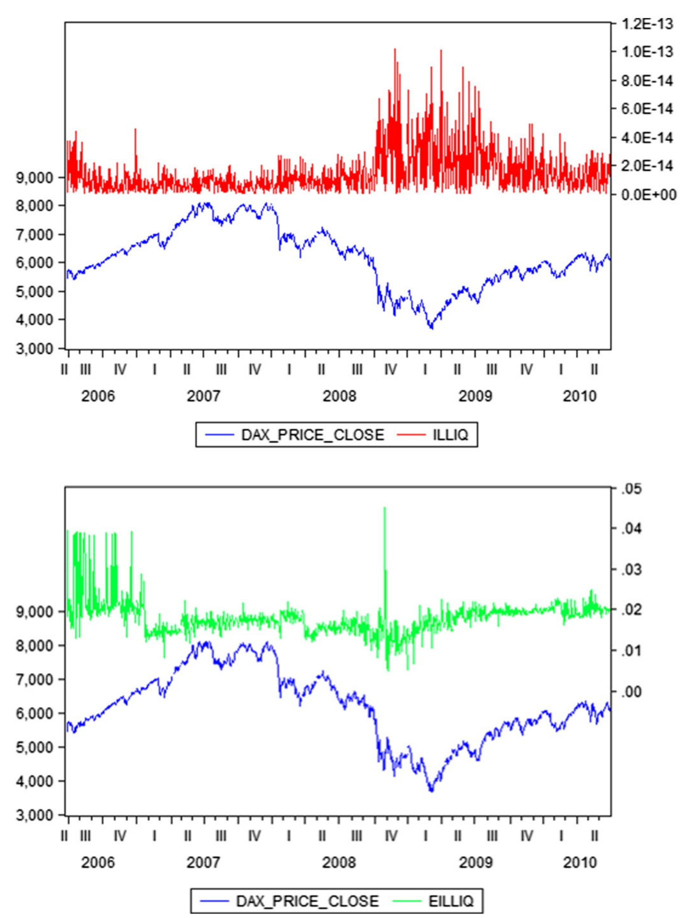

Fig. 1. Daily closing price levels of the DAX index and levels of the illiquidity measures ILLIQ (top) and EILLIQ (bottom). Sample period: June 28, 2006 to June 28, 2010.

Table 2
Descriptive statistics.

	R_CC	R_OC	ILLIQ	ILLIQ_OC	ILLIQUIDITY	EILLIQ
Mean	0.000119	0.000115	0.003448	0.001242	0.000062	0.000061
Median	0.001057	0.000610	0.004538	−0.006041	−0.004041	−0.004008
Maximum	0.107975	0.111413	7.291177	6.720310	1.169855	1.164543
Minimum	−0.074335	−0.071392	−5.345289	−5.943641	−1.150805	−1.135401
Std. Dev.	0.016616	0.014711	1.591264	1.683579	0.205369	0.203436
Skewness	0.216331	0.466864	0.137922	0.017125	0.028791	0.032041
Kurtosis	9.950072	10.898107	4.066844	4.109351	12.014643	12.024103
Jarque–Bera	2048.732	2672.394	51.30187	52.04488	3433.535	3440.779
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.120750	0.116908	3.496196	1.259082	0.062479	0.061895
Sum Sq. Dev.	0.279690	0.219213	2565.040	2871.286	42.72480	41.92403
Observations	1014	1014	1014	1014	1014	1014

Descriptive statistics for the DAX index returns and the illiquidity measures in differenced logarithmic form. The Jarque–Bera (JB) statistic tests the null hypothesis of a normal distribution. Sample period: June 28, 2006 to June 28, 2010.

2.4. Returns and illiquidity

We now investigate the relationship between illiquidity and returns within the multivariate VAR context. For the sake of space, we concentrate on a discussion of the standard illiquidity proxies ILLIQ and EILLIQ, and consider market returns as derived by open–close index quotes. This selection implies that we use standard illiquidity measures and predict one-day ahead trading-period returns. Unreported results, which are available from the authors upon request, show that other combinations of the variables do not derive significantly different results. Hence our major conclusions remain valid under such alternative choices.

