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Is there an illiquidity premium in frontier markets?

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ABSTRACT

We perform a comprehensive examination of the role of stock-level liquidity in the cross-section of frontier market stock returns. Using several popular liquidity measures and a battery of asset pricing tests, we investigate the illiquidity premium in 22 countries for the years 1991–2019. Contrary to typical relationships in developed and emerging markets, we find no evidence of illiquidity premium in frontier equities. Our findings support the hypothesis that for countries not fully integrated with the global economy, the diversification benefits offset the illiquidity, which, in turn, proves less important.

1. Introduction

The illiquidity premium is one of the best established and most pervasive cross-sectional return patterns ever discovered—or is it? Illiquid securities have been shown to outperform liquid ones not only in the U.S. stock market, but also in global developed and emerging markets.[1] However, there is one asset class that has largely escaped the attention of the academic community: frontier equities. Based on the few fragmentary studies available, the liquidity-return relationship in these markets is far from obvious (Batten and Vo, 2014). The major aim of this study is to fill this gap and examine the illiquidity premium in frontier equity markets.

The frontier stock markets are the least developed global equity markets. There are at least two reasons why we find them particularly interesting. First, the term liquidity describes the degree to which large quantities of a given security could be easily sold or bought quickly, at no cost, and without causing an unfavourable movement in the price. It is no surprise that illiquidity may be considered a serious risk factor affecting asset pricing in equity markets. Indeed, this relationship has been confirmed in major developed markets, and it seems even more pronounced in emerging market equities (Bekaert et al., 2007; Amihud et al., 2015). However, the evidence from frontier markets is rather scarce and far from conclusive. Some studies, such as Marshall et al. (2013) comprehensively examine liquidity measurement in frontier equities, but do not concentrate on its role in asset pricing. Liquidity

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[1] See, e.g., for U.S. equities: Amihud and Mendelson (1986a, 1986b, 1989, 1991), Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), Chalmers and Kadlec (1997), Eleswarapu (1997), Datar et al. (1998), Chordia et al. (2001), Amihud (2002), Pastor and Stambaugh (2003), Liu (2006), Acharya and Pedersen (2005), and Huh (2014); for international developed markets: Lee (2011), Amihud (2014), Amihud et al. (2015), and Chiang and Zheng (2015); for emerging markets: Bekaert et al. (2007).

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effects in frontier equities have been studied in relatively few papers available to the international audience, and in most of these, the few frontier markets analysed have simply been treated as emerging economies. For example, in their samples, Bekaert et al. (2007) included Argentina, Amihud et al. (2015) considered Argentina, Bangladesh, Romania, and Sri Lanka, and Lee (2011) incorporated Argentina, Morocco, and Sri Lanka. In addition, Hearn and Piesse (2008), Hearn (2009), and Hearn et al. (2010) investigated the existence of the illiquidity premium in African stock markets, including some frontier ones, namely: Kenya and Morocco. The results of these studies are ambiguous and do not give clear indications about the illiquidity premium.

Even more interestingly, Batten and Vo (2014) and Phong (2016) analysed the effect of stock liquidity on stock returns in the Vietnamese stock market. Astonishingly, both studies found the relationship between liquidity and future payoffs as *positive.*[2] Batten and Vo (2014) argue that liquidity matters for markets which are integrated with the global economy. On the other hand, if the integration is low, the illiquidity premium may be of less importance, as it is compensated for by the diversification benefits of investing in uncorrelated markets.[3] As the integration of global frontier markets remains low (Blackburn and Cakici, 2017; Berger et al., 2011; Zaremba and Maydybura, 2019), we might expect that the liquidity-return relationship in these countries may differ from its counterparts in developed markets. Additionally, the illiquidity premium may be generated by foreign investors requiring an easy entry to and exit from foreign equities. In cases where there is a limited presence of international investors, the discount in the prices of illiquid firms may also be limited.

Second, we find the frontier markets highly interesting per se, as they offer a unique opportunity for international investors and yet, surprisingly, are under-researched. Whereas the emerging markets have become markedly more integrated with the global economy, largely losing their diversification abilities (Carieri et al., 2007), the frontier markets still offer an opportunity for uncorrelated trade for global investors (Berger et al., 2011; Zaremba and Maydybura, 2019). Admittedly, the current capitalization of frontier equities is fairly low, with the aggregate value of the MSCI Frontier Market Index companies slightly above USD 100 billion, constituting less than 0.3% of the global developed markets. However, their importance may be ready to grow. Although the frontier market countries account for almost a quarter of the global land area and more than 20% of the global population, only a small fraction of global GDP comes from these countries (Serkin, 2015). Nonetheless, this gap may shrink in the future, fueled by population growth, natural resources, and productivity improvements (EY, 2016).

In this paper, we are the first to comprehensively examine the illiquidity premium in frontier equity markets. To this end, we investigate data from 22 global stock markets for the years 1991–2019. We consider six different liquidity measures—turnover ratio (Datar et al., 1998), Percent Quoted Closing Spread (Chung and Zhang, 2014), proportion of zero-return days (Lesmond et al., 1999), turnover-adjusted number of zero trading volume days (Liu, 2006), the trading costs approximation of Fong et al. (2017), and the modification of Amihud's (2002) illiquidity ratio developed by Florackis et al. (2011)—and research their role in the cross-section of future stock returns. We apply sorts and cross-sectional regressions, and supplement them with a battery of robustness checks, including examination of different geographical regions, the role of calendar months, inter- and intra-country effects, and subsample and subperiod analyses.

We provide convincing evidence that—unlike in the developed and emerging markets —the illiquid stocks do not offer any major premium. There is no clear cross-sectional pattern of underperformance of liquid shares. Any indications of a positive illiquidity-return relationship are very faint and limited to only high beta stocks, most integrated stocks or the most recent decade. Our findings support the hypothesis of Batten and Vo (2014) that in markets that are not integrated with the global economy, liquidity is a risk factor of negligible importance.

The remainder of the article proceeds as follows. Section 2 discusses the data and variables. Section 3 describes the methods used in baseline tests. Section 4 presents the basic empirical results. Section 5 focuses on further robustness checks. Finally, Section 6 concludes the study.

2. Data and variables

Our study examines the role of several different liquidity measures in frontier markets. In this section, we first discuss data sources and sample preparation methods, liquidity proxies employed in our research, and other control variables.

2.1. Data

We rely on the frontier market classification by MSCI, which currently includes 22 countries from five major geographical regions: the Americas (Argentina), Europe and CIS (Croatia, Estonia, Lithuania, Kazakhstan, Romania, Serbia, and Slovenia), Africa (Kenya, Ivory Coast, Mauritius, Morocco, Nigeria, and Tunisia), the Middle East (Bahrain, Jordan, Kuwait, Lebanon, and Oman), and Asia (Bangladesh, Sri Lanka, and Vietnam). Notably, consistently with the arguments of Batten and Vo (2014), our sample of countries is characterized by low integration with global equity markets. For example, Berger et al. (2011) and Zaremba and Maydybura (2019), who using a similar sample of countries over a comparable period, demonstrate that the frontier markets remain persistently segmented from the developed markets. Also, Bekaert et al. (2011), who propose a valuation-based measure of equity market

[2] A positive relationship between liquidity and returns means that liquid stocks outperform illiquid ones.

[3] A potential limitation of the view of Batten and Vo (2014) could be that the diversification benefits may be offset—and effectively reduced—by elevated transaction costs in frontier equities. However, as demonstrated by Marshall et al. (2015), the trading costs could be mitigated by reduced trading frequency, so that the investors can still benefit from diversification.

Table 1
Composition of the research sample.

	Unfiltered sample		Filtered sample		Percentage of discarded values	
	Firms	Firm-month observ.	Firms	Firm-month observ.	Firms	Firm-month observ.
Americas						
Argentina	139	24,741	123	17,118	12%	31%
Europe & CIS						
Croatia	229	23,837	161	12,760	30%	46%
Estonia	31	4094	26	2685	16%	34%
Lithuania	68	9333	53	5395	22%	42%
Kazakhstan	48	3304	41	2463	15%	25%
Romania	260	36,833	160	7706	38%	79%
Serbia	215	12,636	66	2619	69%	79%
Slovenia	60	5423	42	2933	30%	46%
Africa						
Kenya	72	17,129	54	8002	25%	53%
Ivory Coast	102	10,186	70	5621	31%	45%
Mauritius	110	18,537	102	15,108	7%	18%
Morocco	207	18,891	34	2085	84%	89%
Nigeria	80	9549	68	6630	15%	31%
Tunisia	44	4921	38	3600	14%	27%
Middle East						
Bahrain	43	6070	41	5126	5%	16%
Jordan	179	23,271	139	10,637	22%	54%
Kuwait	156	19,717	155	16,069	1%	19%
Lebanon	11	2349	9	1616	18%	31%
Oman	109	12,497	76	8097	30%	35%
Asia						
Bangladesh	451	75,302	316	23,110	30%	69%
Sri Lanka	347	77,317	188	16,255	46%	79%
Vietnam	1577	111,558	706	29,466	55%	74%
Total						
Frontier markets	4538	527,495	2668	205,101	41%	61%

Note. The table reports the number of firms and firm-month observations in the sample of frontier market equities before and after applying the data quality filters. The last two columns show the percentage of firms and firm-month observations discarded in the filtering process.

segmentation, find that the integration of frontier equity markets is visibly lower than of developed markets.[4] This cross-sectional variation matches the reasoning of Batten and Vo (2014).

Our basic source of data is Datastream and our initial coverage encompasses frontier market companies available in this database, both survivors and non-survivors. We take into account primary securities only and discard exchange-traded funds, closed-end funds, and similar investment vehicles. To be included in our sample in month *t*, a company must have both its month *t* return and month *t-1* market value available. Our sample period runs from January 1991 to April 2019, and its length is dictated by data availability. Overall, our initial sample comprises 4538 firms and 527,495 firm-month observations.

The frontier markets are densely populated with micro-capitalization companies, penny stocks, and securities traded only once in several weeks or months. Notably, Fama and French (2012) and de Moor and Sercu (2015) argue that these types of firms escape regular asset pricing models and should be controlled for in calculations. Hence, to align our study with investment practice and focus on tradeable firms, we apply a set of dynamic filters. Following closely the frontier market study by Zaremba and Maydybura (2019), we drop firms with a previous month market value below USD 20 million and share price not exceeding USD 0.15. Also, we eliminate outlier monthly returns—those lower than −98% or exceeding 500%—to control for potential errors in the database (see Waszczuk, 2014 for a survey of outlier filtering thresholds in asset pricing). Finally, we also remove all zero-return firm-month observations, as in Daske et al. (2008). The filtered sample includes 2668 companies and 205,101 firm-month observations. The details regarding the number of companies and observations before and after applying the filters are presented in Table 1. The fraction of discarded firm-month observations (61%) is similar to that in the study of Zaremba and Maydybura (2019).

Naturally, the quantity and aggregate market value of the considered firms are not constant over time, but gradually increase. The development of our sample and the changes in its size are depicted in Fig. 1.

To mitigate the influence of local inflation rates and exchange rate issues, we follow major studies of asset pricing in frontier and emerging markets and express all prices and returns in U.S. dollars,[5] except for the prices and returns used to compute liquidity

[4] The average segmentation measure in Table 1 of Bekaert et al. (2011) for our sample of countries equals approximately 5% and is almost 70% higher than the analogous average value for developed markets.

[5] See, e.g., Blackburn and Cakici (2017), Cakici et al. (2013), Hanauer and Lauterbach (2019), or Zaremba et al. (2019b).

