Liquidity and mispricing

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Abstract

I document a strong liquidity premium in long/short portfolio returns based on the Stambaugh, Yu, and Yuan (2015) mispricing score. This premium can be mainly attributed to arbitrage asymmetry among very illiquid stocks. To explore this relation in greater detail, I analyze the effect of liquidity shocks on the magnitude of mispricing. In the the overall sample negative liquidity shocks lead to an increase in mispricing. Controlling for the state of the economy by means of the cross-sectional amount of positive and negative liquidity shocks on firm level, in a neutral market environment both negative and positive liquidity shocks lead to an increase in mispricing. In a strong market environment only negative liquidity shocks cause an increase in mispricing. Liquidity and liquidity shocks manifest as strong predictors of future returns, controlling for individual mispricing components as well as composite mispricing. These findings suggest that liquidity is an important determinant of mispricing on international equity markets.

Keywords: Behavioral finance, Asset pricing, Liquidity, International stock markets, Anomalies

JEL: G12, G14, G15, F37

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1. Introduction

The liquidity premium is a well-known phenomenon in asset pricing that describes the return premium charged by investors to compensate for the illiquidity of an asset. A positive relation between illiquidity and expected returns has been documented numerous times in the literature (Amihud, 2002; Amihud et al., 2015; Amihud and Mendelson, 1989; Brennan, Chordia, and Subrahmanyam, 1998; Brennan and Subrahmanyam, 1996; Datar, Naik, and Radcliffe, 1998; Eleswarapu, 1997; Hasbrouck, 2009). Other studies on liquidity describe a positive relation between liquidity risk and expected returns (Acharya and Pedersen, 2005; Bekaert, Harvey, and Lundblad, 2007; Lee, 2011; Liu, 2006; Pastor and Stambaugh, 2003; Sadka, 2006; Watanabe and Watanabe, 2007). More recently, however, in a study on capital market anomalies in the U.S. equity market, Hou, Xue, and Zhang (2018) document the overwhelming result that 96% of 106 observed anomalies in the trading frictions literature cannot be replicated successfully in a single hypothesis testing framework.[1] Among others, the authors find decile-based anomalies based on the following liquidity proxies to be insignificant: Absolute return-to-volume according to Amihud (2002), the bid-ask spread according to Hou and Loh (2016), the high-low spread by Corwin and Schultz (2012), and the Pastor and Stambaugh (2003) liquidity beta. These results, however, are purely based on a univariate test design. Thus, the question arises, if liquidity can perform better in a multivariate setting of asset pricing tests.[2]

In this study, I aim to explore the relation between liquidity and mispricing. In the anomaly-return literature, anomalous return behavior is often documented as a manifestation of mispricing (e.g. Jacobs and Müller, 2019). Mispricing, which is the difference between the market price and the hypothetical fair price in absence of any arbitrage impediments, cannot be observed directly on the market. In order to proxy for mispricing, Stambaugh, Yu, and Yuan (2015) introduce a monthly cross-sectional mispricing score on

[1]To prevent data mining in Finance, Harvey, Liu, and Zhu (2015) propose the usage of a new multiple hypothesis testing framework that induces a higher statistical hurdle.

[2]Hou, Xue, and Zhang (2018) are focused on the analysis of individual anomalies. They also test for the impact of different approaches in the anomaly construction, that is with regard to choice of breakpoints (NYSE stocks vs. all stocks) and return weighting scheme (value- vs. equally-weighted). In their baseline analysis, an anomaly is regarded as insignificant if the average return of its high-minus-low decile carries a t-value with $|t| < 1.96$.

firm level. This aggregate measure contains the information of eleven popular anomalies in the literature that have survived the adjustments of a Fama and French (1993) three-factor model in the U.S. market. They find that a decile-based long/short portfolio based on this composite measure outperforms the average decile-based long/short portfolio return based on all individual anomalies by 61 basis points (bp) per month in the U.S. market. This implies that ranking on mispricing provides a clear benefit over ranking on the individual anomaly variables that are components of mispricing.

As the Stambaugh, Yu, and Yuan (2015) mispricing score is a relative, cross-sectional measure on firm level, a direct comparison of the absolute mispricing between stocks is not possible. For example, assume that a stock on the market has a price that is five times as large (small) as its hypothetical, arbitrage-free price and that this positive (negative) deviation can be attributed to extreme manifestations of the eleven anomalies underlying the mispricing score. Further assuming the stock carries the highest (lowest) mispricing rank in the sample, it would be most overpriced (underpriced) by definition, but we cannot draw any conclusion on its absolute level of mispricing. To measure the absolute level of mispricing would require a thorough fundamental analysis on firm level, also taking into account individual firm-specific influencing factors, which is usually not feasible in asset pricing studies that involve multiple thousands of firms.

Stambaugh, Yu, and Yuan (2015) document that in the U.S. mispricing is larger for stocks with higher arbitrage risk, measured by idiosyncratic volatility (IVOL). They explain the "IVOL puzzle" (e.g. Ang et al., 2006), which refers to a negative relation between expected returns and IVOL, by combining arbitrage risk with arbitrage asymmetry, which states that buying is easier than shorting for a typical equity investor. In an analysis of 5x5 portfolio sorts based on mispricing and IVOL, they document a positive relation between IVOL and average returns of underpriced stocks, but a negative one between IVOL and average returns of overpriced stocks. The latter effect dominates, because of arbitrage asymmetry, which overall leads to the negative IVOL-return relation. Lu, Stambaugh, and Yuan (2017) construct mispricing and its component anomalies for five of the largest markets outside the U.S., namely Canada, France, Germany, Japan and the U.K. In each of those markets, the anomaly long/short spreads are significantly positive and cannot be attributed to data mining in the U.S. Moreover, a similar analysis to Stambaugh, Yu, and Yuan (2015) confirms the negative relation between average abnormal returns and arbitrage risk of overpriced stocks. Additional support for the existence of mispricing on international markets is given by Jacobs (2016). He finds that mispricing according to Stambaugh, Yu, and Yuan (2015) is at least as strong on developed markets as on emerging markets.

In the literature there are two hypotheses on the relation between mispricing and liquidity: (i) Liquidity has a notable influence on mispricing, as in highly illiquid markets, strategies to exploit and effectively dissipate mispricing are difficult to implement. On the other hand, on highly liquid markets with low trading costs, mispricing can be utilized more quickly by arbitrageurs to generate a profit. Evidence for this reasoning is provided for example by Chordia, Roll, and Subrahmanyam (2008), Chordia, Subrahmanyam, and Tong (2014), Daniel, Hirshleifer, and Subrahmanyam (1998), McLean and Pontiff (2016), and Pontiff (1996). However, there is also an opposing effect: (ii) If trading frictions are low, noise trading is likely to increase, which consequently leads to higher mispricing. In the literature, this hypothesis is supported for instance by Baker and Stein (2004), Baker and Wurgler (2006, 2007), and DeVault, Sias, and Starks (2019), using share turnover among other variables to proxy for investor sentiment. Thus, the literature implies that the relation between liquidity and mispricing can be either negative, or positive. My analysis can be regarded as an empirical test of these two contrary hypotheses.

I use monthly liquidity proxies on firm level to designate stocks into liquid and non-liquid markets. This designation can be updated frequently when a firm evolves in the business process and when the associated liquidity proxies are affected. In the literature there is a wide range of proxies that can be used for the measurement of liquidity. To decide which one to use in an international context, I follow the recommendations by Fong, Holden, and Trzcinka (2017), who compare low-frequency liquidity proxies with high-frequency liquidity benchmarks. In particular, I use the closing percent quoted (bid-ask) spread as primary percent-cost liquidity proxy. This spread (in the following abbreviated as "quoted spread") is arguably the most indicative of all liquidity proxies (as stated e.g. in Amihud, 2002 and Lesmond, 2005) and by now is widely available on international markets. The quoted spread is used for example in an influential paper by Amihud and Mendelson (1986), in which the authors introduce a theoretical model that predicts a positive relation between the quoted spread and expected stock returns. Amihud and Mendelson (1989) provide empirical evidence to support this prediction.[3] In addition and for robustness, I also employ the adjusted high-low spread by Corwin and Schultz (2012) and the FHT spread by Fong, Holden, and Trzcinka (2017). Moreover, I use the Amihud (2002) illiquidity measure as a price impact proxy, as it has been established as one of the most influential and widely used liquidity proxies in the literature.[4] Recently, however, some studies have passed criticism on the measure (e.g. Lou and Shu, 2017, Barardehi et al., 2019).

Based on the relative mispricing score constructed at the beginning of the month, I compute monthly quintile-based long/short portfolio returns, and check if they are significantly different on liquid and non-liquid markets. I document strong evidence for a liquidity premium in mispricing across the world. The average liquidity premium based on 48 countries from January 1990 until June 2018 amounts to 55 bp (46 bp) per month, with an associated t-value of 3.48 (2.88), based on independently (dependently) sorted portfolios and value-weighted returns. Interestingly, while there is a considerable difference in mispricing return spreads between liquid and non-liquid markets, the spread is also significant only on liquid markets. In this case, the average return of the spread amounts to 65 bp per month and is significant at the 1% level (based on both, independently and dependently formed portfolios). It follows that although arbitrage can take away a portion of the mispricing that is existent on liquid markets, a certain degree of market inefficiency still remains. In addition, a more detailed analysis of the relation between liquidity and mispricing in 5x5 portfolio sorts reveals that the liquidity premium is mainly driven by the short leg of highly illiquid stocks, that is by the most overpriced stocks in the market.