2.4.1. Model definition and estimation

Three different VAR models are estimated: (i) a model based on returns and ILLIQ, (ii) a model based on returns and EILLIQ, and finally, (iii) a model including returns and both illiquidity measures. These models allow us to investigate the multivariate relationship between the variables and to compare the suitability of the two different illiquidity proxies. The use of two different illiquidity proxies helps us in considering a possible joint hypothesis problem. This problem arises in case no significant illiquidity–return relation is found, which then can either be due to the general lack of such a relation or due to the proxy, which may be inadequate. Estimation of the combined VAR model helps to us shed light on the question whether the two uncorrelated measures capture common or differing illiquidity properties.

The structure of the bivariate VAR is given by model (5)

$$
\begin{aligned}
R_t^{OC} &= \alpha_{1,0} + \sum_{i=1}^{m} \delta_{1,i} R_{t-i}^{OC} + \sum_{j=1}^{n} \beta_{1,j}\,\mathrm{ILL}_{t-j} + \varepsilon_{1,t}, \\
\mathrm{ILL}_t &= \alpha_{2,0} + \sum_{i=1}^{m} \delta_{2,i} R_{t-i}^{OC} + \sum_{j=1}^{n} \beta_{2,j}\,\mathrm{ILL}_{t-j} + \varepsilon_{2,t},
\end{aligned} \tag{5}
$$

where $\alpha_{k,0}$ represents the intercept, $\delta_{k,i}$ is the slope coefficient with respect to the returns and $\beta_{k,j}$ is the slope coefficient of the ILL illiquidity measure (as proxied by ILLIQ or EILLIQ). $\epsilon_{k,0}$ represents uncorrelated white-noise disturbances with zero mean. Note that based on the conditional market return Eq. (1), our main hypothesis is that of a positive lagged relation, i.e.: $\beta_{1,1} = \lambda > 0$.

The models are estimated by maximum likelihood. The optimal lag length in the models is based on the Schwartz Information criterion. The ILLIQ model is estimated including six lags, the EILLIQ and the combined model include four lags. The VAR estimation results are given in Table 4.

2.4.2. ILLIQ model

First are the results on the VAR model based on ILLIQ. Given the adjusted R-squared statistics, the model explains less than 1.0% of the market return variation but 46.7% of the illiquidity variation in our sample. A striking result in Table 4 is that none of the included lags of ILLIQ is significantly related to the current market return. Hence, we cannot reject the null hypothesis, $\beta_{1,1} = \lambda = 0$, stating that illiquidity does not predict market returns. ILLIQ, on the other hand, is found to be highly persistent where all lags of ILLIQ are significantly correlated with current illiquidity. The negative signs of the coefficients for all lagged values of ILLIQ indicate that a rise (drop) in illiquidity is followed by steady decreases (increases) in subsequent illiquidity levels. This persistence shows that ILLIQ is predictable and thereby underlines a pricing relation according to Eq. (1). Illiquidity is also significantly related to past returns: lags one and two show significant negative estimated coefficients, where lag one is significant at the at the 1% level. Hence, current market illiquidity (liquidity) can be thought of being Granger-caused by day-$t-1$ and day $t-2$ market drops (increases). Given the model's results, it is not clear whether the lack of a bidirectional relation between returns and illiquidity—which would include return predictability—is due to an inappropriate measurement of illiquidity or due to lack of the hypothetical relation.

2.4.3. EILLIQ model

Second are the results based on EILLIQ. Given the adjusted R-squared statistics, the model again only explains about 1.0% of the market return variation but 38.6% of the illiquidity variation. However, in contrast to the ILLIQ model, we find that lagged illiquidity has a highly significant impact on current returns. We are able to reject the null hypothesis, $\beta_{1,1} = \lambda = 0$, at the at the 1% significance level. Current illiquidity, as

Table 3
Correlations.

	R_CC	R_OC	ILLIQ	ILLIQ_OC	ILLIQUIDITY	EILLIQ
R_CC	1					
R_OC	0.914436	1				
ILLIQ	0.012277	−0.030875	1			
ILLIQ_OC	−0.030545	−0.047105	0.601648	1		
ILLIQUIDITY	0.080915	0.069371	0.042832	0.012197	1	
EILLIQ	0.080668	0.069249	0.042813	0.012277	0.999993	1

Estimated correlation coefficients, all illiquidity variables are in differenced logarithmic form. Sample period: June 28, 2006 to June 28, 2010.