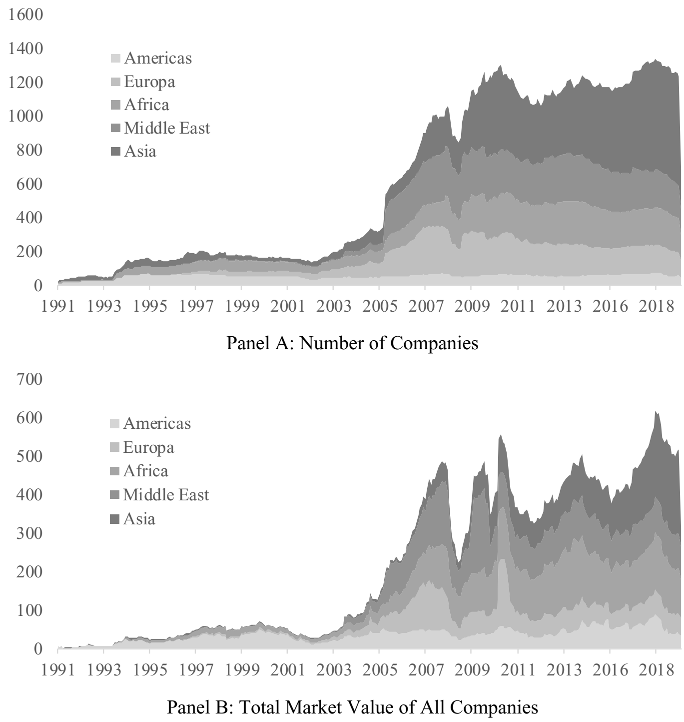

Fig. 1. Evolution of the research sample.
Note. The figure plots the number of companies (Panel A) and their aggregate market value expressed in billion USD (Panel B) in the filtered research sample investigated in this study.

measures. Consistent with this, we proxy the risk-free rate with the three-month T-bill return sourced from French (2019).

2.2. Liquidity measures

Stock liquidity is a broad and elusive concept. The level of liquidity can be defined as the extent to which an investor is able to trade (buy or sell) large quantities of a security at any time, at no cost, and without causing an unfavourable movement in the security's price. Defined as such, liquidity is hard to measure as it encompasses several dimensions, i.e., time (immediacy), quantity (depth), cost (tightness), and price impact (resiliency). No single measure is able to capture all these dimensions simultaneously (Sarr and Lybek, 2002; Chou et al., 2013) and the use of different measures may result in obtaining different indications of the level of liquidity (Sarr and Lybek, 2002; Yeyati et al., 2008; Korajczyk and Sadka, 2008; Kim and Lee, 2014). Thus, in order to encompass all the dimensions mentioned above, we use six different measures to represent liquidity. All the measures are calculated on a monthly basis and in each case, a higher value of the observed variable indicates lower liquidity.

There are numerous studies regarding the measurement of liquidity. Most of the studies carried out in order to identify the best liquidity measure compare the performance of a newly developed proxy with the performance of existing ones. There are, however, some articles where the aim is to conduct a "horse race" of liquidity measures. The first such "horse race" was undertaken by Goyenko et al. (2009), resulting in the recommendation to use the effective tick (Holden, 2009), Holden's (2009) measure, and the LOT Y-split (Goyenko et al., 2009) as a proxy for monthly and annual effective and realized spreads. As the best measure of price impact, Amihud's (2002) illiquidity measure has been indicated (Goyenko et al., 2009).

Fong et al. (2017) showed that the best proxy for the percent transaction cost is the Percent Quoted Closing Spread (PQCS), which is the bid-ask spread quoted at the end of the trading day, and if the PQCS is unavailable, then one should use the Corwin and Schultz (2012) spread estimator and the Fong et al. (2017) measure based on the proportion of zero-return days. As the best proxy for the cost-per-dollar volume, they identified Amihud's (2002) illiquidity measure, PQCS impact, LOT-mixed impact, CS impact, and FHT impact. And, as the best daily measure of percent trading cost and cost-per-dollar volume measure, the daily version of PQCS and Amihud's (2002) illiquidity measure were identified, respectively.

Lesmond (2005) and Ahn et al. (2018) discovered the best measures of liquidity in emerging markets. Lesmond (2005) shows that measures developed by Roll (1984) and Lesmond et al. (1999) perform the best in cross-country analyses. Within countries, liquidity is best measured by the proxy of Lesmond et al. (1999) and, to a lesser extent, by Amihud's (2002) illiquidity measure. Ahn et al. (2018) obtained similar results: the best liquidity measures in emerging markets are those developed by Lesmond et al. (1999) and by Amihud (2002).

Marshall et al. (2013) have run a horse race of various liquidity proxies in the frontier equity markets. They found all examined measures being of a different order of magnitude than benchmark transaction costs, which makes them inappropriate to estimate true spreads. However, some of the proxies perform well in ordering stock by its level of liquidity. Marshall et al. (2013) indicated Amihud's (2002) illiquidity measure and Gibbs model (Hasbrouck, 2004, 2009) as the best performing ones, and several different measures, such as Amivest, (Roll, 1984), FHT (Fong et al., 2017), and Zeros (Lesmond et al., 1999) as adequately performing.

Based on data availability and in order to mitigate some concerns related to differences between the markets analysed, we use six liquidity measures capturing all four dimensions and indicated as best performing in previous studies. The time dimension of liquidity is captured by the Liu (2006) measure (*LIU*), called also the turnover-adjusted number of zero trading volume days. *LIU* captures the continuity of trading—the lower the number of zero trading volume days is, the more continuous trading is:

$$LIU_{i,t} = \left[D_{i,t}^{V=0} + \frac{1/TURN_{i,t}}{Deflator} \right] \times \frac{21}{NoTD_t} \tag{1}$$

where for a stock i in month t, $D^{V=0}$ denotes the number of zero trading volume days, *TURN* is the turnover ratio calculated as given below, *NoTD* is the total number of trading days in a given market, and *Deflator* is chosen to meet the following condition for all sample stocks: $0 < \frac{1/TURN_{i,t}}{Deflator} < 1$.[6]

The quantity dimension is measured with the turnover ratio (*TURN*), as in Datar et al. (1998). Monthly turnover is measured as follows:

$$TURN_{i,t} = \left(\sum_{m=1}^{NoTD_t} \frac{V_{i,m,t}}{NoSH_{i,m,t}} \right) \tag{2}$$

where *V* is the trading volume and *NoSH* denotes the number of outstanding shares. The subscript *m* denotes a day number within the month *t*. We use a reciprocal of the original measure of Datar et al. (1998) to assure consistency with other measures in the positive relationship between the *TURN* values and illiquidity.

In order to capture the cost dimension of liquidity, we use three different liquidity measures. *PQCS* is computed as in Chung and Zhang (2014), based on the bid and ask prices quoted at the end of the trading day:

$$PQCS_{i,t} = \frac{1}{NoTD_t} \sum_{m=1}^{NoTD_t} \frac{ask_{i,m,t} - bid_{i,\mathrm{m},t}}{mid_{i,m,t}} \tag{3}$$

where *mid* is the average of ask and bid prices. Only days with available bid and ask prices were considered in calculating *PQCS*, and we omit days with zero and negative values of the spread.

The next liquidity measure used is the proportion of zero-return days (*ZERO*) by Lesmond et al. (1999):

$$ZERO_{i,t} = \frac{D_{i,t}^{r=0}}{NoTD_t} \tag{4}$$

Furthermore, Fong et al. (2017) developed a simple approximation of trading costs (*FHT*) incorporating *ZERO*. It is based on the return volatility σ and uses the inverse of the cumulative distribution of standardized normal distribution φ:

$$FHT_{i,t} = 2\sigma_{i,t}\phi^{-1}\left[\frac{1 + ZERO_{i,t}}{2}\right] \tag{5}$$

Finally, we use Amihud's (2002) illiquidity ratio (*AMIH*) to reflect the price impact dimension of liquidity. In order to assure comparability among companies with different market capitalizations in different countries, as well as to eliminate the role of different exchange rates, we apply the modified version of Amihud's measure by Florackis et al. (2011). In this modification, dollar trading volume is replaced by the turnover ratio:

$$AMIH_{i,t} = \frac{1}{NoTD_t} \sum_{m=1}^{NoTD_t} \frac{|r_{i,m,t}|}{TURN_{i,m,t}} \tag{6}$$

where $r_{i,m,t}$ denotes daily rates of return.

Various liquidity measures perform differently in predicting future returns. Chalmers and Kadlec (1998) indicate that the estimated illiquidity premium is higher when, as a measure of liquidity, amortized spread is used instead of the quoted spread. Kluger and Stephan (1997) prove that their relative odds ratio (ROR) explains expected returns better than bid-ask spread. Liu (2006) showed the poor return predictability of the turnover ratio and found that pure zero daily trading volumes predict returns better, indicating that stock returns are better predicted by the time dimension of liquidity than by the quantity dimension. Florackis et al. (2011) applied the turnover version of Amihud's (2002) illiquidity measure and found that it performs better in predicting returns than the standard version of Amihud's (2002) ratio. Butt et al. (2017) found that Amihud's (2002) measure predicts a higher illiquidity premium than does the proportion of zero-return days.

[6] We use a deflator equal to 500,000; the choice has no influence on the interpretation of the results.

2.3. Control variables

Besides our major liquidity measures, we use a range of different control variables. We use well-established cross-sectional return predictors from the finance literature. Market value (*MV*) is represented by the natural logarithm of total stock market capitalization at the end of the preceding month (Banz, 1981). Book-to-market ratio (*BM*) for month *t* is the book value of market equity at month *t*-6 over the most recent market capitalization (Rosenberg et al., 1985). Momentum (*MOM*) is the 12-month trailing average log-return with the most recent month skipped (Jegadeesh and Titman, 1993; Fama and French, 1996). *BETA* denotes stock market beta (Frazzini and Pedersen, 2014) and *IVOL* is idiosyncratic volatility (Ali et al., 2003; Ang et al., 2006), both derived from the CAPM and based on a 60-month trailing estimation period. Profitability (Hou et al., 2015) for month *t* is proxied by return on equity (*ROE*) in month *t*-6, which assures better coverage in frontier markets than do slightly more sophisticated measures by, e.g., Novy-Marx (2013). Asset growth (*AG*) is a 12-month change in total assets (Cooper et al., 2008) lagged in a similar way to *ROE*, i.e., from month *t*-18 to *t*-6. The long-run reversal (*REV*) of De Bondt and Thaler (1985) is the mean log-return in months *t*-60 to *t*-13. Skewness (*SKEW*) of the return distribution (Amaya et al., 2015) is the moment coefficient of skewness estimated based on a trailing 24-month period. Cross-sectional seasonality (*SEAS*) is computed following Keloharju et al. (2016), i.e., as the average same-calendar month return through the past 20 years, as available. Finally, value at risk (*VAR*) is estimated as in Bali and Cakici (2004), i.e., as the empirical VaR with a 5%-cutoff point (multiplied by -1). The above-referenced studies demonstrated that stocks with high *BM*, *MOM*, *ROE*, *SEAS*, and *VAR*, and low *BETA*, *MV*, *AG*, *REV*, and *SKEW* outperform their counterparts with low *BM, MOM*, *ROE*, *SEAS*, and *VAR*, and high *BETA*, *MV*, *AG*, *REV*, and *SKEW*. Table 2 demonstrates the statistical properties of all the major return predictors used in the study—including both liquidity measures and control variables—as well as their pair-wise correlation coefficients.

Notably, all the liquidity measures have highly non-normal distributions, exhibiting elevated skewness and kurtosis. This is partly driven by significant outliers, so we take measures to mitigate their influence in further tests.[7] Also, the liquidity measures are noticeably correlated to each other, particularly in the rank-based approach. For instance, Spearman's coefficients between AMIH and other liquidity proxies range from 0.298 to 0.701.

3. Methods

Fama (2015) argues that time-series and cross-sectional tests in asset pricing should be used jointly, as each of them provides unique insights and perspectives. Hence, we conduct both types examinations: the one-way portfolio sorts and cross-sectional regressions.

To perform the sorts, each month *t* we rank all the companies in the sample on the realization of the six liquidity measures—*AMIH*, *PQCS*, *FHT*, *LIU*, *TURN*, and *ZERO*—in month *t*-1 and form equal-weighted and value-weighted quintile portfolios. Also, we build a zero-investment portfolio, which serves as an ad hoc check of monotonicity in the cross-section of returns. This strategy goes long (short) the quintile of most illiquid (most liquid) shares according to the six measures. We evaluate the performance of the single-sorted portfolios with the six-factor model of Fama and French (2018), which nests other popular factor-pricing models of Fama and French (1992, 2015) or Carhart (1997):

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t \tag{7}$$

where R_t is the excess return on a security in month *t*; ε_t denotes the residual term; and α, β_{MKT}, β_{SMB}, β_{HML}, β_{WML}, β_{RMW}, and β_{CMA} are regression coefficients. MKT_t, SMB_t, HML_t, UMD_t, RMW_t, and CMA_t represent monthly returns on factor portfolios: market excess return (MKT), small minus big (SMB), high minus low (HML), up minus down (UMD), robust minus weak (RMW), and conservative minus aggressive (CMA). The factor returns are computed based on all firms available in our sample and closely replicating the procedures in Zaremba and Maydybura (2019). The statistical properties and performance of factor portfolios are demonstrated in Table A1 and Fig. A1 in the Appendix.