Furthermore, I evaluate the short-term impact of firm level liquidity shocks on the magnitude of mispricing. Liquidity shocks are defined as the *negative* difference between the current quoted spread in a given month and its average over the last 12 months. Hence, a high value of the measure indicates that the liquidity of a firm has increased. To analyze the effect on mispricing, I first have to define a point of reference for the state of approximately zero shocks in the cross-section of firms. The mispricing at this point can then be

[3] Other articles that make use of the quoted spread include Christie and Schultz (1994), Huang and Stoll (1996), Lesmond (2005), and Chung and Zhang (2014).

[4] A non-conclusive list of articles that use Amihud's illiquidity includes Acharya and Pedersen (2005), Avramov, Chordia, and Goyal (2006), Watanabe and Watanabe (2007), Kamara, Lou, and Sadka (2008), and Karolyi, Lee, and Dijk (2012).

compared with the one of firms that are underlying more extreme market conditions (i.e. positive or negative liquidity shocks). In this context, I find that the cross-sectional cumulative distribution function of monthly liquidity shocks varies notably over time, and so does the percentile with zero shocks. To account for this pattern I differentiate monthly between the following three scenarios in a quintile-based portfolio analysis: (A) More positive than negative liquidity shocks, (B) approximately equally as many positive as negative shocks, and (C) more negative than positive shocks. For instance, if in a given month the zero shock quantile is 28%, it is assigned to the second liquidity shock quintile portfolio (i.e. the "zero shock" portfolio), assuming the level of liquidity shocks increases with the portfolio quintile rank. In this situation there are more stocks with positive liquidity shocks than with negative ones, so scenario (A) is currently active. I disregard extreme cases when the zero shock quantile falls in the range of the first or last quintile portfolio, because there are only few months in the sample associated with these cases. Independently, I also compute quintile portfolios based on mispricing. At the intersection of the five mispricing and liquidity groups 5x5 portfolios are created. As a result, I document a significant increase in the magnitude of mispricing in case of negative liquidity shocks under both scenarios, A and B, and in case of positive liquidity shocks only under scenario B. Scenario C, on the other hand, does not display any clear pattern in times of crisis.

Another approach to analyze the effect of liquidity shocks on mispricing does not account for the state of the economy over time, but looks at the full sample instead. The downside of this approach is that because of the varying quintile portfolio rank of the zero shock quantile, the distance (measured in terms of quintile ranks) between the most positive or most negative quintile shock portfolio and the zero shock portfolio also varies over time. Because the quintile portfolio ranks are now dynamic, the average 5x5 portfolio returns cannot be presented in a meaningful way anymore. What can be clearly presented, however, are average returns of the quintile difference portfolios of negative and positive shocks in relation to the reference point of zero shocks. An analysis of the abnormal returns of these portfolios reveals that only negative liquidity shocks increase the magnitude of mispricing. This is expected, as economic crises are usually of temporary character, whereas scenario (A) and (B) dominate the overall sample.

Moreover, relying on Fama-MacBeth regressions to predict monthly 1-month ahead stock returns, controlling for market beta, size, book-to-market, short- and long-term reversal, and momentum, I find that mispricing, liquidity, and liquidity shocks prove to be strong return predictors.

My article contributes to several streams in the literature. First, I contribute to the recently heated discussion on the origins of anomalies. One stream of the literature argues that anomalies are mostly the results of data snooping (e.g. Harvey, Liu, and Zhu, 2015; Lo and MacKinlay, 2015). Hou, Xue, and Zhang (2018) and Linnainmaa and Roberts (2018) provide empirical support. Another stream of the literature explains the existence of anomalies by behavioral biases and limits to arbitrage (e.g. Barberis and Thaler, 2003). To provide some examples: Stambaugh, Yu, and Yuan (2015) attribute high arbitrage risk (i.e. IVOL) and arbitrage asymmetry to overpricing. Engelberg, McLean, and Pontiff (2018) document that 97 anomalies on the U.S. market are particularly strong around corporate news and earnings announcement days. They explain this result by investors having biased beliefs about future cash flows. Edelen, Ince, and Kadlec (2016) investigate the eleven anomalies underlying the mispricing score with respect to institutional trading in the U.S. They conclude that biased cash-flow expectations and tracking of firm characteristics due to agency conflicts can be regarded as incentives for institutions to buy particularly overpriced stocks. Jacobs (2016) documents a positive relation between mispricing and firm-specific return variation, a positive relation between mispricing and trading activity (proxied as percentage of days with a zero return), and a positive relation between mispricing and analyst forecast dispersion. Jacobs and Müller (2019) find that anomaly long-short returns do not decline after publication and are related to arbitrage costs in the U.S. and the G7 plus Australia. Chu, Hirshleifer, and Ma (2018) show by means of a natural experiment that actual short sale constraints on the market are positively related to mispricing.[5] I add to these results by exploring the relation between mispricing and stock level liquidity in depth. My finding that the liquidity premium in mispricing is particularly driven by the short-leg (i.e. overpricing) of the most illiquid stocks is consistent with the behavioral finance perspective that limits to arbitrage and arbitrage asymmetry rather than data snooping are a reason for the existence

[5]The natural experiment is the "Rule 202T of Regulation SHO", which was adopted by the Securities and Exchange Commission (SEC) in 2004. It allowed the SEC to exclude designated securities from any short sale price test rules for a limited period of time. Chu, Hirshleifer, and Ma (2018) analyze the suspension of an uptick rule imposed by NYSE/AMEX, which only allowed a short sale to be placed on a plus tick or a zero-plus tick.

of mispricing on international equity markets.

Second, the analysis of the effect of liquidity shocks on the magnitude of mispricing extends the work of Bali et al. (2014), who document that liquidity shocks are positively related to future stock returns, but do not analyze the zero shock quantile, or differentiate between economic states. Furthermore, it differs from the baseline analysis of the interaction between liquidity and mispricing, as stocks that are very liquid or illiquid in the long run carry liquidity shocks of approximately zero. Thus, stocks on the extreme ends of both liquidity dimensions are now regarded as neutral, and stocks that experience the largest short-term changes in either direction are now regarded as the most extreme observations. If liquidity is one of the major determinants of mispricing, liquidity shocks are expected to have a clearly visible effect on mispricing as well. I can confirm this expectation. In addition, the analysis goes along with a monthly designation of the state of the economy. While mispricing persists independent of the level of liquidity shocks under both, a positive and a neutral market environment, it does not under a weak market environment. Thus, the state of the economy seems to play an important role for the determination of the magnitude of mispricing.

Third, my analysis contributes to the analysis of the existence of the liquidity premium in equity markets. Recent papers at this front have provided conflicting results. For instance, Amihud et al. (2015) document a positive liquidity premium on international markets, whereas Hou, Xue, and Zhang (2018) find insignificant anomalies based on a large variety of liquidity proxies in the U.S. In line with Hou, Xue, and Zhang (2018), I find a negative liquidity premium based on the quoted spread on international markets. The average value-weighted premium amounts to -68 bp (t-value: -4.52). However, this pattern can be explained by controlling for mispricing: When liquidity is scarce, arbitrage asymmetry is particularly pronounced, which leads to a negative average long leg of the long-short strategy, driven by overpricing. The short leg of the most liquid stocks cannot offset this effect. On the contrary, driven by underpricing, the average short leg appears positive.

Fourth, my paper extends the literature on the existence and drivers of cross-sectional return phenomena on international markets. Studies with an international focus include for example Ang et al. (2009), Bekaert, Hodrick, and Zhang (2009), Chui, Titman, and Wei (2010), Eleswarapu and Venkataraman (2006), Fama and French (2012, 2017), Jacobs

(2016), Jacobs and Müller (2019), McLean, Pontiff, and Watanabe (2009), and Watanabe et al. (2013). The importance of this stream in the literature is emphasized for instance by Karolyi (2016), who states that academic research in Finance suffers from a serious home bias, that is most of the studies published in the top journals in the field of Finance are focused on the U.S., despite the economic relevance of other markets.

2. Empirical approach

2.1. Measuring mispricing and liquidity

Mispricing according to Stambaugh, Yu, and Yuan (2015) comprises the following eleven anomalies from the literature that have survived the risk adjustments of a Fama and French (1993) three-factor model:

- Financial distress (Campbell, Hilscher, and Szilagyi, 2008)
- O-Score bankruptcy probability (Ohlson, 2008)
- Net stock issues (Ritter, 1991; Loughran and Ritter, 1995; Fama and French, 2008)
- Composite equity issues (Daniel and Titman, 2006)
- Total accruals (Sloan, 1996)
- Net operating assets (Hirshleifer et al., 2004)
- Momentum (Jegadeesh and Titman, 1993)
- Gross profitability (Novy-Marx, 2013)
- Asset growth (Cooper, Gulen, and Schill, 2008)
- Return on assets (Fama and French, 2006; Chen, Novy-Marx, and Zhang, 2011)
- Investment-to-assets (Titman, Wei, and Xie, 2004; Xing, 2008)

In the revised, international edition of the mispricing score, two of the eleven anomalies are not constructed due to data limitations: Financial distress and the O-Score (Lu, Stambaugh, and Yuan, 2017).[6] Moreover, the underlying models of those anomalies have been calibrated for the U.S. market only. Thus, I exclude them from the mispricing construction throughout the paper. A detailed description of each of the remaining nine anomalies of the original mispricing score can be found in Table A6 of the appendix.