Table 4
VAR estimation results for the relationship between open–close market returns and the illiquidity measures, ILLIQ and EILLIQ. Standard errors are presented in parentheses and *t*-statistics in square brackets. Sample period: June 28, 2006 to June 28, 2010.

Model	*R_OC* — ILLIQ		*R_OC* — EILLIQ			*R_OC* — ILLIQ — EILLIQ			
	R_t^{OC}	ILLIQ$_t$		R_t^{OC}	EILLIQ$_t$		R_t^{OC}	ILLIQ$_t$	*EILLIQ*$_t$
R_{t-1}^{OC}	0.056994*	−8.998008***	R_{t-1}^{OC}	0.041447	−1.224362***	R_{t-1}^{OC}	0.043036	−8.33257***	−1.259487***
	(0.03171)	(2.50793)		(0.03188)	(0.34376)		(0.03198)	(2.61262)	(0.3453)
	[1.79711]	[−3.58782]		[1.30021]	[−3.56165]		[1.34572]	[−3.18935]	[−3.64751]
R_{t-1}^{OC}	0.014927	−4.713975*	R_{t-2}^{OC}	0.036736	−1.002013***	R_{t-2}^{OC}	0.034621	−4.187038	−1.030593***
	(0.03189)	(2.52223)		(0.03211)	(0.34625)		(0.03235)	(2.64288)	(0.3493)
	[0.46802]	[−1.86897]		[1.14415]	[−2.89388]		[1.07017]	[−1.58427]	[−2.95046]
R_{t-3}^{OC}	−0.03996	−0.728645	R_{t-3}^{OC}	−0.028482	−1.006323***	R_{t-3}^{OC}	−0.032457	0.716983	−1.015464***
	(0.03186)	(2.51943)		(0.03227)	(0.34803)		(0.0324)	(2.64677)	(0.34981)
	[−1.25425]	[−0.28921]		[−0.88254]	[−2.89152]		[−1.00181]	[0.27089]	[−2.90287]
R_{t-4}^{OC}	0.067814**	−0.085276	R_{t-4}^{OC}	0.059434*	−0.510897	R_{t-4}^{OC}	0.061816*	2.050216	−0.52708
	(0.03184)	(2.51785)		(0.03238)	(0.34916)		(0.0325)	(2.6553)	(0.35094)
	[2.12989]	[−0.03387]		[1.83567]	[−1.46323]		[1.90189]	[0.77212]	[−1.50190]
R_{t-5}^{OC}	−0.059802*	5.953533**	EILLIQ$_{t-1}$	0.007503***	−0.750833***	ILLLQ$_{t-1}$	−0.000099	−0.862903***	−0.004451
	(0.03177)	(2.51203)		(0.00289)	(0.03118)		(0.00038)	(0.03132)	(0.00414)
	[−1.88258]	[2.37001]		[2.59523]	[−24.0828]		[−0.25829]	[−27.5546]	[−1.07552]
R_{t-6}^{OC}	0.005584	3.794989	EILLIQ$_{t-2}$	0.002876	−0.539126***	ILLLQ$_{t-2}$	−0.000651	−0.66444***	−0.002521
	(0.03184)	(2.51754)		(0.00345)	(0.03717)		(0.00049)	(0.03984)	(0.00527)
	[0.17540]	[1.50742]		[0.83455]	[−14.5048]		[−1.33408]	[−16.6764]	[−0.47871]
ILLLQ$_{t-1}$	−0.000126	−0.917636***	EILLIQ$_{t-3}$	−0.001658	−0.417506***	ILLLQ$_{t-3}$	−0.000021	−0.369249***	−0.004900
	(0.00039)	(0.0312)		(0.00342)	(0.03689)		(0.00049)	(0.03982)	(0.00526)
	[−0.31903]	[−29.4156]		[−0.48475]	[−11.3181]		[−0.04292]	[−9.27345]	[−0.92654]
ILLLQ$_{t-2}$	−0.000746	−0.776364***	EILLIQ$_{t-4}$	0.002228	−0.210585***	ILLLQ$_{t-4}$	0.000133	−0.149277***	−0.002291
	(0.00052)	(0.0414)		(0.00281)	(0.03025)		(0.00038)	(0.03123)	(0.00413)
	[−1.42602]	[−18.7547]		[0.79420]	[−6.96046]		[0.34898]	[−4.77924]	[−0.55492]
ILLLQ$_{t-3}$	−0.000188	−0.557245***	C	0.000067	−0.000151	EILLIQ$_{t-1}$	0.007287**	−0.204776	−0.749435***
	(0.00059)	(0.04631)		(0.00046)	(0.00497)		(0.00289)	(0.23642)	(0.03125)
	[−0.32112]	[−12.0333]		[0.14710]	[−0.03038]		[2.51795]	[−0.86614]	[−23.9841]
ILLLQ$_{t-4}$	−0.000207	−0.402619***	R^2	0.018262	0.390963	EILLIQ$_{t-2}$	0.002741	−0.22261	−0.539167***
	(0.00058)	(0.04622)	Adj. R^2	0.010416	0.386095		(0.00345)	(0.28161)	(0.03722)
	[−0.35365]	[−8.71183]					[0.79517]	[−0.79048]	[−14.4860]
ILLLQ$_{t-5}$	−0.000448	−0.29396***				EILLIQ$_{t-3}$	−0.001855	−0.048301	−0.417669***
	(0.00052)	(0.0412)					(0.00342)	(0.27957)	(0.03695)
	[−0.85977]	[−7.13465]					[−0.54197]	[−0.17277]	[−11.3036]
ILLLQ$_{t-6}$	−0.000399	−0.175557***				EILLIQ$_{t-4}$	0.002034	−0.184368	−0.209979***
	(0.00039)	(0.03105)					(0.00281)	(0.22939)	(0.03032)
	[−1.01742]	[−5.65458]					[0.72435]	[−0.80374]	[−6.92609]
C	0.000078	−0.00091				C	0.000067	0.001345	−0.000143
	(0.00046)	(0.03659)					(0.00046)	80.03765)	(0.00498)
	[0.17053]	[−0.02488]					[0.14621]	[0.03573]	[−0.02873]
R^2	0.017467	0.473276				R^2	0.022608	0.440516	0.392161
Adj. R^2	0.005617	0.466923				Adj. R^2	0.010844	0.433782	0.384845