We supplement the examination of the portfolios from one-way sorts with two additional tests. The GRS tests of Gibbons et al. (1989) are applied to verify whether the six-factor model alphas on all five single-sorted portfolios are equal to zero. On the other hand, the simulation-based tests of monotonic relationship (MR) by Patton and Timmermann (2010) are used to verify whether the raw and abnormal returns on the quintile portfolios increase monotonically along with the underlying illiquidity.

The second baseline method employed is cross-sectional regressions is the cross-sectional regressions following Fama and MacBeth (1973). In this method, each month we regress month *t* stock returns on liquidity measures in month *t*-1 and with different control variables:

$$R_{i,t} = \beta_0 + \beta_X X_{i,t-1} + \sum_{j=1}^{J} \beta_j K_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

where $R_{i,t}$ is the monthly excess return on stock *i* in month *t*; $X_{i,t-1}$ is one of the liquidity measures (*AMIH*, *PQCS*, *FHT*, *LIU*, *TURN*, or *ZERO*); $K_{i,t-1}$ refers to the set of control variables outlined in Section 2.3; β_0, β_X, and β_j are regression parameters; and $\varepsilon_{i,t}$ denotes the residual.[8] In the baseline approach, we apply the regressions to raw excess return, but for the sake of robustness we follow also

[7] Importantly, we experiment also with winsorizing and trimming liquidity measures at various cutoff points; these operations have no qualitative influence on the overall results.

[8] For the purpose of cross-sectional regressions, we transform all the monthly measures to rank and scale them from 0 to 1. This operation is aimed

Table 2
Statistical properties of major variables used in the study.

	AMIH	PQCS	FHT	LIU	TURN	ZERO	BETA	MV	BM	MOM	ROE	AG	REV	IVOL	SEAS	SKEW	VAR
Panel A: Descriptive Statistics of the Pooled Sample																	
Mean	20,624.3	0.044	0.025	4.271	5730.7	0.397	0.709	4.689	−0.399	0.008	0.106	0.769	0.008	0.091	0.000	0.187	−0.230
Std. deviation	602,555.5	0.068	0.698	6.087	485,785.9	0.331	0.672	1.305	0.857	0.044	0.633	0.182	0.021	0.043	0.088	0.980	0.167
Skewness	98.8	5.889	397.724	1.299	428.7	0.557	0.797	0.947	−1.234	0.317	−17.123	6.347	0.186	2.576	−1.595	−0.219	−1.657
Kurtosis	12,912.6	50.266	165,440.800	0.331	184,956.0	−1.050	2.077	0.591	5.588	11.479	1023.717	72.917	2.462	16.570	62.639	3.143	7.687
Minimum	0.0	0.000	0.000	0.000	0.0	0.000	−5.414	2.996	−9.105	−0.727	−28.298	0.001	−0.182	0.001	−3.488	−4.587	−1.711
1st quartile	18.5	0.012	0.005	0.000	40.3	0.105	0.246	3.633	−0.837	−0.014	0.046	0.693	−0.004	0.063	−0.031	−0.313	−0.300
Median	123.8	0.024	0.012	0.955	181.5	0.300	0.599	4.419	−0.321	0.005	0.111	0.736	0.007	0.085	0.001	0.191	−0.199
3rd quartile	944.1	0.050	0.025	7.305	836.3	0.667	1.051	5.486	0.151	0.028	0.187	0.796	0.020	0.111	0.033	0.707	−0.125
Maximum	109,549,800.0	1.000	292.810	20.990	209,624,900.0	1.000	4.526	11.607	4.036	0.692	17.256	4.456	0.180	0.539	1.482	4.587	2.494
Observations	188,544.0	130,803	187,282	187,445	187,445.0	204,315	76,120	205,101	163,219	185,551	162,862	156,150	122,541	76,120	176,541	196,307	201,000
Panel B: Average Monthly Descriptive Statistics																	
Mean	12,271.2	0.046	0.027	4.567	4877.5	0.415	0.693	4.600	−0.334	0.010	0.074	0.780	0.010	0.098	0.005	0.175	−0.244
Std. deviation	181,486.4	0.056	0.084	5.892	47,319.9	0.323	0.640	1.254	0.767	0.042	0.413	0.166	0.020	0.044	0.095	0.973	0.172
Skewness	14.9	3.727	7.137	1.236	10.4	0.466	0.920	0.927	−0.675	0.508	−3.415	3.684	−0.084	2.022	−0.628	−0.120	−1.566
Kurtosis	315.3	26.519	103.023	0.434	147.4	−1.038	1.202	0.431	3.540	7.791	136.028	35.639	1.935	10.165	18.159	2.685	6.676
Minimum	0.0	0.007	0.000	0.007	2.1	0.001	−0.770	3.005	−4.112	−0.167	−5.733	0.380	−0.064	0.022	−0.578	−3.774	−1.263
1st quartile%	27.2	0.019	0.006	0.174	51.0	0.134	0.245	3.584	−0.753	−0.014	0.031	0.705	−0.002	0.069	−0.034	−0.337	−0.316
Median	132.3	0.031	0.014	1.604	181.7	0.342	0.532	4.316	−0.301	0.008	0.103	0.750	0.009	0.090	0.005	0.180	−0.214
3rd quartile%	846.9	0.052	0.029	7.520	789.1	0.678	1.032	5.382	0.133	0.032	0.167	0.817	0.022	0.117	0.045	0.699	−0.134
Maximum	5,162,197.0	0.494	1.827	20.204	1,064,446.0	1.000	2.790	9.212	1.788	0.224	3.249	2.250	0.077	0.362	0.479	3.920	0.254
Observations	552.9	384	549	550	549.7	599	223	601	479	544	478	458	359	223	518	576	589
Panel C: Average Monthly Pairwise Pearson's Correlation Coefficients																	
AMIH		0.245	0.286	0.136	0.281	0.090	−0.073	0.028	−0.019	−0.005	0.025	−0.015	0.015	0.057	−0.005	0.008	−0.061
PQCS			0.541	0.479	0.251	0.390	−0.154	−0.236	0.063	0.000	−0.059	−0.073	−0.031	0.166	−0.024	−0.067	−0.083
FHT				0.488	0.211	0.483	−0.100	−0.175	0.076	−0.008	−0.023	−0.047	−0.028	0.072	−0.022	−0.004	−0.077
LIU					0.348	0.808	−0.204	−0.213	0.033	−0.042	0.006	−0.088	−0.031	−0.060	−0.006	−0.006	0.060
TURN						0.267	−0.072	0.000	−0.020	−0.009	0.013	−0.032	0.007	0.050	−0.003	−0.005	−0.023
ZERO							−0.269	−0.246	0.033	−0.030	−0.002	−0.078	−0.068	−0.089	−0.015	−0.004	0.161
Panel D: Average Monthly Pairwise Spearman's Correlation Coefficients																	
AMIH		0.492	0.489	0.510	0.701	0.298	−0.131	0.012	−0.063	−0.061	0.045	−0.028	0.035	−0.012	0.004	0.018	0.011
PQCS			0.594	0.596	0.439	0.474	−0.231	−0.319	0.079	−0.053	−0.131	−0.120	−0.026	0.095	−0.020	−0.035	−0.038
FHT				0.633	0.411	0.788	−0.069	−0.254	0.140	−0.061	−0.074	−0.083	−0.079	−0.007	−0.054	−0.003	0.033
LIU					0.685	0.739	−0.170	−0.150	0.036	−0.078	−0.039	−0.118	−0.041	−0.136	−0.003	−0.004	0.132
TURN						0.541	−0.186	0.033	−0.084	−0.065	0.041	−0.060	0.037	−0.072	0.014	0.026	0.100
ZERO							−0.225	−0.232	0.051	−0.046	−0.037	−0.081	−0.065	−0.116	−0.024	−0.006	0.225

Note. The table presents the statistical properties of the six major liquidity measures used in the study—*AMIH* (Amihud, 2002; Florackis et al., 2011), *PQCS* (Chung and Zhang, 2014), *FHT* (Fong et al., 2017), *LIU* (Liu, 2006), *TURN* (Datar et al., 1998), and *ZERO* (Lesmond et al., 1999)—as well as other control variables described in Section 2.3: stock market beta (*BETA*), market value (*MV*), book-to-market ratio (*BM*), momentum (*MOM*), profitability (*ROE*), asset growth (*AG*), long-term reversal (*REV*), idiosyncratic volatility (*IVOL*), seasonality (*SEAS*), skewness (*SKEW*), and tail risk (*VAR*). *Panel A* shows descriptive statistics derived from the pooled sample of all the firm-month observations, *Panel B* displays the means of monthly cross-sectional statistics, and panels *C* and *D* present average monthly Pearson's product-moment and Spearman's rank-based correlation coefficients, respectively.

Brennan et al. (1998) and use risk-adjusted returns from the CAPM. The risk-adjusted returns, in this case, are computed as the difference between the actual return realization and the CAPM-implied return based on a trailing 60-month estimation period.[9]

To further assure the validity of our results, we calculate the regressions in several specifications. First, we perform univariate tests, including only one return-predictive variable, i.e., the liquidity measure $X_{i,t-1}$. Second, we perform broad multivariate tests including all the eleven control variables described in Section 2.3. Third, we experiment also with smaller selections of control variables. We chose the subsets of variables that underlie the factor portfolios in several established asset pricing models: the three factor model of Fama and French (1992, 1993): *BETA*, *MV*, and *BM*; the four-factor model of Carhart (1997): *BETA*, *MV*, *BM*, and *MOM*; the five-factor model of Fama and French (2015): *BETA*, *MV*, *BM*, *ROE*, and *AG*; and the six-factor model of Fama and French (2018): *BETA*, *MV*, *BM*, *MOM*, *ROE*, and *AG*.

4. Baseline empirical results

We start our investigations with the examinations of portfolio sorts, and, subsequently, continue with cross-sectional regressions. To begin with, we want to see whether sorting stocks into portfolios by liquidity measures translates into a cross-sectional pattern in returns. The results of the examinations of the one-way sorted portfolios are displayed in Table 3 and Fig. 2 presents cumulative returns on zero-investment long-short portfolios formed on *AMIH*.

Contrary to the prevailing evidence from developed and emerging markets, we cannot see any clear relationship between liquidity and future returns for any of the investigated measures. None of the long-short portfolios—either in the equal-weighted or value-weighted frameworks—produces positive and significant mean returns or alphas. These observations are also confirmed by the MR and GRS tests. In fact, though predominantly insignificant, we see that the illiquid stocks usually underperform rather than outperform liquid shares. This resembles the findings of Batten and Vo (2014), who also found no illiquidity premium in Vietnam, rather than the prevailing evidence from developed and emerging markets.

Having checked the preliminary return patterns with the sorts, we now continue with the cross-sectional regressions in the style of Fama and MacBeth (1973). The results, which are demonstrated in Table 4, corroborate our findings from Table 3. No slope coefficient, either in univariate or in multivariate regressions (in any of the specifications), proves positive and significant. On the other hand, some of them, such as *PQCS* or *LIU*, are negative at a low level of significance. The only consistently important return predictors are *BM* and *MOM*, which generally matches the findings of Blackburn and Cakici (2017) and Zaremba and Maydybura (2019) that value and momentum are the most important return drivers in frontier equities. Stock liquidity does not seem to belong to this club. Again, our outcomes contradict the findings from developed markets, highlighting the limited importance of liquidity in frontier stock markets.[10]

5. Further robustness checks

Our baseline results demonstrate lack of evidence for any significant illiquidity premium in frontier equities. To further confirm these findings, we conduct a battery of robustness checks. In particular, a) we check the role of liquidity in different global regions, b) we examine the role of inter-country and intra-country effects, c) we perform a subsample analysis, as well as investigation of the liquidity premia in d) different subperiods and e) calendar months. Note that for brevity, out of the six liquidity measures studied we limit the presentation to Amihud's ratio (*AMIH*), which is generally considered the broadly acknowledged, popular, and efficient liquidity metric (Ahn et al., 2018; Fong et al., 2017; Goyenko et al., 2009), working very well also for frontier markets (Marshall et al., 2013).