The construction of the anomalies requires information on the fiscal year end of the firms, as generally a publishing lag of four months is assumed (Stambaugh, Yu, and Yuan, 2015). For this purpose, I rely on the variables "datadate" for the U.S. and "WC05350" for all other countries. In case of a missing value for the fiscal year end in Worldscope, I complement the following information based on country affiliation: (1) For Australia and Pakistan I assume June of year t to July of year $t+1$, (2) for India, Japan and New Zealand I use April of year t to March of year $t+1$, (3) for South Africa I use March of year t to February of year $t+1$, and (4) for all other countries I use the worldwide most represented period from January to December of year t.[7]

Mispricing is constructed in line with Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017): Every month, I rank stocks independently based on the nine remaining anomalies for the international mispricing score based on Lu, Stambaugh, and Yuan (2017). The sorting process is implemented in a way that the highest anomaly rank is matched to the value of the anomaly variable with the lowest average abnormal return as documented in the literature. The ranks are computed for each country separately (i.e. country-neutral). This approach is common in international asset pricing (e.g. Rouwenhorst, 1998, and Jacobs, 2016), and ensures a more even distribution of countries in the global ranking. Next, I construct the ranking percentiles from the individual ranks per anomaly and country-month. Finally, a stock's aggregate mispricing score can be computed as the arithmetic average of its individual anomaly ranking percentiles. Following Stambaugh, Yu, and Yuan (2015), I apply the following screens to provide a minimum level of data coverage per country-month: First, I require at least 30 stocks with a non-missing anomaly variable for the construction of an individual anomaly ranking. Second, at least

[6]Jacobs (2016) on the other hand uses both Financial distress and the O-score to compute mispricing internationally.

[7]WC05350 is globally covered very well. If any arbitrary accounting variable is available, usually the field is also non-missing. Thus, the inferences throughout this article are not dependent on this complement. In chapter 3.3, I also implement a more conservative approach that consists of using a six-months lag following the previous end of the year (e.g. Fama and French, 1993).

five individual anomaly variables must be non-missing to create the composite mispricing rank of a given stock.

To measure liquidity, I primarily use the quoted spread (qs) as a proxy, which is calculated in a given day d as follows:[8]

$$qs_d = \frac{ask_d - bid_d}{(ask_d + bid_d)/2}$$

I also compute the adjusted high-low spread (*adj hls*) as defined in Corwin and Schultz (2012):

$$adj\ hls = \frac{2(e^a - 1)}{1 + e^a}$$

with:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

$$\beta = \sum_{j=0}^{1} \left[ln \left(\frac{H^o_{d+j}}{L^o_{d+j}} \right) \right]^2$$

$$\gamma = \left[ln \left(\frac{H^o_{d,d+1}}{L^o_{d,d+1}} \right) \right]^2$$

H^o is the observed high price, L^o is the observed low price, and $H^o_{d,d+1}$ and $L^o_{d,d+1}$ refer to the observed 2-day high price and 2-day low price, respectively. *adj hls* represents a constant spread estimate over the two-day estimation period. A monthly estimate can be obtained by averaging across the overlapping 2-day intervals in a given month.

Another proxy for the quoted spread that is defined monthly is given by Fong, Holden, and Trzcinka (2017), the so-called FHT spread (fht_m):

$$fht_m = 2 * \sigma_{non-zeros} * N^{-1} \left(\frac{1 + zero\_pct}{2} \right)$$

with $\sigma_{non-zeros}$ as the standard deviations of daily firm level returns in a given month that are unequal to zero, N^{-1} as the inverse normal cumulative distribution function, and $zero\_pct$

[8]For simplicity, I drop the stock index i throughout this section.

as the percentage of days per month in which the daily return equals zero.

As price impact proxy I rely on illiquidity according to Amihud (2002), computed monthly as follows:

$$illiq_m = \left(\frac{1}{D}\sum_{d=1}^{D}\frac{|ret_d|}{prc_d * vol_d}\right) * 10^6$$

with $|ret_d|$, prc_d and vol_d, as absolute return, price and volume, in a given day d respectively, and D as trading days per month.

I implement a number of screens to ensure a minimum level of data quality in the computation of liquidity proxies: (i) For the U.S., a negative price sign in CRSP indicates that the closing price at the end of a trading day is not available and the average of the bid and ask price is used instead (with a negative sign being used as a symbol, not as a mathematical sign). In these cases I use the absolute value instead. (ii) If the price is zero, it is set to missing. (iii) If the ask price is lower than the bid price, both, the bid and the ask price, are set to missing. (iv) If the ask and the bid price are simultaneously zero, they are set to missing. (v) I delete daily returns larger than 200% to remove unreasonable outliers (e.g. Griffin, Kelly, and Nardari, 2010). (vi) I also delete returns in case of strong daily reversals, defined as follows: R_{t-1} or $R_t = 1.0$, and at the same time $(1+R_{t-1}) * (1+R_t) - 1 < 0.2$. (vii) If the ratio of the current price and the price of the previous day is larger than 1.5, or smaller than 0.5, the current as well as the previous price are set to missing (Lesmond, 2005). Additionally, I set the current return to missing. (viii) I trim quoted spreads that exceed 1.0 and set the corresponding bid and ask prices to missing (Jain, 2003). (ix) To account for non-trading days (in countries other than the U.S.), I implement a screen in the sense of Karolyi, Lee, and Dijk (2012): If the count of local zero returns is more than 99% of the total observations per exchange-day, all variables related to the measurement of liquidity are set to missing.

The implementation of the Corwin and Schultz (2012) adjusted high-low spread requires additional screens suggested by the authors: (x) For the U.S., CRSP generally uses bid and ask prices for low and high prices, respectively, if a stock does not trade at all (i.e. it carries zero volume). This may be beneficial for a researcher who analyzes just the high-low spread. To ensure that in this case the high-low spread is not mixed up with the quoted spread, bid and ask prices are replaced by the most recent non-missing low and high prices, respectively. (xi) If a stock trades only once during the day, or always at the same price, the high-low spread cannot be computed. In these cases, I also set the low and high prices to the most recent non-missing low and high prices, respectively. (xii) Stock prices can move significantly overnight (e.g. French and Roll, 1986; Harris, 1986). To prevent an underestimation of the spread portion of the high-low price ratio, an adjustment for overnight changes has to be undertaken. The closing price in day d is compared with the range of prices given by the high and low price in day $d+1$. If the close in d is below the low in $d+1$, the price is assumed to have risen overnight from the close to the new low in $d+1$. Thus, the high and low prices in $d+1$ are decreased by the overnight change. Accordingly, if the close in d is above the high in $d+1$, the high and low prices are increased by the overnight change. (xiii) Finally, negative high-low spreads are possible by construction, for instance when the variance of a given stock over two days is more than twice as large as the single-day variance in periods of high volatility. Following Corwin and Schultz (2012), negative spreads are set to zero.

Next, the daily liquidity proxies are averaged per firm-month. (xiv) Following Fong, Holden, and Trzcinka (2017), I require at least eleven non-zero returns and five observations with a volume larger than zero to ensure a minimum of firm level liquidity per month. (xv) Lastly, all liquidity proxies are winsorized at the 99.9% and 0.1% levels per country-month.

2.2. Data

I collect stock market and accounting data from CRSP and Compustat, respectively, for the U.S., and from Datastream and Worldscope, respectively, for the rest of the world. The sample period runs from the beginning of January 1990 until the end of June 2018. The start date is chosen by intention, as internationally data coverage has increased a lot at that time.[9]

In the construction of the sample I use active and dead stocks to obviate a survivorship bias. To ensure that only common stocks are analyzed, I implement a series of filters: For the U.S., I analyze NYSE, AMEX, and NASDAQ stocks with CRSP share codes of 10 or 11.

[9] The annual record for most companies in developed market ex U.S. starts in the mid 1980s for medium sized firms and in the mid 1990s for small sized firms. Furthermore, Worldscope includes emerging markets only starting from the 1990s (Worldscope Database, Data Definitions Guide Issue 15, March 2018).

For the rest of the world, I perform the following filters (e.g. Ince and Porter, 2006; Griffin, Kelly, and Nardari, 2010; Karolyi, Lee, and Dijk, 2012; Fong, Holden, and Trzcinka, 2017; and Schmidt et al., 2017): (1) In case of multiple securities per firm, I use only major stocks. (2) The security type must be equity. (3) Only primary quotations of a security are considered. (4) Firms are located and listed in the associated countries. (5) A firm's currency must equal the currency of the associated domestic country. (6) Firms whose "NAME", "ENAME" or "ECNAME" field indicates non-common equity affiliation (i.e. ADRs, investment trusts, REITs, mutual funds, preferred stocks or warrants) are dropped.[10]

Daily (and monthly) returns for countries besides the U.S. are computed from the total return index in USD. Following Ince and Porter (2006), I delete zero returns and market capitalizations from the end of the sample up to the first non-zero return on firm level to account for stale prices in case of delistings.[11] I also delete returns and market capitalizations in case of unadjusted prices that are larger than one million USD. Similarly to the daily return screens, I delete monthly returns and market capitalizations if the return is larger than 990% (Schmidt et al., 2017), or in cases of strong monthly reversals defined as follows: R_{t-1} or R_t $= 3.0$ and at the same time $(1+R_{t-1}) * (1+R_t) - 1 < 0.5$ (Griffin, Kelly, and Nardari, 2010).

The result is a comprehensive international data set spanning more than 87,000 unique firms, 565 million firm days, and 52 countries from 1990-01 until 2018-06. Panel A of Table 1 provides descriptive statistics on the latest market developments. The aggregate stock market capitalization (common equity only) in 2018-06 amounts to 72.3 trillion USD. In relative terms, the U.S. market has the largest weight, with 38.54%, followed by the Chinese market with 10.39%, and Japan with 8.5%. The same ranking occurs in terms of dollar volume: The U.S. have a total dollar volume of 4.4 trillion, followed by China with 1.1 trillion and Japan with 0.5 trillion. If non-missing observations for liquidity and mispricing at the beginning of the month are required, Panel B of Table 1 shows that the final sample consists of more than 60,000 firms and 6.8 million firm months from 1990-01 to

[10]To be more specific, a stock is removed only, if the harmful word fulfills the following two conditions: There is a whitespace (or a tab) before the keyword and there is a whitespace or a dot after the keyword, or the name field ends with the keyword. The keywords under consideration are mostly collected from the following studies: Ince and Porter (2006), Griffin, Kelly, and Nardari (2010), and Karolyi, Lee, and Dijk (2012).