* Indicates significance at the 10% level.
** Indicates significance at the 5% level.
*** Indicates significance at the 1% level.

in the ILLIQ model, is negatively correlated with all lags of illiquidity, which again points out that the illiquidity proxy is highly persistent. Illiquidity is again negatively related to past returns, where the coefficients at lags one, as well as those at two and three are highly significant. This confirms the findings of the ILLIQ model, while a significant bidirectional relation between returns and illiquidity is now documented in the EILLIQ model. The latter is consistent with our hypothesis that aggregate illiquidity is priced on the market level.

2.4.4. Combined model

Third are the results on ILLIQ and EILLIQ simultaneously. A target of the estimation of this combined model is to investigate whether the EILLIQ measure is by itself able to capture illiquidity risk or whether explanatory power is strengthened by additional aspects as delivered by the ILLIQ measure. Given the adjusted R-squared statistics, the model explains about 1.1% of the market return variation, 43.4% of the ILLIQ illiquidity variation and 38.5% of the EILLIQ illiquidity variation. From the results in Table 4 we also see that the combined model behaves very similarly to the first two individual models and thereby confirms the findings above. As the increase in the combined models' adjusted R-squared statistics is marginal. From this perspective it can be concluded that both measures proxy aspects of liquidity but, despite being hardly correlated, do not add predictability in a joint setting. This finding suggests that EILLIQ dominates ILLIQ as a measure of illiquidity. Summing up, there is an overall compensation for illiquidity which is better captured by the EILLIQ proxy. The VAR model based on EILLIQ is the model whose results represent the main findings of our present study.

3. Conclusion

In the spirit of the pricing of non-diversifiable risks on the market level, this paper finds significant evidence for temporary illiquidity premia in market returns and hence the pricing of aggregate market illiquidity. Using the German stock market as an example, the fund-based illiquidity measure EILLIQ is found to deliver significant and consistent results on the dynamic bivariate relation between market illiquidity and market returns. Future research on alternative measures and alternative versions of existing illiquidity measures, as well as approaches that split illiquidity into expected and unexpected components, may derive even more detailed results on this important relation.

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