5.1. The illiquidity premium in different global regions

We commence the robustness tests with the examination of the illiquidity premium in different global regions as defined by MSCI: the Americas, Europe, Africa, the Middle East, and Asia. To this end, we form equal-weighted and value-weighted quintile portfolios from sorts on *AMIH*, based on firms listed in the individual regions. We evaluate their performance with the six-factor model (6) with its factors derived from the returns in the particular regions. The outcomes are displayed in Table 5.

We find no evidence of illiquidity premium in the researched subsamples. Nowhere do the illiquid stocks markedly outperform the liquid stocks. This finding refers to all the examined settings, including both raw and risk-adjusted returns on value-weighted and equal-weighted portfolios.

(*footnote continued*)
purely to mitigate the role of outliers and distributions strongly deviating from normality. Importantly, the rank transformation does not qualitatively influence the results, and our conclusions hold also for the raw data.

[9] Skoulakis (2008) and Petersen (2009) indicate that, in certain situations, the application of panel data regression may be more suitable than the most typical Fama-MacBeth regressions. Thus, for robustness, we apply also two-way cluster-robust panel regressions (Cameron et al., 2011; Thompson, 2011). This alternative approach yields no qualitative difference in the results, so for brevity, we do not report the detailed outcomes.

[10] Marshall et al. (2013) emphasize the necessity to extend the holding period to at least three months in frontier markets in order to avoid the detrimental impact of transaction costs. To account for that, we perform an additional robustness check, and reproduce the cross-sectional regressions with the use of three-month returns. The results do not lead to qualitatively different conclusions.

Table 3
Performance of portfolios from one-way sorts on liquidity measures.

	Equal-weighted portfolios								Value-weighted portfolios							
	Low	2	3	4	High	H-L	MR	GRS	Low	2	3	4	High	H-L	MR	GRS
Panel A: Sorts on AMIH																
R	1.02***	0.67**	0.67**	0.30	0.65**	−0.37	76.33		0.91**	0.60*	0.42	−0.03	0.53	−0.38	72.66	
	(2.72)	*(2.13)*	*(2.33)*	*(1.02)*	*(2.26)*	*(−1.09)*			*(2.26)*	*(1.91)*	*(1.19)*	*(−0.25)*	*(1.44)*	*(−1.05)*		
Vol	6.94	5.84	5.27	4.72	4.99	6.85			7.91	6.06	5.87	5.23	6.27	7.83		
α	0.46*	0.21	0.22	0.04	0.10	−0.37	31.14	39.78	0.24	0.33**	0.07	−0.28	0.01	−0.23	29.49	24.90
	(1.75)	*(1.33)*	*(1.35)*	*(0.23)*	*(0.38)*	*(−1.07)*			*(0.91)*	*(2.35)*	*(0.37)*	*(−1.53)*	*(0.04)*	*(−0.58)*		
Panel B: Sorts on CPQS																
R	0.78**	0.81**	0.45	0.59	0.13	−0.66*	70.59		0.96***	0.68**	0.76*	0.36	−0.19	−1.15***	76.06	
	(2.06)	*(2.44)*	*(1.05)*	*(1.56)*	*(0.35)*	*(−1.81)*			*(2.92)*	*(2.07)*	*(1.79)*	*(0.99)*	*(−0.55)*	*(−2.80)*		
Vol	6.01	5.82	6.52	6.75	6.06	6.25			5.70	5.81	6.52	6.73	6.74	7.05		
α	0.46	0.27	0.16	0.37	0.10	−0.37	11.93	78.96	0.51	0.27	0.55	0.18	−0.16	−0.68	21.85	47.65
	(1.18)	*(0.62)*	*(0.42)*	*(0.89)*	*(0.21)*	*(−0.52)*			*(1.53)*	*(0.61)*	*(1.34)*	*(0.38)*	*(−0.30)*	*(−1.01)*		
Panel C: Sorts on FHT																
R	1.12**	0.76**	1.11***	0.53**	0.60**	−0.52	93.18		0.78	0.70*	1.28***	0.53	0.40	−0.38	92.05	
	(2.17)	*(2.18)*	*(3.63)*	*(2.03)*	*(2.08)*	*(−1.27)*			*(1.46)*	*(1.65)*	*(3.26)*	*(1.51)*	*(1.04)*	*(−0.85)*		
Vol	9.48	6.26	5.80	5.11	5.26	8.56			9.63	7.57	7.33	6.87	6.50	9.13		
α	0.41**	0.19	0.32**	0.02	0.06	−0.35	31.48	29.04	−0.08	0.09	0.44**	0.19	−0.23	−0.15	26.32	29.48
	(2.03)	*(1.23)*	*(2.04)*	*(0.15)*	*(0.24)*	*(−1.04)*			*(−0.48)*	*(0.54)*	*(2.24)*	*(0.85)*	*(−0.75)*	*(−0.42)*		
Panel D: Sorts on LIU																
R	1.03***	0.74***	0.41	0.57*	0.55**	−0.48	62.34		1.08***	0.81***	0.24	0.29	0.37	−0.71*	86.39	
	(2.66)	*(2.61)*	*(1.50)*	*(1.88)*	*(2.18)*	*(−1.38)*			*(2.78)*	*(2.75)*	*(0.74)*	*(0.80)*	*(1.10)*	*(−1.78)*		
Vol	7.49	5.51	5.09	5.05	4.86	7.66			7.76	5.95	5.80	5.57	5.96	8.27		
α	0.58**	0.28	0.01	0.09	0.08	−0.50	50.78	20.81	0.59**	0.41***	−0.05	−0.21	0.01	−0.58	57.60	2.34**
	(2.25)	*(1.49)*	*(0.08)*	*(0.46)*	*(0.32)*	*(−1.33)*			*(2.23)*	*(2.68)*	*(−0.24)*	*(−1.04)*	*(0.02)*	*(−1.19)*		
Panel E: Sorts on TURN																
R	0.99**	0.69**	0.51*	0.38	0.70***	−0.29	63.75		0.69	0.78**	0.34	0.36*	0.46	−0.23	72.98	
	(2.35)	*(2.22)*	*(1.88)*	*(1.50)*	*(2.71)*	*(−0.81)*			*(1.37)*	*(2.31)*	*(1.10)*	*(1.65)*	*(1.25)*	*(−0.55)*		
Vol	8.16	5.90	4.80	4.29	4.75	7.88			9.05	6.76	5.10	4.69	6.15	8.56		
α	0.18	0.32*	0.23	0.12	0.20	0.01	4.10**	46.92	−0.16	0.57***	0.13	0.06	−0.03	0.13	27.21	2.88**
	(0.57)	*(1.76)*	*(1.50)*	*(0.72)*	*(0.85)*	*(0.03)*			*(−0.49)*	*(3.08)*	*(0.77)*	*(0.36)*	*(−0.13)*	*(0.26)*		
Panel F: Sorts on ZERO																
R	1.22**	0.78**	0.57*	0.77***	0.27	−0.95*	86.28		1.04*	0.79*	0.59*	0.52**	0.06	−0.99*	63.35	
	(2.07)	*(2.27)*	*(1.85)*	*(3.37)*	*(1.07)*	*(−1.80)*			*(1.81)*	*(1.90)*	*(1.82)*	*(2.08)*	*(−0.03)*	*(−1.69)*		
Vol	10.74	6.67	5.24	4.24	4.14	9.88			10.50	7.47	5.66	4.71	8.39	11.40		
α	0.24	0.02	0.03	0.43**	−0.12	−0.36	66.80	1.74**	0.11	0.08	0.21	0.18	−0.48*	−0.58	63.16	37.60
	(1.04)	*(0.09)*	*(0.25)*	*(2.40)*	*(−0.59)*	*(−1.11)*			*(0.71)*	*(0.41)*	*(1.06)*	*(0.92)*	*(−1.65)*	*(−1.48)*		

Note. The table reports the performance of equal-weighted and value-weighted quintile portfolios from one-way sorts on six different liquidity measures: *AMIH* (Amihud, 2002; Florackis et al., 2011), *PQCS* (Chung and Zhang, 2014), *FHT* (Fong et al., 2017), *LIU* (Liu, 2006), *TURN* (Datar et al., 1998), and *ZERO* (Lesmond et al., 1999). High (Low) are the portfolios of companies with the highest (lowest) variables, and *H-L* is the zero-investment portfolio going long (short) the *High* (*Low*) portfolios. *R* is the mean monthly excess return, *Vol* is the standard deviation, and *α* is the alpha from the six-factor model of Fama and French (2018). The numbers in brackets are bootstrap (for *R*) and Newey and West (1987) adjusted (for *α*) *t*-statistics. *GRS* and *MR* are *p*-values from the tests of Gibbons et al. (1989) and Patton and Timmermann (2010), respectively. *R*, *α*, *GRS*, and *MR* are expressed in percentage terms. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

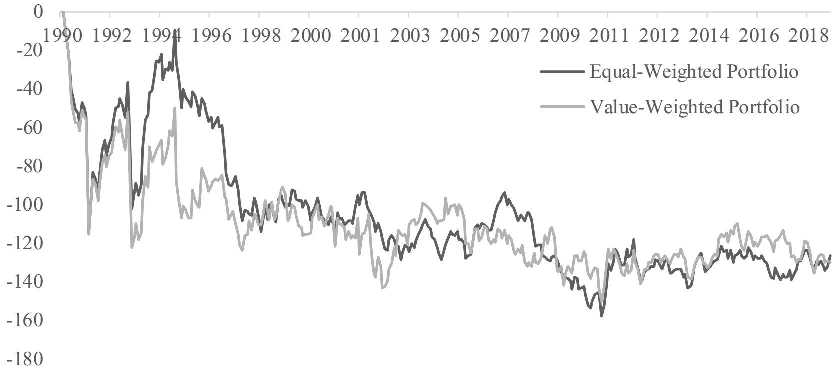

Fig. 2. Cumulative returns on long-short portfolios formed on illiquidity.
Note. The figure presents the cumulative returns on the zero-investment equal-weighted and value-weighted portfolios formed on Amihud's (2002) illiquidity measure (*AMIH*). The portfolios go long (short) the quintile of stocks with the highest (lowest) value of *AMIH*. The returns are cumulated additively and expressed in percentage terms.

5.2. *The role of intra-country and inter-country effects*

In the case of some cross-sectional patterns, the direction of the relationship between expected returns and underlying variables tends to be different at the stock level and country level. For example, the idiosyncratic risk tends to be correlated negatively with future returns in individual stocks (Ang et al., 2006) and non-negatively or positively in country indices (Bali and Cakici, 2010; Umutlu, 2019). In consequence, it is possible that our multi-market results are driven, for instance, by cross-country effects, whereas the individual stock markets still display the positive illiquidity-return relationship. Hence, we test the role of inter-country and intra-country effects.

To estimate the intra-country effects, we form equal-weighted and value-weighted zero-investment tertile portfolios going long (short) the stocks with the highest (lowest) *AMIH*. Contrary to earlier exercises, we use tertiles instead of quintiles to cope with the limited number of stocks in different countries. Subsequently, we weight the equal-weighted and value-weighted strategies equally or according to country market capitalization, respectively. In consequence, we obtain the long-short liquidity portfolios "cleaned" from the influence of the cross-country effects.

Moreover, to assess the inter-country effect, we calculate average equal-weighted and value-weighted monthly *AMIH* measures for each of the 22 considered countries. Next, based on the respective averages, we form long-short equal-weighted and value-weighted portfolios of countries, where the single country returns are calculated as the payoffs on capitalization-weighted portfolios of all the stocks in a given stock market. Hence, we obtain the inter-country effects, driven purely by cross-country liquidity differences.

Finally, for comparison, we compute returns on long-short tertile portfolios from sorts on *AMIH*, based on the pooled sample of all the firms covered. The portfolios are formed using the same procedure as discussed in Section 3.1, but the quintiles are substituted with tertiles. The results of this exercise are reported in Table 6.