[11]In case of a stock delisting, Datastream continuously reports the last available price for the following time to the end of the sample period.

2018-06. Iceland, Luxembourg and Venezuela are dropped from the sample because mispricing cannot be calculated in those countries in the sample period. Czech Republic is included, but not in the analyses with the quoted spread and the adjusted high-low spread, as it does not provide any coverage for these measures. Comparing average daily liquidity per month across countries based on the quoted spread, Canada is leading with a value of 8.3%, followed by Australia with 7.0% and Singapore with 6.2%. If countries are ranked by Amihud's illiquidity, Sri Lanka has the first spot, followed by Indonesia and Russia. Even though illiquidity is winsorized and a series of screens regarding daily returns and dollar volumes are performed, the measure is still significantly affected by high return and small dollar volume outliers. This result can also be observed in other studies (e.g. Fong, Holden, and Trzcinka, 2017, Table V, p. 1377). Without further data limitations and in terms of interpretation, these values should be treated with caution.[12] For an analysis that is based primarily on liquidity rankings to obtain portfolio sorts, however, further adjustments (besides trimming) would not lead to different inferences. Table 2 reports the time-series averages of the monthly cross-sectional Pearson correlation coefficients of the mispricing-related anomaly variables, the liquidity proxies, as well as various control variables that are used throughout this article. The average correlations between the alternative liquidity proxies are high, ranging from 31.4% between the quoted spread and illiquidity to 45.0% between the quoted spread and the high-low spread and 65.4% between the quoted spread and the FHT spread. The correlation between the quoted spread and size, and between the quoted spread and idiosyncratic volatility, amounts to -53.4% and 45.7%, respectively. Furthermore, liquidity shocks are negatively correlated with idiosyncratic volatility (-12.4%).

Figure 1 displays the average monthly global time-series of the four liquidity proxies. Amihud's illiquidity is multiplied by a factor of 200 (instead of 10^6) in this analysis, to obtain a comparable scale with the other variables. The figure reveals clearly visible spikes in illiquidity during economic crises of global impact, as for example the oil shock in 1990, or the insolvency of Lehman Brothers in 2008. All four liquidity proxies seem to capture the economic crises very well. Notably, Amihud's illiquidity experiences a shift upwards

[12] The spikes in illiquidity occur mostly for small stocks with little dollar volume. This can occur due to currency conversion: If a foreign currency is weak against the dollar, the dollar volume is smaller than the volume based on local currency. The currency conversion is needed, however, to compare measures across countries.

from about 0.005 to 0.03 during the Asian financial crisis in 1996, which only recedes back to previous levels in 2004. The adjusted high-low spread as well as the FHT spread seem to be good percent-cost liquidity proxies, as they reveal a similar behavior over time as the quoted spread, which is considered the percent-cost benchmark.

3. Mispricing spreads in liquid vs. non-liquid markets

To compare mispricing between liquid and non-liquid markets, every month I classify the universe of stocks into liquid and non-liquid markets based on the median quoted spread. Furthermore, I divide stocks into five mispricing groups. This second sorting step is implemented in two different ways: Independent or dependent on the liquidity sorting in the first step. In the independent-sort approach, the sorting based on mispricing is performed unconditional on liquidity, and 2x5 portfolios are constructed at the intersections of the two liquidity and the five mispricing groups. In the dependent-sort approach, the creation of the mispricing score and the associated sorting is performed for liquid and non-liquid markets separately, which also results in 2x5 portfolios. I create quintile-based long-short portfolios based on mispricing for each type of market.

The independent-sort approach has the advantage that it makes use of more information at any given point in time by ranking all available stocks on mispricing and liquidity, but in return it must be ensured that portfolios are diversified. This can be verified by looking at the amount of stocks in extreme portfolios, for instance at the intersection of overpricing and high liquidity. The dependent-sort approach on the contrary ensures that enough stocks are contained in each of the portfolios, but the rankings on mispricing and liquidity are not as strong, as fewer stocks are considered (i.e. roughly 50%) compared to the independent-sort approach.

To ensure that portfolios are diversified, I additionally impose two requirements in the formation: First, there must be at least 30 stocks with non-missing liquidity and mispricing per country-month for a country to be included in the breakpoint calculation (Stambaugh, Yu, and Yuan, 2015). Second, after the breakpoint calculation and the assignment of stocks to portfolios, I require at least five stocks per portfolio and country-month.

3.1. Benchmark results

Panel A of Table 3 reveals that the average long/short portfolio returns based on mispricing are significantly different on liquid and non-liquid markets in the independent-sort portfolio approach. The average difference in the monthly long/short return spreads is economically meaningful with 55 bp (43 bp) per month, measured by value-weighted (equally-weighted) returns. The associated t-value in case of value-weighting (equally-weighting) is 3.48 (4.52). The point estimate of the long/short strategy on the liquid (non-liquid) market amounts to 65 bp (120 bp) with value-weighted returns, and 108 bp (151 bp) with equally-weighted returns. All of the point estimates are significant at the 1% level. Thus, on both liquid and non-liquid markets an investment strategy based on mispricing performs very successfully. Furthermore, there is a significant liquidity premium in mispricing long/short spreads.

With respect to the differences between the individual anomaly long/short returns on liquid and non-liquid markets, in case of value-weighted returns, four of them are statistically significant at least at the 5% level, namely accruals, the gross profitability premium, net stock issues and composite equity issues. In case of equally-weighted returns, net operating assets, asset growth, investment-to-assets, return on assets and momentum are significant at least at the 5% level. To assume that liquidity has a significant effect on every single anomaly would be rather enthusiastic. The anomalies where liquidity does not appear to be very relevant, in particular return on assets and momentum in case of value-weighted returns, might be driven more heavily by other influences, which exceed the cost of bearing liquidity risk. For example Hillert, Jacobs, and Müller (2014) state that momentum is particularly strong for firms that are covered well by the media. Irrational investors might just buy stocks that are heavily advertised in any case, independent of any liquidity impediments. That being said, the main focus of this analysis remains to investigate the relation between the composite mispricing measure and liquidity.

The previous results can be principally carried over to the dependent-sort portfolio analysis in Table 3, Panel B. In case of value-weighted returns the average difference in returns of the high/low mispricing strategies between liquid and non-liquid markets is 46 bp per month (t-value: 2.88), and in case of equally-weighted returns it amounts to 31 bp per month (t-value: 3.20). Four of the differences in the individual long/short anomaly spreads between liquid and non-liquid markets are significant at least at the 5% level in case of value-weighted returns, and five of them in case of equally-weighted returns.

In sum, I find economically meaningful and statistically significant differences in long/short portfolio returns based on mispricing between liquid and non-liquid markets in all four of the implemented tests, that is for independent-sort and dependent-sort portfolios, with value-weighted and equally-weighted returns in either instance.

3.2. Abnormal return analysis

In the previous section, the portfolio analysis is based on raw returns. A more conservative approach that is standard in the literature on anomalies is to analyze abnormal returns relative to a Fama and French (1993) three-factor model. To implement this approach, I construct a global Fama-French three-factor model, using country-neutral breakpoints in the factor formation. For the construction of small minus big (SMB) and high minus low (HML), I require a non-missing market capitalization in June of year t, a non-missing market capitalization in December of year $t-1$, and positive book equity at the fiscal year ending in $t-1$ (Fama and French, 1993). The breakpoints used to construct HML and SMB are the 30% and the 70% book-to-market quantiles and the median market capitalization per country-month. In June of every year, I pool all country-based portfolio assignments to obtain global portfolios.

The results are shown in Table 4. The overall picture remains unchanged: In all four specifications under consideration, the average difference in abnormal long/short portfolio returns based on mispricing between liquid and non-liquid markets is economically large, ranging from 28 bp in case of dependent-sort portfolios and equally-weighted returns to 42 bp in case of independent-sort portfolios and equally-weighted returns, and statistically significant at least at the 5% level, carrying t-values between 1.99 and 4.22. The individual long/short anomaly spreads and the spread differences across markets overall reveal similar average abnormal returns to the average raw returns in the previous analysis, but sometimes the associated significance levels are changing (e.g. the difference between the long/short spreads on net operating assets becomes significant in both sorting approaches under value-weighted returns).

Overall, it can be inferred that the benchmark results of the previous section prove to withstand the risk adjustments of a global Fama-French three-factor model.

3.3. Robustness

To check the robustness of the previous findings, I perform a subsample analysis and evaluate the effects of a series of changes to the critical assumptions in the portfolio construction. Table 5 provides the results. Unless otherwise stated, I report abnormal long/short returns based on mispricing with respect to a global Fama-French three-factor model, constructed from independently sorted 5x2 portfolios based on mispricing and the quoted spread. Furthermore, breakpoints are calculated in a country-neutral way, the complete global sample is analyzed (in particular, the countries of Panel B, Table 1), and a four-month publishing lag is employed to compute the anomalies underlying the mispricing score.