Panel A of Table 6 presents the mean returns on the zero-investment portfolios formed on *AMIH* in individual countries. Observe that in only two stock markets—in Jordan and Lebanon—the payoffs are on average significantly positive. In the other 20 cases, the mean returns are predominantly non-differentiable from zero or, in a few instances, negative.

Panel B summarizes the performance of liquidity strategies implemented using the inter-country and intra-country framework. Importantly, none of them uncovers a positive illiquidity premium. Both at the country level and at the level of individual firms, the premium is insignificant. Indeed, liquidity appears to play no major role in global frontier markets.

5.3. *Subsample analysis*

In the next robustness test, we verify whether the insignificance of the relationship between liquidity and stock returns in frontier markets is independent of the type of equities or market subsample. To check this, we split our full equity universe by different variables and check the performance within. In particular, we form tertile portfolios from two-way dependent sorts on additional control variables and *AMIH*. In the first pass, we rank all the firms available in a given month on one of the control variables, i.e., *BETA*, *MV*, *BM*, *MOM*, *ROE*, *AG*, *SKEW*, *SEAS*, *REV*, *IVOL*, or VAR. In the second pass, within each tertile, we sort the stocks into three portfolios based on *AMIH*, and we also form long-short portfolios based on *AMIH* within each of the tertiles of the control variables. For conciseness, we limit our analysis to equal-weighted portfolios only. The results are shown in Table 7.

The performance of portfolios from double-sorts confirms the robustness of our phenomenon. We observe a lack of any illiquidity premium within virtually all the market segments. The lone exceptions are high beta stocks; in this case, the long-short portfolio records a six-factor model alpha of 0.65% (*t*-stat = 2.22). This observation may, in fact, support the hypothesis of Batten and Vo (2014) that the lack of a illiquidity premium in frontier stocks is likely to be linked with their low integration with the global

Table 4
Results of monthly cross-sectional regressions.

	Panel A: raw excess returns						Panel B: risk-adjusted returns					
	AMIH	PQCS	FHT	LIU	TURN	ZERO	AMIH	PQCS	FHT	LIU	TURN	ZERO
Univariate Tests												
β_X	−0.03	−0.80*	−0.42	−0.52	−0.25	−0.47	−0.51	−0.84	−0.59	−0.66	−0.45	−1.04
	(−0.08)	*(−1.70)*	*(−1.29)*	*(−1.58)*	*(−0.74)*	*(−1.26)*	*(−1.16)*	*(−1.54)*	*(−1.17)*	*(−1.40)*	*(−0.81)*	*(−1.51)*
$\overline{R^2}$	1.10	1.52	1.04	1.07	1.25	1.15	1.91	1.22	1.20	1.56	2.64	2.14
Multivariate Tests												
β_X	0.27	−0.62*	−0.26	−0.90*	−0.61	−0.39	0.27	−0.63*	−0.26	−0.90*	−0.61	−0.40
	(0.56)	*(−1.87)*	*(−0.48)*	*(−1.80)*	*(−1.17)*	*(−0.64)*	*(0.56)*	*(−1.84)*	*(−0.48)*	*(−1.80)*	*(−1.17)*	*(−0.64)*
β_{BETA}	−0.51	0.18	−0.66	−0.70	−0.63	−0.72	−0.15	0.54	−0.31	−0.35	−0.28	−0.37
	(−1.14)	*(0.30)*	*(−1.47)*	*(−1.56)*	*(−1.41)*	*(−1.58)*	*(−0.38)*	*(0.85)*	*(−0.75)*	*(−0.84)*	*(−0.75)*	*(−0.87)*
β_{MV}	−0.08	−0.10	−0.01	−0.02	−0.02	0.07	−0.08	−0.10	−0.01	−0.02	−0.02	0.06
	(−0.70)	*(−1.00)*	*(−0.05)*	*(−0.16)*	*(−0.26)*	*(0.45)*	*(−0.70)*	*(−1.02)*	*(−0.05)*	*(−0.17)*	*(−0.27)*	*(0.44)*
β_{BM}	0.75***	0.46**	0.70***	0.62***	0.52***	0.80***	0.75***	0.46**	0.70***	0.62***	0.52***	0.80***
	(3.10)	*(2.45)*	*(3.12)*	*(2.93)*	*(2.69)*	*(3.76)*	*(3.10)*	*(2.45)*	*(3.12)*	*(2.93)*	*(2.69)*	*(3.76)*
β_{MOM}	21.89***	26.48***	22.19***	19.73***	19.15***	20.62***	21.92***	26.55***	22.21***	19.76***	19.18***	20.64***
	(3.63)	*(6.42)*	*(3.90)*	*(3.52)*	*(3.46)*	*(3.59)*	*(3.63)*	*(6.42)*	*(3.90)*	*(3.52)*	*(3.46)*	*(3.55)*
β_{ROE}	3.09**	0.36	3.26**	3.31**	2.94**	2.75**	3.09**	0.36	3.26**	3.31**	2.94**	2.75**
	(2.10)	*(0.25)*	*(2.02)*	*(2.19)*	*(2.44)*	*(2.04)*	*(2.10)*	*(0.25)*	*(2.02)*	*(2.19)*	*(2.44)*	*(2.04)*
β_{AG}	−0.76	−0.12	−0.60	−0.81	−1.12	−0.17	−0.76	−0.12	−0.61	−0.82	−1.12	−0.17
	(−0.43)	*(−0.11)*	*(−0.35)*	*(−0.42)*	*(−0.57)*	*(−0.10)*	*(−0.43)*	*(−0.10)*	*(−0.35)*	*(−0.42)*	*(−0.57)*	*(−0.10)*
β_{REV}	−5.20	−2.13	−11.54	−12.80	−10.90	−4.92	−5.29	−2.20	−11.63	−12.87	−10.98	−5.01
	(−0.41)	*(−0.19)*	*(−0.96)*	*(−1.03)*	*(−0.84)*	*(−0.48)*	*(−0.42)*	*(−0.19)*	*(−0.97)*	*(−1.04)*	*(−0.85)*	*(−0.49)*
β_{IVOL}	−6.59	−4.95	−5.12	−5.19	−4.46	−1.60	−6.63	−5.00	−5.16	−5.23	−4.49	−1.64
	(−1.54)	*(−0.83)*	*(−1.12)*	*(−1.10)*	*(−0.92)*	*(−0.34)*	*(−1.55)*	*(−0.84)*	*(−1.13)*	*(−1.11)*	*(−0.93)*	*(−0.34)*
β_{SEAS}	3.09	−0.09	3.29	2.29	1.55	2.00	3.09	−0.07	3.29	2.29	1.55	2.00
	(0.86)	*(−0.02)*	*(0.87)*	*(0.62)*	*(0.42)*	*(0.53)*	*(0.86)*	*(−0.01)*	*(0.87)*	*(0.62)*	*(0.42)*	*(0.53)*
β_{SKEW}	−0.12	−0.25	−0.10	−0.14	−0.12	−0.05	−0.12	−0.25	−0.10	−0.14	−0.12	−0.05
	(−0.49)	*(−1.29)*	*(−0.49)*	*(−0.66)*	*(−0.56)*	*(−0.24)*	*(−0.49)*	*(−1.29)*	*(−0.49)*	*(−0.66)*	*(−0.56)*	*(−0.24)*
β_{VAR}	−1.60	−1.22	−1.16	−1.40	−1.58	−1.05	−1.59	−1.21	−1.15	−1.40	−1.57	−1.04
	(−0.85)	*(−0.66)*	*(−0.78)*	*(−0.79)*	*(−0.76)*	*(−0.65)*	*(−0.85)*	*(−0.66)*	*(−0.78)*	*(−0.78)*	*(−0.75)*	*(−0.65)*
$\overline{R^2}$	14.90	10.79	15.40	15.61	15.47	14.88	15.62	11.54	16.09	16.31	16.19	15.66
Alternative specifications												
β_X^{F3}	−0.10	−0.19	−0.53	−0.98*	−0.55	−0.58	−0.10	−0.19	−0.53	−0.99*	−0.55	−0.58
	(−0.23)	*(−0.35)*	*(−1.26)*	*(−1.94)*	*(−1.09)*	*(−0.98)*	*(−0.23)*	*(−0.35)*	*(−1.26)*	*(−1.94)*	*(−1.09)*	*(−0.98)*
β_X^{F4}	0.26	−0.17	−0.17	−0.76	−0.15	−0.37	0.26	−0.17	−0.17	−0.76	−0.16	−0.37
	(0.60)	*(−0.35)*	*(−0.43)*	*(−1.58)*	*(−0.32)*	*(−0.64)*	*(0.60)*	*(−0.35)*	*(−0.43)*	*(−1.58)*	*(−0.32)*	*(−0.64)*
β_X^{F5}	−0.07	−0.37	−0.45	−0.93*	−0.27	−0.24	−0.07	−0.37	−0.46	−0.94*	−0.27	−0.24
	(−0.15)	*(−0.98)*	*(−0.92)*	*(−1.77)*	*(−0.53)*	*(−0.37)*	*(−0.15)*	*(−0.98)*	*(−0.93)*	*(−1.77)*	*(−0.54)*	*(−0.37)*
β_X^{F6}	0.02	−0.39	−0.33	−0.79	0.31	−0.05	0.02	−0.38	−0.33	−0.79	0.31	−0.05
	(0.04)	*(−1.11)*	*(−0.68)*	*(−1.60)*	*(0.59)*	*(−0.08)*	*(0.04)*	*(−1.10)*	*(−0.68)*	*(−1.61)*	*(0.59)*	*(−0.07)*

Note. The table reports the average slope coefficients (β, multiplied by 100) of the cross-sectional regressions following Fama and MacBeth (1973). The raw excess returns (*Panel A*) and risk-adjusted returns (*Panel B*) are regressed on liquidity measures and additional control variables. β_X represents a coefficient of one of the liquidity measures *X*, indicated in the top row of the table: rank-transformations of *AMIH* (Amihud, 2002; Florackis et al., 2011), *PQCS* (Chung and Zhang, 2014), *FHT* (Fong et al., 2017), *LIU* (Liu, 2006), *TURN* (Datar et al., 1998), and *ZERO* (Lesmond et al., 1999). The control variables are: stock market beta (*BETA*), market value (*MV*), book-to-market ratio (*BM*), momentum (*MOM*), profitability (*ROE*), asset growth (*AG*), long-term reversal (*REV*), idiosyncratic volatility (*IVOL*), seasonality (*SEAS*), skewness (*SKEW*), and tail risk (*VAR*). $\overline{R^2}$ is the average monthly cross-sectional adjusted coefficient of determination (expressed in percentages). The top section demonstrate the results of univariate tests; the middle section focuses on the regressions incorporating all the possible control variables; the bottom section demonstrates the slope coefficients of the liquidity measures from regressions including a limited number of control variables. The regression specifications in the bottom section correspond with variables underlying established multifactor asset pricing models: β_X^{F3} controls for *BETA*, *MV*, and *BM*, which underlie the three-factor model of Fama and French (1993); β_X^{F4} controls for BETA, MV, BM, and MOM, which underlie the four-factor model of Carhart (1997); β_X^{F5} controls for *BETA*, *MV*, *BM*, *ROE*, and *AG*, which underlie the five-factor model of Fama and French (2015); and β_X^{F6} controls for *BETA*, *MV*, *BM*, *MOM*, *ROE*, and *AG*, which underlie the six-factor model of Fama and French (2018). The numbers in brackets are Newey and West (1987) adjusted *t*-statistics. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Returns on portfolios formed on liquidity in different global regions.

	Equal-weighted portfolios						Value-weighted portfolios					
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
Panel A: Americas												
R	1.06*	0.46	1.19**	0.42	0.69	−0.37	1.01	0.44	1.28**	0.13	0.73	−0.28
	(1.80)	*(0.84)*	*(2.23)*	*(0.71)*	*(1.31)*	*(−1.06)*	*(1.64)*	*(0.73)*	*(1.97)*	*(0.07)*	*(1.36)*	*(−0.59)*
α	0.40	−0.12	0.51*	−0.17	0.28	−0.12	0.40	−0.32	0.53*	−0.60*	0.41	0.01
	(1.51)	*(−0.48)*	*(1.94)*	*(−0.78)*	*(1.13)*	*(−0.36)*	*(1.23)*	*(−1.11)*	*(1.67)*	*(−1.92)*	*(1.58)*	*(0.02)*
Panel B: Europe												
R	1.25***	1.18***	0.82	0.83*	0.80	−0.45	1.44***	1.17**	0.53	0.59	0.32	−1.12**
	(2.84)	*(2.70)*	*(1.61)*	*(1.77)*	*(1.52)*	*(−1.29)*	*(3.02)*	*(2.52)*	*(0.93)*	*(1.05)*	*(0.53)*	*(−2.12)*
α	0.53*	0.38*	0.01	−0.07	−0.17	−0.71*	0.45*	0.11	−0.19	0.11	−0.12	−0.58
	(1.82)	*(1.78)*	*(0.07)*	*(−0.37)*	*(−0.80)*	*(−1.74)*	*(1.80)*	*(0.42)*	*(−0.47)*	*(0.30)*	*(−0.42)*	*(−1.26)*
Panel C: Africa												
R	0.86***	0.75**	1.08***	1.21***	1.21***	0.35	0.72**	0.63**	0.83**	1.31***	0.87**	0.15
	(3.19)	*(2.55)*	*(2.73)*	*(2.80)*	*(2.74)*	*(0.85)*	*(2.49)*	*(2.02)*	*(2.06)*	*(3.39)*	*(2.11)*	*(0.32)*
α	0.13	−0.10	0.28	0.12	−0.14	−0.27	0.32	−0.04	−0.03	0.14	−0.12	−0.44
	(0.92)	*(−0.61)*	*(1.54)*	*(0.65)*	*(−0.70)*	*(−1.18)*	*(1.14)*	*(−0.25)*	*(−0.15)*	*(0.75)*	*(−0.61)*	*(−1.10)*
Panel D: Middle East												
R	−0.11	0.11	−0.01	0.38*	0.29	0.40	0.01	0.28	0.01	0.33	0.15	0.15
	(−0.35)	*(0.32)*	*(0.04)*	*(1.67)*	*(1.02)*	*(1.13)*	*(0.00)*	*(0.81)*	*(0.14)*	*(1.14)*	*(0.51)*	*(0.36)*
α	−0.35*	0.10	0.17	0.04	−0.07	0.28	−0.29	−0.01	0.25	−0.05	−0.21	0.08
	(−1.73)	*(0.63)*	*(1.03)*	*(0.16)*	*(−0.34)*	*(0.90)*	*(−1.12)*	*(−0.03)*	*(1.37)*	*(−0.27)*	*(−0.77)*	*(0.17)*
Panel E: Asia												
R	1.27**	0.86	0.46	0.52	0.52	−0.75	1.15*	0.50	0.19	0.43	0.02	−1.12*
	(2.14)	*(1.45)*	*(0.83)*	*(1.10)*	*(1.25)*	*(−1.32)*	*(1.87)*	*(0.99)*	*(0.25)*	*(0.85)*	*(−0.11)*	*(−1.93)*
α	0.55	0.46	0.00	0.31	−0.06	−0.60	0.39	0.00	−0.17	0.20	−0.37	−0.76
	(1.26)	*(1.41)*	*(−0.01)*	*(1.00)*	*(−0.22)*	*(−1.05)*	*(0.85)*	*(0.00)*	*(−0.60)*	*(0.68)*	*(−1.19)*	*(−1.36)*

Note. The table reports the performance of equal-weighted and value-weighted quintile portfolios from one-way sorts on *AMIH* (Amihud, 2002; Florackis et al., 2011) in different global regions. *R* is the mean monthly excess return and *α* is the alpha from the six-factor model of Fama and French (2018). The numbers in brackets are bootstrap (for *R*) and Newey and West (1987) adjusted (for *α*) *t*-statistics. *R* and *α* are expressed in percentage terms. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The portfolios are formed separately in subsamples of companies listed in the Americas (*Panel A*), Europe (*Panel B*), Africa (*Panel C*), the Middle East (*Panel D*), and Asia (*Panel E*).

economy. The high-beta firms are those in which prices would most vividly co-move with international equities, so the diversification benefits would be the smallest in this case. Also, the high-beta companies are usually the ones with a high contribution to national equity indices and, in consequence, with potentially higher participation of international institutional investors. Importantly, the global institutions may be interested in the ability to enter and exit a given country easily, so stock liquidity may be something that matters.[11]

5.4. Subperiod analysis

We are also interested in the role of liquidity in different subperiods. Hence, we take a closer look at the long-short quintile portfolios from sorts on *AMIH*, which are shown in Panel A of Table 3. In particular, we examine the mean returns and six-factor model alphas in different subperiods. Thus, we split the full research period into halves based on the median return through the past 36 months (bull markets and bear markets), standard deviation of returns on *MKT* portfolio through the past 60 months, average idiosyncratic risk from CAPM estimated based on a trailing 60-month period, and cross-sectional dispersion of stock returns measured with standard deviation. We also check returns within the month of positive and negative *MKT* returns, and global expansions and recessions as defined by the OECD (Federal Reserve Bank of St. Louis, 2019). Finally, we simply split the sample into two consecutive halves: January 1991–February 2005 and March 2005–April 2019, and three consecutive decades: 1990s, 2000s, and 2010s.

[11] To shed some further light on the issue of the relationship between diversification opportunities and the liquidity premium, we perform an additional examination. We use R^2 coefficient as the simplest popular measure of integration (see, e.g., Bekaert and Harvey, 1995, Carieri et al., 2007, Dumas et al., 2003; Schotman and Zalewska, 2006) and check its role for the liquidity premia in different market segments. We estimate R^2 as the trailing 60-month coefficient of determination from the regression on MKT factor, and perform two-way sorts similar to those in Table 7. The results, demonstrated in Table A2 in the Appendix, are partly in line with the view of Batten and Vo (2014) that the liquidity premium might be linked with the diversification benefits. In the subset of highly correlated stocks, the zero-investment portfolio going long (short) the least liquid (most liquid) stocks produces a mean monthly return of 0.10% (t = stat = 0.38) and a significant alpha of 0.47% (t-stat = 1.93). On the other hand, in the segment of stocks characterized by low correlation, the mean return and alpha equals −0.66% and − 0.46%, respectively, with the corresponding t-values of −2.27 and − 1.57, respectively.

Table 6
The role of intra-country and inter-country effects in the illiquidity premium.

Panel A: Single-Country Portfolios

	Equal-weighted portfolios			Value-weighted portfolios			N
	R	*t*-stat	Vol	R	*t*-stat	Vol	
Americas							
Argentina	−0.26	*(−1.03)*	5.25	−0.31	*(−0.71)*	8.33	309
Europe							
Croatia	−0.23	*(−0.80)*	4.21	0.11	*(0.26)*	4.76	163
Estonia	−0.13	*(−0.31)*	8.43	0.26	*(0.39)*	9.56	265
Lithuania	−0.30	*(−0.98)*	6.68	0.31	*(0.36)*	7.76	251
Kazakhstan	0.31	*(0.20)*	13.51	0.87	*(0.57)*	16.85	118
Romania	−0.54	*(−0.82)*	9.39	−1.48**	*(−2.02)*	9.97	208
Serbia	−1.99***	*(−3.48)*	6.09	−1.62***	*(−2.72)*	6.90	119
Slovenia	−0.18	*(−0.33)*	6.92	−0.40	*(−0.90)*	7.11	263
Africa							
Kenya	0.40	*(0.92)*	8.19	−0.19	*(−0.25)*	8.95	338
Ivory Coast	−0.56*	*(−1.77)*	3.67	0.02	*(0.00)*	4.33	118
Mauritius	0.16	*(0.74)*	3.50	0.24	*(1.10)*	3.42	291
Morocco	−0.54	*(−0.83)*	7.13	−0.24	*(−0.27)*	7.28	114
Nigeria	−0.47*	*(−1.88)*	3.64	−0.51**	*(−2.14)*	3.38	160
Tunisia	−0.66	*(−1.16)*	7.04	−0.59	*(−0.75)*	9.02	132
Middle East							
Bahrain	−0.58	*(−1.18)*	5.38	−0.55	*(−1.00)*	6.60	182
Jordan	1.15***	*(3.68)*	4.75	0.80*	*(1.94)*	5.59	161
Kuwait	−0.34	*(−0.85)*	6.18	−0.36	*(−0.74)*	6.73	183
Lebanon	0.39	*(1.03)*	7.00	0.85*	*(1.79)*	7.92	193
Oman	0.18	*(0.57)*	4.00	0.41	*(1.10)*	4.38	166
Asia							
Bangladesh	−0.16	*(−0.21)*	9.62	−0.15	*(−0.23)*	11.70	304
Sri Lanka	−0.69*	*(−1.86)*	6.19	−0.94***	*(−2.66)*	6.80	339
Vietnam	−0.33	*(−0.57)*	6.04	−0.66	*(−1.00)*	8.08	147

Panel B: Multi-Country Portfolios

	Equal-weighted portfolios			Value-weighted portfolios		
	Intra-country portfolios	Inter-country portfolios	Pooled-sample portfolios	Intra-country portfolios	Inter-country portfolios	Pooled-sample portfolios
Panel A: Returns on Illiquidity Portfolios Under Different Implementations						
R	−0.22	−0.23	−0.32	−0.25	−0.15	−0.43
	(−1.25)	*(−0.80)*	*(−1.14)*	*(−1.13)*	*(−0.54)*	*(−1.52)*
Vol	3.31	7.84	5.68	4.33	9.07	6.10

Note. *Panel A* presents the performance of zero-investment equal-weighted and value-weighted tertile portfolios from sorts on *AMIH* in individual frontier markets. The portfolios go long (short) the companies with the highest (lowest) *AMIH*. *Panel B* reports the performance of zero-investment long-short portfolios formed on *AMIH* and implemented using different methods. The portfolios are value-weighted (right section) or equal-weighted (left section). Intra-country portfolios are equal-weighted portfolios of the single-country long-short portfolios, demonstrated in *Panel A*. Inter-country portfolios go long (short) the entire country portfolios with the highest (lowest) average *AMIH* measure. Pooled-sample portfolios are formed within a pooled sample of all stocks in all countries. *R* is the mean monthly return and *t*-stat (in brackets) is the corresponding bootstrap *t*-statistic. *Vol* is the standard deviation of returns, and *N* is the number of monthly observations. *R* and *Vol* are expressed in percentage terms. The asterisks *, **, and *** denote values significantly differing from zero at the 10%, 5%, and 1% levels, respectively.

The results of the subsample analysis in Table 8 confirm our baseline outcomes by showing the lack of a reliable illiquidity premium in any of the subperiods. Nonetheless, the content of Table 8 yields some interesting insights. First, the negative illiquidity premium is particularly pronounced during bull markets, turning positive on a raw return basis (though insignificant) in the bear markets. This evokes the arguments of Watanabe and Watanabe (2008), Jensen and Moorman (2010), and Ben-Rephael et al. (2015), who linked the illiquidity premium with the level of market-wide liquidity: it is strong in falling markets when everyone seeks liquidity, and low in bull markets when investors' appetites rise and they are less concerned about liquidity issues (Brunnermeier and Pedersen, 2009).

The second interesting observation is that the relationship seems to turn from negative to positive in consecutive decades. This, again, would support the hypothesis of Batten and Vo (2014). If the frontier markets become more developed and integrated over time, we may expect that their cross-sectional return patterns will gradually more closely resemble their counterparts from developed

Table 7
Performance of portfolios based on AMIH in subsamples.