Model (1) reveals that a positive and significant difference in abnormal returns between long/short mispricing portfolios of liquid and non-liquid markets can also be found only in the U.S. market. This result confirms the existence of the documented liquidity premium for the largest market in the sample. In model (2), I analyze all countries besides the U.S. The difference in abnormal returns between long/short mispricing portfolios of liquid and non-liquid markets is significant in terms of equally-weighted returns (t-value: 3.19), but not in terms of value-weighted returns (t-value: 1.82). This implies that small stocks have a notable influence on the success of the investment strategy particularly outside the U.S. In model (3), I am using a conservative six-month publishing lag following the end of the year $t-1$ in the construction of the nine anomalies underlying the international mispricing score. This approach is in line with Fama and French (1993) and used for instance by Jacobs (2016) in the construction of the anomalies underlying the mispricing score. The resulting difference in abnormal returns of the long/short mispricing portfolios is very similar (identical) to the benchmark case, with a point estimate of 44 bp (42 bp) and an associated t-value of 2.79 (3.99) in case of value-weighted (equally-weighted) returns. Model (4) reveals that the liquidity premium becomes stronger through use of global (instead of country-neutral) breakpoints, for both value-weighted and equally-weighted returns. This perspective might be particularly relevant for industry professionals, who are willing to bear country-specific risks to increase expected returns. Model (5) shows that the construction of breakpoints based on big stocks, defined as stocks within the top 90% of aggregate market capitalization in a country,[13] has a negative influence on the liquidity premium: The difference in abnormal returns between long/short mispricing portfolios of liquid and non-liquid markets drops to 19 bp per month in case of value-weighted returns (t-value: 1.35). This finding can be explained by an increased dilution of illiquid and liquid stocks by use of big stock breakpoints, which in turn deceases the average return of the quintile portfolio with the most illiquid stocks. This effect does not exist with equally-weighted returns: The point estimate of the difference in abnormal returns amounts to 55 bp (t-value: 4.35) in this case. In models (6), (7) and (8), I vary the liquidity proxy in the portfolio sorts. In case of the FHT spread, the liquidity premium occurs only for equally-weighted returns. In case of Amihud's illiquidity, it is positive but not significant at the 5% level under both return-weighting schemes. In case of the adjusted high-low spread, it amounts to 57 bp (46 bp) measured by value-weighted (equally-weighted) returns and is significant at the 1% level in either case.

The empirical findings presented so far provide strong evidence for the existence of a liquidity premium in international long/short portfolio returns based on mispricing. This premium, however, might be simply a manifestation of other anomalies or risks from the literature, for instance the size effect, which is closely related to liquidity.[14] Table A1 displays that independent 5x2 portfolio sorts based on mispricing and each of the following cross-sectional return phenomena: Size, book-to-market, leverage, co-skewness, and idiosyncratic volatility, do not lead to a significant difference in abnormal returns based on value-weighted returns. Thus, the observed liquidity premium cannot be explained by any of those effects taken by themselves.[15]

[13] In an alternative, undocumented specification, every month, I first calculate the top percentage aggregate market capitalization which corresponds to using a median size breakpoint based on NYSE stocks in the U.S. The resulting value can then be used to compute the corresponding size breakpoints for all other countries besides the U.S. Inferences in this case are very similar to the 90% rule.

[14] In my sample, the average correlation between size and liquidity amounts to -53.4%, see Table 2.

[15] Stambaugh, Yu, and Yuan (2015) find a very strong relation between IVOL and mispricing in the U.S. market. I repeat their analysis and get quantitatively almost identical results. On international equity markets, however, the relation between IVOL and mispricing does not appear to be as strong as the relation between liquidity and mispricing (compare Table 4 with Table A1).

4. Deconstructing the liquidity premium in mispricing spreads

The previous analysis which is focused on 2x5 portfolio sorts on liquidity and mispricing is conservative in that only two portfolios are formed with regard to the liquidity sort. In the anomaly-return literature, decile portfolios are typically used if data coverage is rich, as for instance in the U.S., or quintile portfolios on international markets, which cover also many of the smaller countries with a lower data coverage. In this chapter, the amount of portfolios based on liquidity is raised to five to bring it to the same level as the amount of portfolios based on mispricing.

The 5x5 portfolios are constructed each month by sorting stocks independently on liquidity and mispricing. I use region-neutral breakpoints to guarantee a minimum level of regional portfolio diversification (e.g. Fama and French, 2012; Fama and French, 2017) and analyze the four regions as defined by Fama and French,[16] that is North America, Europe, Asia Pacific ex Japan, and Japan, and additionally emerging markets. Furthermore, I require at least 125 stocks per country-month.[17] At the intersections of the five liquidity groups and the five mispricing groups, 25 portfolios are created.

The properties of the portfolios are shown in Table 6. Panel A reveals that the quoted spread within each mispricing category increases monotonically from the most underpriced to the most overpriced stocks, as shown in the last column ("All stocks"). This effect is driven by the more illiquid stocks, as the pattern appears more even in the two most liquid quintile categories. In panel B, mispricing within each level of liquidity increases monotonically from liquid stocks to illiquid ones, as shown in the last row ("All stocks"). This increase is driven more by the overpriced stocks than by the underpriced ones, as the pattern appears more even in the three most underpriced quintile categories. Note that the average mispricing of all stocks is not equal to 50% precisely, which is expected given the way mispricing is computed.[18] Panel C confirms these results: Among stocks that are most underpriced (overpriced), the number of stocks increases from the most illiquid (liquid) stocks

[16] See e.g. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_3developed.html.

[17] This screen ensures that countries are only included in the analysis when they have reached a certain level of market maturity. Changing the threshold (i.e. to 75 or 0 stocks) does not lead to different inferences.

[18] Every month, the relative anomaly ranks are averaged across anomalies to construct a composite mispricing score per stock.

to the most liquid (illiquid) ones. Among the most liquid (illiquid) stocks, the number of stocks increases from stocks that are most overpriced (underpriced) to the ones that are most underpriced (overpriced). Especially noticeable, the number of stocks of the portfolio with the most overpriced and most illiquid stocks amounts to 825 and is overall the highest observed value. Consequently, underpricing seems to be positively correlated with liquidity, whereas overpricing seems to be positively correlated with illiquidity, with the latter effect dominating.

Similarly to stocks with high volatility, as argued in Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2015), illiquid stocks are prone to being valued with excessive optimism or pessimism by noise traders, because they are difficult to value. Moreover, noise traders are typically bound by shorting impediments, which leads to a limit in negative demand for stocks that are viewed with high pessimism. On the other hand, there is no such limit for positive demand due to excessive optimism. Combining these two effects, it follows that highly illiquid stocks are more likely to be overpriced than underpriced as a consequence of noise trader sentiment. This argument is closely related to Stambaugh, Yu, and Yuan (2015), who analyze the relation between mispricing and idiosyncratic volatility, assuming that stocks with high volatility are also highly illiquid.[19] However, as pointed out by Stambaugh, Yu, and Yuan (2015), non-sentiment components of noise-trader demand, for example the slow recognition of information that is relevant to value stocks, can also increase mispricing despite the level of volatility, or despite the level of liquidity, following the previous argument.

Table 7 presents the average abnormal returns of the portfolios with respect to a global Fama-French three factor model. Within the most liquid stocks, the average returns are positive, except for the most overpriced portfolio, and decreasing in the mispricing score from 59 bp to -22 bp. The average difference in returns between the most overpriced and most underpriced portfolio equals -80 bp (t-value: -5.27). Within the most illiquid stocks, the average returns are negative, except for the most underpriced portfolio, and strongly decreasing in the mispricing score, from 59 bp to -159 bp. The average difference in returns between the most overpriced and most underpriced portfolio equals -218 bp (t-value: -

[19] In Table 2, I document an average monthly correlation of 45.7% between IVOL and the quoted spread.

11.36). The average return of the difference-in-difference portfolio amounts to -137 bp (t-value: -6.03). Assuming an investor is long in underpriced and short in overpriced stocks, this translates to an average return of 137 bp per month. The analysis also confirms that the arbitrage asymmetry effect can be mainly attributed to the most illiquid stocks, as within the overpriced quintile group the average return of these stocks amounts to -159 bp (t-value: -7.38), whereas the average return of the most liquid stocks only amounts to -22 bp (t-value: -1.31). The difference between the latter two portfolios is -138 bp (t-value: -5.74). On the other hand, if liquidity proxies for arbitrage risk similarly to IVOL, we would expect that within the underpriced stock category the average return of the most illiquid stocks is significantly higher than the average return of the most liquid stocks. This, however, is not the case internationally. As the table demonstrates, among underpriced stocks the average return of both the most liquid and the most illiquid stocks amounts to 59 bp, with a t-value of 5.23 (3.85) in case of the most liquid (illiquid) stocks. I infer that arbitrageurs are likely reluctant to fully utilize all arbitrage opportunities even for the most liquid stocks, which might be a consequence of using a global sample that also includes small countries with fewer information transparency and higher arbitrage risk. Indeed, I find that for the US, and also for the developed markets (including the U.S.), the difference in returns is positive and statistically significant, providing additional support for this conjecture. The results of these additional analyses are shown in the Appendix (Table A2 and Table A3). Figure 2 plots the average returns of the 25 portfolios in the international sample and thus illustrates the documented relation between liquidity and mispricing.

The last row ("All stocks") shows that in case of a univariate sorting based on liquidity, there is a negative liquidity premium. The average difference in returns between the highest and the lowest quoted spread portfolio amounts to -68 bp (t-value: -4.52). This result is characteristic for a value-weighted return analysis of portfolios ranked by liquidity (see e.g. Hou, Xue, and Zhang, 2018) and illustrates a size effect in the liquidity dimension. Given the previously documented, positive liquidity premium in long/short mispricing spreads, which is mainly driven by the short leg (i.e. overpricing) of the most illiquid stocks, this result is not surprising. As a large fraction of the quintile portfolios among the most illiquid (liquid) stocks are carrying a negative (positive) return, the average return of the most illiquid (liquid) stocks is also negative (positive). Consequently, both the long and the short leg of the strategy have signs which are in support of a negative premium.

5. Liquidity shocks and mispricing

In this section, I analyze the effect of firm level liquidity shocks on mispricing. The analysis once again relies on 5x5 portfolio sorts, with liquidity shocks ($liqu$) computed as the negative difference between the current quoted spread and its average over the last 12 months:

$$liqu_{i,t} = -(qs_{i,t} - avg\_qs_{i|t-12,t-1})$$

First, the cross-sectional quantile of stocks with approximately zero liquidity shocks has to be identified. The mispricing at this point serves as a point of reference, to which the mispricing of firms that are experiencing positive or negative liquidity shocks will be compared. I find that the cross-sectional cumulative distribution function of liquidity shocks varies considerably over time, that is the zero shock quantile changes its position often between the five available portfolio ranks. For example, if the zero shock quantile amounts to 68%, it is assigned to the fourth liquidity shock quintile portfolio, which I refer to as the "zero shock" portfolio hereafter.[20] As the quintile positions of the portfolio ranks must be constant over time to allow for the analysis of abnormal returns relative to a state of zero liquidity shocks, I differentiate between the following three scenarios per month:[21]

(A) There are more positive then negative shocks (strong market environment):

$q_{0.2} < q_{zero} \leq q_{0.4}$

(B) There are approximately equally as many positive as negative shocks (neutral market environment):

$q_{0.4} < q_{zero} \leq q_{0.6}$

(C) There are more negative than positive shocks (weak market environment):

$q_{0.6} < q_{zero} \leq q_{0.8}$

[20] A more precise, but also more verbose formulation to describe the portfolio would be: "comprising liquidity shocks that are close to zero". For brevity, I use the term "zero shock portfolio" throughout the text.

[21] In the analysis, high (low) liquidity shocks are associated with a (high) low quintile portfolio rank.

with q_p as a quantile of liquidity shocks with threshold p, and q_{zero} as the specific quantile with liquidity shocks equal to zero. While generally also stocks with liquidity shocks unequal to zero can be part of any of the three zero shock ranges, the empirical analysis further below reveals that the associated values are principally close to zero. All three scenarios provide a suitable time period for the analysis: Scenario A covers 234 months, scenario B 333 months, and scenario C 76 months. The designation of the zero shock quantile is performed in a region-neutral way, so a given month can be part of multiple scenarios at the same time when the designation varies between regions. Note that there are hardly any cases (i.e. < 10 months) when the zero shock quantile falls into the range of the first quintile portfolio (i.e. only positive shocks), or into the range of the last quintile portfolio (i.e. only negative shocks), thus these cases can be neglected. Figure 3 provides an overview of the three subsamples.

Table 8 presents the properties of the 25 portfolios under the three scenarios, with panel A, B, and C representing scenario A, B, and C, respectively. The zero shock portfolio displays *liqu* close to zero under all three scenarios. Moreover, in all three panels *liqu* of each mispricing category increases monotonically from the most overpriced to the most underpriced stocks, as shown in the last column ("All stocks"). This average increase must be interpreted with caution, as within the individual liquidity shock quintile groups it occurs only for negative shocks, whereas for positive shocks *liqu* increases from the most underpriced to the most overpriced stocks. Overpriced stocks seem to be particularly susceptible to liquidity shocks, as they are carrying the highest values of *liqu* (absolute values) under both positive and negative shocks. This pattern can be explained by the presence of arbitrage asymmetry, that is generally fewer arbitrage is undertaken among overpriced than among underpriced stocks, which induces a higher susceptibility of overpriced stocks to receive liquidity shocks in either direction, assuming the market is generally more efficient among underpriced stocks.[22] Furthermore, I find that the average amount of stocks among negative liquidity shocks increases monotonically from underpriced stocks to overpriced ones, which provides support for the documented connection between negative liquidity shocks and overpricing. If there are more positive than negative liquidity shocks in the economy

[22]This argument can be made in the context of the Stambaugh, Yu, and Yuan (2015) mispricing score, as no assumptions are made on the absolute price deviations from the fair values.

(panel A), this pattern can be also observed for positive shocks.

Table 9 displays the average abnormal returns with respect to a global Fama-French three factor model. The analysis is similar to section 4, but this time the focus lies on the average difference in returns between portfolios with positive and negative liquidity shocks and the zero shock portfolio. First, I look at the average returns of the 25 portfolios. Next, I also compute difference-portfolios within each mispricing group by subtracting the return of the zero shock portfolio from the returns of each of the liquidity shock quintile portfolios. As one of the liquidity shock quintile portfolios constitutes the zero shock portfolio by definition, the associated difference-portfolio carries a return of zero. I also compute the average returns of these difference-portfolios.

In case of a strong market environment (Panel A), the average return within negative liquidity shocks amounts to 108 bp (t-value: 4.76) for the most underpriced stocks, and to -120 bp (t-value: -4.16) for the most overpriced stocks, with the difference between the most overpriced and most underpriced portfolios equal to -228 bp (t-value: -7.43). The average return within the zero shock group amounts to 66 bp (t-value: 3.63) for the most underpriced stocks, and to -32 bp (t-value: -1.21) for the most overpriced stocks, with the difference between these portfolios equal to -99 bp (t-value: -3.55). The lower section of Panel A displays the return changes of the liquidity shock portfolios with respect to the zero shock portfolio for each mispricing group. Among negative liquidity shocks, the change of the most overpriced stocks is equal to -88 bp (t-value: -3.32), the change of the most underpriced stocks is equal to 42 bp (t-value: 1.44), and the total change in the mispricing spread amounts to -129 bp (t-value: -3.37). Among positive liquidity shocks, the return change for the most underpriced stocks amounts to 109 bp (t-value: 5.02), and for the most overpriced stocks to -42 bp (t-value: -1.53), with the difference between these portfolios equal to -151 bp (t-value: -5.72). The analysis of difference-portfolios reveals that neither the returns of the five mispricing portfolios nor the mispricing return spread change significantly relative to the zero shock portfolio. Thus, the magnitude of mispricing is not influenced severely by positive liquidity shocks in a strong market environment.

In case of a neutral market environment (Panel B), the average return among negative liquidity shocks is 39 bp (t-value: 2.50) for the most underpriced stocks, and -102 bp (t-value: -4.65) for the most overpriced stocks. The return difference between these portfolios is equal to -141 bp (t-value: -6.24). Within the zero shock group, the average return amounts to 60 bp (t-value: 4.82) for the most underpriced stocks, and to -27 bp (t-value: -1.42) for the most overpriced stocks, with the difference between these portfolios equal to -88 bp (t-value: -4.97). Within positive liquidity shocks, the average return is 117 bp (t-value: 6.87) for the most underpriced stocks, and -31 bp (t-value: -1.29) for the most overpriced stocks. The return difference between these portfolios amounts to -148 bp (t-value: -6.49). The lower part of the table reveals that the mispricing spread under both negative and positive liquidity shocks changes significantly relative to the zero shock portfolio. In case of negative shocks, the change is -53 bp (t-value: -2.13) and can be mainly attributed to the change in the short leg of the strategy, which amounts to -74 bp (t-value: -3.50). In case of positive shocks, the change amounts to -60 bp (t-value: -2.29) and can be mostly attributed to the change in the long leg of the strategy, which amounts to 56 bp (t-value: 3.22). Thus, in a neutral market environment, both positive and negative liquidity shocks have a significant effect on the magnitude of mispricing.

Finally, Panel C reveals that in case of a weak market environment, none of the 25 average portfolio returns are significant. This is likely a consequence of the turmoil, which can typically be observed on financial markets during crisis periods. If the ranking is performed only by mispricing, the column "All stocks" reveals that the mispricing return spread is not significant in this case. This is mainly due to the long leg of the strategy that carries an average return of -69 bp (t-value: -1.26) and stands in contrast with the long legs of Panel A and B, which are equal to 70 bp (t-value: 4.64) and 60 bp (t-value: 5.98), respectively. The short leg in contrast amounts to -125 bp (t-value: -1.44), which is lower than the corresponding values in Panel A and B, which are equal to -27 bp (t-value: -1.16) and -36 bp (t-value: -2.35), respectively. The lower section of the table shows that there are significant return changes from the zero shock portfolio to negative liquidity shocks in case of the third and fourth mispricing groups, but the change of the most overpriced group is not significant. However, the subsample consists only of 70 months, therefore these results should be treated with caution. Possibly the underlying crises have to be analyzed separately to control for any crisis-specific effects. Figure 4 plots the average abnormal returns of the 25 portfolios under each of the three scenarios.

Another way to conduct the analysis is to ignore the economic state of the market and to analyze the full sample instead. Due to the variation of the cross-sectional zero-shock quantile over time, the distances between the portfolio quintile ranks of the most positive and most negative liquidity shock portfolios and the rank of the zero shock portfolio are now dynamic. It follows that the average 5x5 portfolio returns cannot be presented in a conclusive way anymore.[23]

If the goal is to make a statement on the effect of liquidity shocks on mispricing, the extreme quintile portfolios with the most positive or most negative shocks in relation to the zero shock portfolio are of peculiar interest.[24] Thus, to solve the issue with respect to a clear presentation of results, I only analyze the return difference between the most negative shock portfolio and the zero shock portfolio on the one hand, and between the most positive shock portfolio and the zero shock portfolio on the other hand. If for instance the economy is in a downturn, which implies there are much more negative shocks in the cross-section than positive ones and the zero shock portfolio has the highest quintile rank, the average return of the negative difference portfolio is computed as the average difference in returns between the first quintile portfolio and the zero shock portfolio, whereas the average return of the positive difference portfolio is equal to zero, as the zero shock portfolio confirms with the fifth quintile portfolio in this example.

I conduct the analysis in two ways: (i) Using global breakpoints; and (ii) using regional breakpoints and averaging the results across regions. In (i), in accordance with the previous analysis, every month I first compute the cross-sectional zero-shock quantile to determine the zero shock portfolio based on the global sample. Next, 25 portfolios are calculated at the intersections of the five mispricing and the five liquidity shock groups. Moreover, within each mispricing group I create difference-portfolios with respect to the zero shock portfolio.