	Mean excess returns				Six-factor model alphas			
	Low AMIH	Medium AMIH	High AMIH	H-L AMIH	Low AMIH	Medium AMIH	High AMIH	H-L AMIH
Panel A: AMIH vs. BETA								
High BETA	0.26	0.26	0.47	0.22	−0.41	−0.29	0.25	0.65**
	(0.34)	*(0.41)*	*(0.86)*	*(0.76)*	*(−1.32)*	*(−0.95)*	*(1.04)*	*(2.22)*
Medium BETA	0.90***	1.01***	0.36	−0.55	0.53*	0.52**	0.08	−0.44
	(2.59)	*(2.89)*	*(1.18)*	*(−1.61)*	*(1.67)*	*(2.07)*	*(0.34)*	*(−1.17)*
Low BETA	1.03***	0.53*	0.29	−0.73**	0.88***	0.32	0.23	−0.65*
	(3.49)	*(1.84)*	*(0.95)*	*(−2.34)*	*(2.72)*	*(1.19)*	*(0.88)*	*(−1.65)*
Panel B: AMIH vs. MV								
High MV	0.48*	0.49	0.55*	0.07	−0.03	0.29*	0.10	0.13
	(1.65)	*(1.59)*	*(1.89)*	*(0.09)*	*(−0.18)*	*(1.79)*	*(0.48)*	*(0.45)*
Medium MV	0.86**	0.78**	0.44	−0.42	0.52*	0.15	0.08	−0.45
	(2.26)	*(2.22)*	*(1.27)*	*(−1.23)*	*(1.94)*	*(0.67)*	*(0.34)*	*(−1.44)*
Low MV	0.95**	1.06***	0.44	−0.51	0.38	0.35*	0.03	−0.35
	(2.43)	*(2.90)*	*(1.44)*	*(−1.27)*	*(1.43)*	*(1.76)*	*(0.12)*	*(−0.96)*
Panel C: AMIH vs. BM								
High BM	0.78	1.17**	0.91**	0.13	0.17	0.39	0.41*	0.25
	(1.57)	*(2.46)*	*(1.99)*	*(0.19)*	*(0.51)*	*(1.54)*	*(1.70)*	*(0.68)*
Medium BM	0.65	0.52	0.10	−0.56	0.10	−0.02	−0.25	−0.35
	(1.36)	*(1.44)*	*(0.10)*	*(−1.55)*	*(0.24)*	*(−0.07)*	*(−1.01)*	*(−0.79)*
Low BM	0.50	0.28	−0.25	−0.76**	0.54**	0.22	−0.27	−0.81**
	(1.44)	*(0.90)*	*(−1.10)*	*(−2.47)*	*(2.24)*	*(1.33)*	*(−1.32)*	*(−2.49)*
Panel D: AMIH vs. MOM								
High MOM	1.08***	0.96***	1.47***	0.39	0.51*	0.22	0.41	−0.10
	(2.91)	*(2.94)*	*(4.36)*	*(0.96)*	*(1.85)*	*(0.77)*	*(1.22)*	*(−0.20)*
Medium MOM	0.82**	0.49*	0.64**	−0.18	0.77**	0.26	0.45*	−0.32
	(2.52)	*(1.94)*	*(2.09)*	*(−0.74)*	*(2.49)*	*(1.48)*	*(1.89)*	*(−1.31)*
Low MOM	−0.19	0.00	−0.09	0.09	−0.29	0.15	0.14	0.43
	(−0.44)	*(−0.07)*	*(−0.40)*	*(0.17)*	*(−0.97)*	*(0.88)*	*(0.59)*	*(1.20)*
Panel E: AMIH vs. ROE								
High ROE	0.79*	0.67*	0.40	−0.39	0.05	0.14	0.10	0.04
	(1.67)	*(1.88)*	*(1.14)*	*(−1.02)*	*(0.20)*	*(0.67)*	*(0.47)*	*(0.12)*
Medium ROE	0.24	0.33	−0.05	−0.29	−0.14	0.01	−0.35	−0.20
	(0.51)	*(0.93)*	*(−0.29)*	*(−0.75)*	*(−0.45)*	*(0.05)*	*(−1.38)*	*(−0.48)*
Low ROE	0.07	0.90**	0.20	0.13	−0.56*	0.30	−0.08	0.48
	(0.04)	*(1.99)*	*(0.24)*	*(0.23)*	*(−1.83)*	*(1.15)*	*(−0.31)*	*(1.28)*
Panel F: AMIH vs. AG								
High AG	0.45	0.70	0.34	−0.11	−0.42	0.20	−0.15	0.27
	(0.95)	*(1.56)*	*(0.71)*	*(−0.41)*	*(−1.60)*	*(0.67)*	*(−0.68)*	*(0.81)*
Medium AG	−0.03	0.71*	0.06	0.09	−0.72*	0.17	−0.24	0.48
	(−0.27)	*(1.65)*	*(−0.01)*	*(0.30)*	*(−1.83)*	*(0.65)*	*(−0.79)*	*(1.38)*
Low AG	0.52	0.54	−0.09	−0.61	0.01	−0.04	−0.23	−0.23
	(1.04)	*(1.23)*	*(−0.39)*	*(−1.42)*	*(0.02)*	*(−0.15)*	*(−1.04)*	*(−0.63)*
Panel G: AMIH vs. REV								
High REV	0.26	0.27	0.15	−0.11	−0.01	0.04	0.09	0.11
	(0.49)	*(0.70)*	*(0.27)*	*(−0.23)*	*(−0.04)*	*(0.17)*	*(0.31)*	*(0.26)*
Medium REV	0.51	0.66**	0.57**	0.06	−0.10	0.44*	0.44**	0.53*
	(1.43)	*(2.05)*	*(1.97)*	*(0.31)*	*(−0.36)*	*(1.91)*	*(2.08)*	*(1.72)*
Low REV	1.29***	1.18***	0.70*	−0.60*	0.66**	0.66***	0.22	−0.44
	(3.28)	*(3.07)*	*(1.89)*	*(−1.75)*	*(2.03)*	*(3.41)*	*(0.92)*	*(−1.15)*
Panel H: AMIH vs. IVOL								
High IVOL	0.42	0.70*	0.43	0.02	0.14	0.64**	0.33	0.18
	(1.10)	*(1.79)*	*(1.09)*	*(−0.02)*	*(0.39)*	*(2.16)*	*(1.08)*	*(0.38)*
Medium IVOL	1.21***	0.85**	0.26	−0.95***	0.55**	0.58**	0.02	−0.53
	(3.23)	*(2.09)*	*(0.66)*	*(−2.75)*	*(2.18)*	*(2.22)*	*(0.08)*	*(−1.42)*
Low IVOL	0.36	0.35	0.57*	0.21	−0.27	−0.13	0.29	0.55
	(0.75)	*(0.94)*	*(1.80)*	*(0.66)*	*(−0.75)*	*(−0.47)*	*(1.20)*	*(1.40)*
Panel I: AMIH vs. SKEW								
High SKEW	0.89***	0.49*	0.55*	−0.33	0.76***	0.08	0.20	−0.56
	(3.07)	*(1.76)*	*(1.71)*	*(−1.36)*	*(2.80)*	*(0.37)*	*(0.66)*	*(−1.62)*
Medium SKEW	0.63*	0.77**	0.37	−0.26	0.22	0.23	−0.07	−0.29
	(1.75)	*(2.49)*	*(1.03)*	*(−0.83)*	*(0.95)*	*(1.34)*	*(−0.33)*	*(−0.84)*
Low SKEW	0.75**	0.63**	0.50	−0.25	0.18	0.28	0.12	−0.06

(*continued on next page*)

Table 7 (*continued*)

	Mean excess returns				Six-factor model alphas			
	Low AMIH	Medium AMIH	High AMIH	H-L AMIH	Low AMIH	Medium AMIH	High AMIH	H-L AMIH
	(2.21)	*(2.00)*	*(1.53)*	*(−0.79)*	*(0.70)*	*(1.41)*	*(0.75)*	*(−0.18)*
Panel J: AMIH vs. SEAS								
High SEAS	1.06***	0.75**	0.92***	−0.14	0.68***	0.61***	0.68**	0.01
	(2.89)	*(2.32)*	*(2.65)*	*(−0.47)*	*(2.65)*	*(3.12)*	*(2.34)*	*(0.02)*
Medium SEAS	0.54**	0.75**	0.68**	0.14	0.37*	0.57***	0.30*	−0.08
	(2.08)	*(2.36)*	*(2.13)*	*(0.29)*	*(1.66)*	*(3.42)*	*(1.72)*	*(−0.29)*
Low SEAS	0.14	0.10	0.00	−0.14	−0.16	−0.02	−0.38**	−0.22
	(0.43)	*(0.29)*	*(−0.15)*	*(−0.51)*	*(−0.58)*	*(−0.09)*	*(−2.22)*	*(−0.74)*
Panel K: AMIH vs. VAR								
High VAR	0.88***	0.56**	0.27	−0.61**	0.65**	0.38**	−0.22	−0.86***
	(3.39)	*(2.13)*	*(1.01)*	*(−2.28)*	*(2.51)*	*(2.38)*	*(−1.27)*	*(−3.17)*
Medium VAR	1.08***	0.83***	0.73**	−0.35	0.47*	0.42***	0.55***	0.08
	(3.04)	*(2.87)*	*(2.34)*	*(−1.09)*	*(1.87)*	*(2.59)*	*(2.58)*	*(0.24)*
Low VAR	0.37	0.41	0.52	0.16	−0.09	−0.26	−0.03	0.06
	(0.96)	*(1.01)*	*(1.45)*	*(0.29)*	*(−0.32)*	*(−0.78)*	*(−0.11)*	*(0.16)*

Note. The table reports mean excess returns (left section) and six-factor model alphas (right section) on equal-weighted tertile portfolios from two-way dependent sorts. In the first pass, the companies are sorted into tertiles based on different control variables: stock market beta (*BETA*), market value (*MV*), book-to-market ratio (*BM*), momentum (*MOM*), profitability (*ROE*), asset growth (*AG*), long-term reversal (*REV*), idiosyncratic volatility (*IVOL*), seasonality (*SEAS*), skewness (*SKEW*), and tail risk (*VAR*). In the second pass, within each control variable tertile, the stocks are sorted again into *AMIH* tertiles. H-L denotes the long-short portfolios going long (short) the firms with the highest (lowest) *AMIH* score within the tertile of a given control variable. The values in brackets are *t*-statistics estimated using bootstrapping (for *R*) or the Newey and West (1987) method (for regression coefficients). *R* and *α* are expressed in percentages. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Performance of liquidity factor portfolios in subperiods.

	Panel A: Equal-weighted portfolios				Panel B: Value-weighted portfolios			
	R	$t\text{-}stat_R$	α	$t\text{-}stat_\alpha$	R	$t\text{-}stat_R$	α	$t\text{-}stat_\alpha$
Bull markets	−1.21**	*(−2.51)*	−1.79**	*(−1.97)*	−1.22**	*(−2.02)*	−1.61*	*(−1.83)*
Bear markets	0.77	*(1.28)*	−1.10**	*(−2.19)*	0.76	*(1.17)*	−0.57	*(−0.78)*
Positive months	−0.19	*(−0.62)*	−0.29	*(−0.70)*	−0.10	*(−0.28)*	−0.05	*(−0.16)*
Negative month	−0.17	*(−0.46)*	−0.26	*(−0.48)*	−0.12	*(−0.22)*	0.03	*(0.04)*
High volatility	0.08	*(−0.07)*	−0.47	*(−0.82)*	0.11	*(0.01)*	−0.05	*(−0.07)*
Low volatility	−0.15	*(−0.43)*	0.24	*(0.66)*	−0.19	*(−0.53)*	0.05	*(0.14)*
High idiosyncratic risk	−0.68	*(−1.58)*	−0.57	*(−1.19)*	0.04	*(0.11)*	0.22	*(0.56)*
Low idiosyncratic risk	0.13	*(0.42)*	0.37	*(1.29)*	−0.25	*(−0.48)*	0.26	*(0.92)*
High dispersion	−0.42	*(−0.72)*	−0.41	*(−0.64)*	−0.75	*(−1.12)*	−0.60	*(−0.87)*
Low dispersion	−0.33	*(−1.27)*	−0.19	*(−0.71)*	−0.02	*(0.04)*	0.11	*(0.31)*
Expansions	0.14	*(0.20)*	0.13	*(0.29)*	0.06	*(0.14)*	0.05	*(0.14)*
Recessions	−0.86	*(−1.39)*	−0.85*	*(−1.76)*	−0.81	*(−1.24)*	−0.34	*(−0.50)*
First half	−0.72	*(−1.15)*	−0.51	*(−0.89)*	−0.57	*(−0.86)*	0.02	*(0.03)*
Second half	−0.03	*(−0.11)*	0.49	*(1.14)*	−0.20	*(−0.54)*	0.35	*(0.83)*
1990s	−0.91	*(−1.04)*	−0.53	*(−0.72)*	−0.88	*(−0.98)*	−0.22	*(−0.28)*
2000s	−0.37	*(−1.09)*	−0.09	*(−0.23)*	−0.32	*(−0.53)*	0.27	*(0.50)*
2010s	0.26	*(0.67)*	0.87*	*(1.87)*	0.13	*(0.29)*	0.36	*(0.69)*

Note. The table reports the mean monthly returns (*R*) and six-factor model alphas (*α*) on the zero-investment equal-weighted and value-weighted portfolios formed on Amihud's illiquidity measure (*AMIH*) in different subperiods. The portfolios go long (short) the quintile of stocks with the highest (lowest) value of *AMIH*. The values in brackets are *t*-statistics estimated using the bootstrap (for *R*) or the Newey and West (1987) (for *α*) method. *R* and *α* are expressed in percentages. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. *Bull markets* (*Bear markets*) refer to months following the 36-month trailing positive (negative) return. *Positive months* (*Negative months*) are months with above-zero (below-zero) *MKT* returns. *High* (*low*) *volatility*, *idiosyncratic volatility*, and *dispersion* refer to months with above-median (below-median) 60-month trailing standard deviation of *MKT* returns, average cross-sectional *IVOL* estimated in months *t*-60 to *t*-1, and cross-sectional dispersion of stock returns in month *t*. *Expansion* (*Recession*) months are defined according to the OECD-based recession indicators for OECD and non-member economies from the peak through the trough (Federal Reserve Bank of St. Louis, 2019). *First half* and *Second half* indicate the periods January 1991–February 2005 and March 2005–April 2019, respectively. *1990s*, *2000s*, and *2010s* indicate performance in the three respective decades, i.e., January 1991–December 2000, January 2001–December 2010, and January 2011–April 2019.