[23]Assume for instance the zero shock portfolio occupies the first quintile rank in 50% of the months in the sample. This means that at least 80% of the stocks have liquidity shocks larger than zero. If the zero shock portfolio holds the second quintile rank in the other 50% of the months, at least 60% of the stocks have liquidity shocks larger than zero, and at least 20% of the stocks have liquidity shocks lower than zero. At this point it is not straightforward how to proceed: One could simply report the average return of the zero shock portfolio, but then in the analysis of the portfolio with quintile rank 1 or 2, when the zero shock portfolio does not occupy that same rank, only 50% of the data would be available for the computation of the average return. Also in a tabular illustration of average returns, it would be unclear where to position the zero shock portfolio and where to position the other two portfolios that involve data up to the second quintile rank.

[24]In the anomaly-return literature, typically high-low return spreads are analyzed. Using a high-zero and low-zero approach accounts for the fact that under scenario B, both positive and negative shocks lead to an increase in mispricing. A typical high-low analysis would not account for this two-sided effect and eliminate a considerable fraction of mispricing in the sample.

The returns of the difference-portfolios are calculated as the return differences between each liquidity shock portfolio and the zero shock portfolio. In (ii), I perform the same analysis in a region-neutral approach. The resulting portfolio returns are then averaged across regions to obtain global estimates. Table 10 presents the results. The change in the mispricing spread due to negative liquidity shocks in case of (i) amounts to -49 bp (t-value -1.91), and in case of (ii) to -70 bp (t-value: -3.52). In comparison, the change in the mispricing spread due to positive liquidity shocks is not significant under either approach. I conclude that independent of the economic state only negative liquidity shocks increase the magnitude of mispricing.

6. Fama-MacBeth regressions to predict stock returns

In this section, I analyze the return predictive ability of liquidity and liquidity shocks, each in combination with each of the nine individual anomaly variables based on Lu, Stambaugh, and Yuan (2017) international mispricing, as well as composite mispricing, in monthly market-value-weighted least squares (VWLS) Fama and MacBeth (1973) type of regressions. I consider the following standard return predictors as controls: Short-term reversal, momentum, long-term reversal, log(ME) and log(B/M), (e.g. Daniel, Hirshleifer, and Sun, 2019) and β, calculated from monthly rolling regressions of daily excess stock returns in the previous month on a global market risk premium. I also control for individual country effects. The dependent variable is the firm level stock return at the end of the current month. The analysis runs from 1990-01 until 2018-06, based on data availability. The dependent variables are winsorized at the top and bottom 1% level and standardized to have a mean of zero and unit standard deviation, to ease the comparison of the coefficients.

Table 11 Panel A reports the regression results for liquidity. In model (1) to (4), I include each of the four liquidity proxies separately with standard controls. The common finding for the quoted spread, Amihud's illiquidity and the FHT spread is that illiquidity negatively and significantly forecasts future stock returns, which once again confirms the negative liquidity premium in a value-weighted regression based analysis. Only the coefficient on the adjusted high-low spread appears positive but not significant. In model (5) to (16), I focus on the quoted spread exclusively, as it has been regarded as the benchmark liquidity proxy throughout this article.[25] In model (5) to (13), I also add each of the individual anomaly variables underlying the composite mispricing score, namely accruals, net operating assets, asset growth, investment-to-assets, gross profitability premium, net stock issues, composite equity issues, return on assets, and momentum separately to the independent variables.[26] The coefficients on the quoted spread are consistently negative and significant, that is in model (5) to (13) when each of the mispricing component anomalies is added separately, in model (14) when all the mispricing components are added simultaneously, and in model (15) and (16) when the composite mispricing score is added individually and as an interaction term with the quoted spread, respectively. Moreover, the coefficients on the individual anomaly variables in model (5) to (13) have consistently the expected signs and the associated t-values indicate strong statistical significance in all cases. Model (14) reveals that the inclusion of all individual anomaly components simultaneously leads to a similar coefficient and t-value on the quoted spread as in the previous models. In model (15) and (16) I analyze the relation between liquidity and mispricing. As before, liquidity proves to be a strong negative predictor of future returns. Mispricing carries a highly negative and statistically significant coefficient, which implies as expected that the cross-sectional overpricing (underpricing) of a stock predicts negative (positive) future returns. Model (16) shows that there is no significant interaction effect between mispricing and the quoted spread. In undocumented analyses, I also find similar non significant interaction effects between the quoted spread and each of the nine individual mispricing component anomalies.

Panel B reports the regression results of the previous analysis if the quoted spread is replaced by liquidity shocks, constructed primarily based on the quoted spread. Model (17) shows that liquidity shocks significantly predict future returns, a finding, that has been also documented by Bali et al. (2014) in the US market. Model (18) confirms this finding when liquidity shocks are computed based on Amihud's illiquidity instead of the quoted spread. For the rest of the analysis, I focus on liquidity shocks based on the quoted spread exclu-

[25]Undocumented results show that inferences are similar for Amihud's illiquidity, the FHT spread, and the adjusted high-low spread.

[26]For illustration purposes momentum is included twice in the table, once as a mispricing component and once as a control variable labeled as $r(t-12,t-2)$. Thus, the control is removed in model (13) and model (14) when the mispricing component is included instead.

sively, to stay consistent with the previous portfolio analysis in chapter 5. In model (19) to (27), I add each of the individual anomaly variables underlying the composite mispricing score separately to the predictors. The coefficients on liquidity shocks are positive and significant in each of the models. Also, the coefficients on the individual anomaly variables have the expected signs and the associated t-values indicate strong statistical significance in each of the cases. In model (28), I find that the inclusion of all individual anomaly components simultaneously does not affect the coefficient and the significance on liquidity shocks. Model (29) reveals that both mispricing and liquidity shocks are strong predictors of future returns, and model (30) reveals that there is no significant interaction between liquidity shocks and mispricing.

In Table A5 of the appendix, I also implement the default OLS Fama and MacBeth (1973) type of regressions. The main difference to the VWLS approach is that the coefficients on the quoted spread are consistently positive and significant. Thus, it seems that the positive liquidity premium which has often been documented in the literature (e.g. Amihud et al., 2015) is mainly driven by microcaps, which have a strong effect on results in a OLS regression framework.

7. Conclusion

I explore the relation between mispricing according to Stambaugh, Yu, and Yuan (2015) and liquidity measured by the quoted bid-ask spread. Judging by a series of 5x2 portfolio analyses based on mispricing and liquidity, I document a strong liquidity premium in long/short portfolio returns based on mispricing. This result is independent of the way returns are computed (value-weighted vs. equally-weighted) and of the approach portfolios are formed (independent-sort vs. dependent-sort). A more detailed 5x5 portfolio analysis based on liquidity and mispricing reveals that the observed liquidity premium is mainly driven by the short leg (i.e. overpricing) of highly illiquid stocks, which illustrates the existence of arbitrage asymmetry in this quintile. These findings imply that arbitrageurs are more likely to exploit mispricing for liquid securities than for non-liquid ones (e.g. Chordia, Roll, and Subrahmanyam, 2008; Chordia, Subrahmanyam, and Tong, 2014; Daniel, Hirshleifer, and Subrahmanyam, 1998; McLean and Pontiff, 2016; Pontiff, 1996).

To shed more light on the relation between liquidity and mispricing, I analyze the effect of short-term liquidity shocks on the magnitude of mispricing in 5x5 portfolio sorts. Taking account of the fact that the amount of positive and negative liquidity shocks varies significantly over time, I differentiate between the following three economic states: More positive than negative liquidity shocks (strong market environment), equally as many positive as negative shocks (neutral market environment), and more negative than positive shocks (weak market environment). In a strong and in a neutral market environment, the magnitude of mispricing increases due to negative shocks. In a neutral market environment, the magnitude of mispricing also increases due to positive shocks as the positive underpricing-return relation is pronounced when liquidity increases. In case of a weak market environment, which is the smallest among the three subsamples in terms of observations and includes for instance the period of the subprime crisis in 2008, there is no clear pattern in the average portfolio returns. I infer that the state of the market environment is important to understand the varying effect of liquidity shocks on the price discovery process on international markets. In the overall sample without controlling for the market environment, the magnitude of mispricing is pronounced only in case of negative liquidity shocks.

In addition, based on Fama-MacBeth cross-sectional regressions, I find strong return predictability associated with liquidity and liquidity shocks, controlling for mispricing and a series of well-known return predictors of the literature. In sum, it appears that liquidity is particularly important for the explanation of cross-sectional return patterns in a bivariate or multivariate test setting, as opposed to a univariate one. Hou, Xue, and Zhang (2015) for instance show that in the U.S. liquidity does not perform well in a univariate setting for a wide range of liquidity proxies.

An implication of my paper, which goes along the steadily growing literature with the target to shrink the amount of meaningful and statistically proven stock characteristics with return predictive ability (e.g. Harvey, Liu, and Zhu, 2015; Linnainmaa and Roberts, 2018; Kozak, Nagel, and Santosh, 2019), is that a greater hurdle to determine the existence of an anomaly can be simply achieved by analyzing if the anomaly exists only for the portion of liquid stocks in a given sample (e.g. determined by the median liquidity per month).

Based on these results, several directions of further research are possible. First, the Stambaugh, Yu, and Yuan (2015) mispricing score is measured in relative terms. It would be desirable to construct a mispricing measure in absolute terms to allow for the evaluation of the economic magnitude of mispricing on stock level. Second, it would be interesting to see if the documented liquidity premium can be carried over to anomalies different from the ones that are mispricing components. Third, the short- and long-run impact of country-based liquidity crises on mispricing long/short spreads could be analyzed.