Table 9
Performance of liquidity factor portfolios in different calendar months.

	Panel A: Equal-weighted portfolios				Panel B: Value-weighted portfolios			
	R	$t\text{-}stat_R$	α	$t\text{-}stat_\alpha$	R	$t\text{-}stat_R$	α	$t\text{-}stat_\alpha$
January	1.58	*(1.27)*	−0.52	*(−0.48)*	1.13	*(0.74)*	0.43	*(0.51)*
February	1.55	*(1.39)*	0.84	*(1.08)*	1.43	*(1.21)*	0.75	*(0.84)*
March	−0.84	*(−1.01)*	1.42*	*(1.83)*	−1.23	*(−0.86)*	1.67	*(1.07)*
April	−0.71	*(−0.66)*	0.97	*(0.68)*	−1.43	*(−1.21)*	1.45	*(1.51)*
May	−0.38	*(−0.38)*	−1.34**	*(−2.38)*	−0.15	*(−0.08)*	−0.13	*(−0.22)*
June	−0.29	*(−0.42)*	0.50	*(0.70)*	−1.10	*(−0.89)*	0.04	*(0.03)*
July	−2.69*	*(−1.66)*	−3.95***	*(−5.66)*	−1.93	*(−1.15)*	−3.17***	*(−3.37)*
August	−0.65	*(−0.73)*	−0.77	*(−1.39)*	−0.48	*(−0.49)*	−1.19	*(−1.60)*
September	−0.59	*(−0.69)*	−0.40	*(−0.96)*	−0.26	*(−0.28)*	0.01	*(0.01)*
October	0.07	*(0.18)*	−0.82	*(−0.92)*	0.44	*(0.45)*	−0.36	*(−0.33)*
November	−0.42	*(−0.50)*	−0.56	*(−1.48)*	0.45	*(0.50)*	0.46	*(0.70)*
December	−1.17	*(−0.45)*	0.84	*(0.99)*	−1.46	*(−0.54)*	1.28	*(1.54)*

Note. The table reports the mean monthly returns (R) and six-factor model alphas (α) on the zero-investment equal-weighted and value-weighted portfolios formed on Amihud's illiquidity measure (*AMIH*) in different calendar months. The portfolios go long (short) the quintile of stocks with the highest (lowest) value of *AMIH*. The values in brackets are t-statistics estimated using the bootstrap (for R) or Newey and West (1987) (for α) method. R and α are expressed in percentages. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

economies. On the other hand, these findings seem contrary to the findings of Ben-Rephael et al. (2015)) and Harris and Amato (2019) who found that stock liquidity premia decrease over time.

5.5. Calendar seasonalities in the illiquidity premium

Finally, we also test the illiquidity premium in different calendar months. For example, Eleswarapu and Reinganum (1993), Eleswarapu (1997), Liu (2006), and Lou and Shu (2017), among others, argue that the outperformance of illiquid firms is particularly visible in January. To detect such patterns, we estimate mean returns and six-factor model alphas in individual calendar months. Table 9 reveals the results.

The results of this analysis do not uncover any unusual calendar pattern. Admittedly, there is some variability of payoffs, and the mean returns in July seem particularly pronounced. Interestingly, contrary to the majority of other months, the mean returns and alphas in January and February were historically positive (though insignificant). This phenomenon matches evidence from developed stock markets where illiquid shares also outperform at the beginning of the year (Eleswarapu and Reinganum, 1993; Eleswarapu, 1997).

To sum up, the robustness checks confirm the validity of our baseline observation: there is no significant illiquidity premium in frontier markets. Furthermore, some evidence seems to be in line with the integration hypothesis of Batten and Vo (2014) regarding liquidity pricing in frontier equities.

6. Concluding remarks

Our study examines the illiquidity premium in frontier equity markets. Using a sample of 22 countries for the years 1991–2019 and a battery of different tests, we research the role of six different measures of liquidity. We find no evidence of a significant illiquidity premium in frontier markets. As with Batten and Vo (2014), we link the insignificance of the illiquidity premium with low integration of frontier equity markets with the global economy and the limited role of international investors.

Our results not only cast new light onto asset pricing and liquidity issues in frontier stock markets, they have also a straightforward practical implication: investors in frontier markets should not pursue the illiquidity premium; instead, they should focus on large-cap high-beta companies. Their higher tradability is not fully discounted in the stock price, allowing for decent payoffs without accepting excessive risk.

Further studies on the topics discussed in this paper may be pursued in several directions. Finally, it would be valuable to comprehensively examine the relationship between the illiquidity premia and stock market integration around the world. Our limited sample of countries does not fully allow for such test, but extending it to developed and emerging countries, as well as incorporating multiple integration measures (Bekaert et al., 2011; Pukthuanthong and Roll, 2009; Zaremba et al., 2019a), would help to uncover the full nature of the relationship between the local illiquidity premium and international financial market integration.

Second, it would be interesting to see how liquidity and associated trading costs affect the performance of different factor strategies in frontier markets, e.g., value or momentum. This issue is important not only because the trading costs may limit the illiquidity premium, but also because they may diminish the diversification benefits of frontier equities (Marshall et al., 2015). Hence, any future tests of the relationship between market integration and illiquidity premium should consider also the impact of transaction costs.

Finally, an investigation into why only certain markets demonstrate a positive illiquidity premium (e.g., Jordan and Lebanon) and others demonstrate remarkably negative ones (e.g., Serbia) may yield some interesting and practical observations.

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Appendix A. Appendix

Table A1
Returns on frontier market asset pricing factor portfolios.

	MKT	SMB	HML	UMD	RMW	CMA
Descriptive Statistics						
R	0.53	−0.26	1.13***	0.97***	−0.08	−0.22
	(1.29)	*(−0.55)*	*(3.01)*	*(2.83)*	*(−0.09)*	*(−0.86)*
Vol	7.21	8.05	6.93	6.29	5.75	5.10
Min	−34.26	−91.02	−40.02	−16.81	−26.51	−22.16
Max	64.23	34.52	27.96	30.64	24.77	34.78
Skew	2.32	−4.32	−0.88	0.60	−0.08	0.65
Kurt	23.69	52.14	7.51	3.75	4.34	9.11
Pairwise Correlation Coefficients						
MKT		−0.73	0.31	−0.24	−0.33	−0.13
SMB			−0.12	0.04	0.14	0.28
HML				−0.32	−0.43	0.03
UMD					0.30	0.10
RMW						−0.26

Note. The table reports the statistical properties of returns on the six asset pricing factors of the Fama and French (2018) model estimated in the frontier markets: market excess return (*MKT*), small minus big (*SMB*), high minus low (*HML*), up minus down (*UMD*), robust minus weak (*RMW*), and conservative minus aggressive (*CMA*). *R* is the mean monthly return, *Vol* is the volatility of excess returns, *Min* and *Max* are minimum and maximum monthly returns, *Skew* is skewness, and *Kurt* is kurtosis. The bottom section shows the Pearson's product-moment correlation coefficients between pairs of asset pricing factors. *R*, *Vol*, *Min*, and *Max* are reported in percentage terms. The values in brackets are bootstrap *t*-statistics, and the asterisks *, **, and *** indicate the values significantly differing from zero at the 10%, 5%, and 1% levels, respectively.

Table A2
Performance of portfolios from two-way sorts on AMIH and R^2.

	Mean excess returns				Six-factor model alphas			
	Low AMIH	Medium AMIH	High AMIH	H-L AMIH	Low AMIH	Medium AMIH	High AMIH	H-L AMIH
High R^2	0.34	0.58	0.43	0.10	−0.34*	0.06	0.14	0.47*
	(0.65)	*(1.44)*	*(0.94)*	*(0.38)*	*(−1.68)*	*(0.36)*	*(0.64)*	*(1.93)*
Medium R^2	0.57**	0.63***	0.39	−0.18	0.13	0.33*	0.03	−0.09
	(2.29)	*(2.66)*	*(1.44)*	*(−0.86)*	*(0.69)*	*(1.91)*	*(0.17)*	*(−0.35)*
Low R^2	1.01***	0.65***	0.35	−0.66**	0.65**	0.38	0.18	−0.46
	(3.24)	*(2.79)*	*(1.48)*	*(−2.27)*	*(2.47)*	*(1.54)*	*(1.11)*	*(−1.57)*

Note. The table reports mean excess returns (left section) and six-factor model alphas (right section) on equal-weighted tertile portfolios from two-way dependent sorts. In the first pass, the companies are sorted into tertiles based on R^2, i.e., the time-series coefficient of determination from the regression on the MKT factor based on a 60-month estimation period. In the second pass, within each control variable tertile, the stocks are sorted again into *AMIH* tertiles. *H-L* denotes the long-short portfolios going long (short) the firms with the highest (lowest) *AMIH* score within the tertile of R^2. The values in brackets are *t*-statistics estimated using bootstrapping (for *R*) or the Newey and West (1987) method (for regression coefficients). *R* and α are expressed in percentages. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

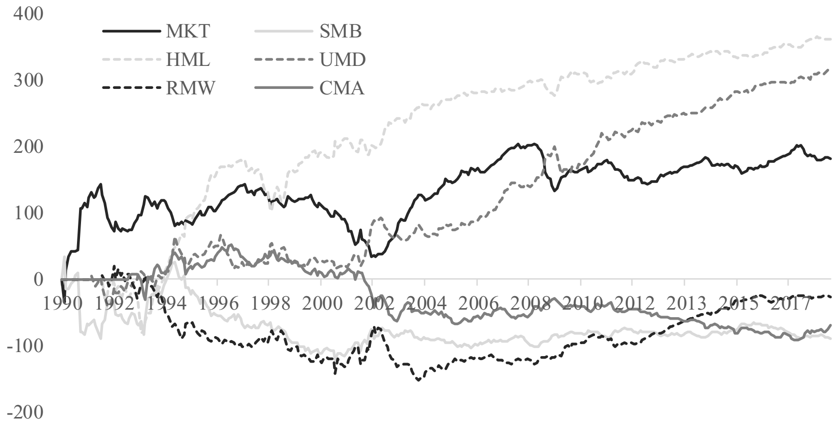

Fig. A1. Performance of the asset pricing factor portfolios in frontier markets.
Note. The figure presents the cumulative returns on the six asset pricing factors of the Fama and French (2018) model estimated in the frontier markets: market excess return (*MKT*), small minus big (*SMB*), high minus low (*HML*), up minus down (*UMD*), robust minus weak (*RMW*), and conservative minus aggressive (*CMA*). The returns are cumulated additively and expressed in percentage terms.

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