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Table 1: **Summary statistics**

The table presents summary statistics for the full sample from January 1990 until June 2018 (Panel A), and for the restricted sample with valid liquidity (i.e. non-missing quoted spread, qs) and valid mispricing (Panel B). Panel A shows the total unique number of stocks (column 2), the June 2018 total market capitalization in millions USD and in % (column 3 and 4, respectively), and US dollar volume and standard volume both in millions (column 5 and 6, respectively). In Panel B, start and end refer to the earliest and to the last date when a country can be included or when it is excluded from the sample, respectively, either due to data availability or because of data requirements. Column 10 contains firm months in thousands. Column 11 to 14 display the following average daily liquidity measures: (1) The quoted bid-ask spread (qs), (2) the Corwin and Schultz (2012) adjusted high-low spread (adj hls), (3) the Fong, Holden, and Trzcinka (2017) spread proxy (fht), and (4) the Amihud (2002) measure of illiquidity (illiq) multiplied by 10^6. Column 15 and 16 report the average monthly total market capitalization in millions USD and in %, respectively. The last row (Aggregate) states the sums over all countries, except for the start and end date, where it is the minimum and maximum, respectively, and except for the four liquidity measures and the market capitalization in column 15, where it depicts the average. Non-common equity is generally excluded. All liquidity measures are winsorized at the 0.1% and at the 99.9% level.

	Panel A: Full sample					*Panel B: Firms with valid liquidity and mispricing score*									
country	Number of stocks	Market cap. June 2018	Market cap. (%) June 2018	dvol June 2018	vol June 2018	Start	End	Number of stocks	Firm months	qs	adj hls	fht	illiq	Market cap. avg.	Market cap. avg. (%)
Argentina	202	47,166	0.07	683	383.5	1996-05-31	2018-06-30	104	13	0.030	0.024	0.028	6.39	36,568	0.11
Australia	3,869	1,408,515	1.95	75,921	39,382.9	1990-01-31	2018-06-30	2,737	275	0.070	0.061	0.073	29.91	668,745	2.03
Austria	278	139,456	0.19	3,880	112.8	1990-01-31	2018-06-30	164	19	0.021	0.006	0.023	8.15	69,175	0.21
Belgium	442	400,570	0.55	12,443	290.8	1990-01-31	2018-06-30	231	30	0.017	0.009	0.017	4.08	199,698	0.61
Brazil	543	493,452	0.68	34,508	6,499.5	1996-05-31	2018-06-30	251	24	0.046	0.019	0.041	9.75	309,637	0.94
Canada	8,678	1,743,759	2.41	82,366	9,612.9	1990-01-31	2018-06-30	3,811	356	0.083	0.041	0.075	61.03	810,489	2.46
Chile	482	239,059	0.33	3,192	20,519.6	1993-05-31	2018-06-30	214	24	0.039	0.058	0.035	6.05	122,769	0.37
China	3,800	7,515,031	10.39	1,063,139	579,030.0	1995-05-31	2018-06-30	3,652	395	0.004	0.021	0.005	0.99	2,390,332	7.25
Columbia	250	113,659	0.16	588	396.9	2002-05-31	2018-06-30	55	4	0.023	0.025	0.022	1.28	90,597	0.27
Czech Republic	394	32,316	0.04	428	30.5	1998-05-31	2006-04-30	53	1	na	na	0.019	14.40	13,537	0.04
Denmark	493	384,145	0.53	17,566	414.5	1990-01-31	2018-06-30	322	44	0.031	0.016	0.034	12.66	134,338	0.41
Egypt	1,153	45,503	0.06	782	2,695.7	2004-05-31	2018-06-30	147	15	0.040	0.021	0.010	2.76	50,513	0.15
Finland	331	263,869	0.36	11,776	1,159.8	1990-01-31	2018-06-30	221	30	0.029	0.012	0.033	6.30	142,156	0.43
France	2,630	2,570,524	3.55	115,752	3,628.8	1990-01-31	2018-06-30	1,590	170	0.027	0.009	0.025	9.54	1,293,077	3.92
Germany	2,335	2,214,947	3.06	170,582	3,898.0	1990-01-31	2018-06-30	1,373	130	0.034	0.011	0.019	12.94	909,365	2.76
Greece	437	47,857	0.07	1,153	629.3	1990-01-31	2018-06-30	379	56	0.035	0.020	0.030	103.80	62,357	0.19
Hong Kong	2,243	3,335,933	4.61	121,528	185,480.1	1990-01-31	2018-06-30	1,999	238	0.029	0.093	0.027	6.66	1,052,572	3.19
Hungary	212	26,272	0.04	759	92.2	2000-05-31	2017-04-30	68	5	0.048	0.025	0.032	61.10	22,801	0.07
Iceland	94	9,830	0.01	300	2,878.3										
India	6,274	2,140,965	2.96	96,582	29,477.2	1994-12-31	2018-06-30	3,419	347	0.026	0.038	0.013	149.47	739,031	2.24
Indonesia	712	438,760	0.61	5,626	44,303.5	1993-05-31	2018-06-30	629	49	0.034	0.242	0.051	160.98	158,336	0.48
Ireland	126	100,449	0.14	3,477	295.0	2000-07-31	2017-03-31	72	6	0.049	0.033	0.052	36.64	75,887	0.23
Israel	898	171,921	0.24	4,477	1,189.3	1995-05-31	2018-06-30	530	52	0.037	0.015	0.017	9.01	98,753	0.30
Italy	786	676,122	0.93	59,358	15,948.9	1990-01-31	2018-06-30	551	68	0.016	0.013	0.007	1.04	451,954	1.37
Japan	5,637	6,146,667	8.50	509,948	36,815.2	1990-01-31	2018-06-30	5,308	988	0.011	0.008	0.022	1.44	3,391,865	10.28
Jordan	251	21,472	0.03	13	13.5	2007-05-31	2018-06-30	82	6	0.037	0.017	0.033	20.08	1,250	0.00
Korea	3,307	1,584,844	2.19	195,783	23,000.7	1990-01-31	2018-06-30	2,512	291	0.007	0.012	0.009	0.75	530,760	1.61
Luxembourg	67	16,291	0.02	10	0.5										
Malaysia	1,668	420,944	0.58	11,257	31,950.5	1990-01-31	2018-06-30	1,287	195	0.038	0.064	0.038	40.83	214,950	0.65
Mexico	362	306,244	0.42	6,682	2,571.4	1993-05-31	2018-06-30	185	20	0.039	0.019	0.020	43.91	156,536	0.47
Morocco	131	63,738	0.09	540	33.3	2006-08-31	2018-06-30	82	6	0.029	0.010	0.020	3.31	55,738	0.17
Netherlands	469	734,462	1.02	45,216	2,614.5	1990-01-31	2018-06-30	261	38	0.017	0.009	0.015	3.58	409,389	1.24

[Continued on next page]

country	Number of stocks	Market cap. June 2018	Market cap. (%) June 2018	dvol June 2018	vol June 2018	Start	End	Number of stocks	Firm months	qs	adj hls	fht	illiq	Market cap. avg.	Market cap. avg. (%)
New Zealand	396	91,879	0.13	2,136	793.9	1995-05-31	2018-06-30	223	22	0.033	0.028	0.051	23.00	37,392	0.11
Norway	724	335,992	0.46	11,873	2,401.6	1990-01-31	2018-06-30	485	45	0.032	0.017	0.041	8.10	143,854	0.44
Pakistan	658	68,122	0.09	1,014	2,400.8	1993-11-30	2018-06-30	248	30	0.023	0.060	0.024	73.69	28,848	0.09
Peru	388	64,159	0.09	112	105.4	1998-05-31	2018-06-30	106	8	0.047	0.038	0.028	4.82	29,295	0.09
Philippines	415	235,382	0.33	2,021	19,428.8	1993-05-31	2018-06-30	298	41	0.044	0.204	0.073	46.23	90,539	0.27
Poland	1,173	158,809	0.22	4,471	958.3	1997-05-31	2018-06-30	699	65	0.027	0.021	0.024	56.35	101,497	0.31
Portugal	273	68,404	0.09	2,461	1,587.0	1990-01-31	2018-06-30	122	13	0.033	0.016	0.041	52.91	49,579	0.15
Russia	1,338	534,386	0.74	8,739	578,317.2	2003-05-31	2018-06-30	314	23	0.025	0.077	0.022	158.28	536,721	1.63
Singapore	1,027	408,930	0.57	12,780	12,172.6	1990-01-31	2018-06-30	957	122	0.062	0.062	0.065	61.99	225,219	0.68
South Africa	1,057	492,843	0.68	25,945	5,220.1	1990-02-28	2018-06-30	731	70	0.052	0.049	0.073	118.41	255,498	0.77
Spain	565	780,244	1.08	36,099	8,358.5	1990-03-31	2018-06-30	314	40	0.015	0.012	0.014	1.10	460,991	1.40
Sri Lanka	366	16,403	0.02	41	222.6	2001-08-31	2018-06-30	253	26	0.058	0.100	0.054	165.76	10,512	0.03
Sweden	1,481	651,526	0.90	34,697	4,058.6	1990-01-31	2018-06-30	944	93	0.034	0.021	0.034	22.91	315,024	0.96
Switzerland	565	1,460,065	2.02	77,635	1,472.1	1990-01-31	2018-06-30	373	58	0.017	0.009	0.021	1.61	791,431	2.40
Taiwan	2,550	1,203,541	1.66	123,025	69,348.7	1995-05-31	2018-06-30	2,268	292	0.027	0.019	0.010	3.50	549,839	1.67
Thailand	1,033	472,701	0.65	30,309	76,050.4	1991-05-31	2018-06-30	827	111	0.021	0.113	0.036	61.20	165,173	0.50
Turkey	555	169,998	0.24	30,012	23,994.3	1993-05-31	2018-06-30	446	62	0.009	0.020	0.016	1.53	124,010	0.38
United Kingdom	6,740	3,299,882	4.56	182,712	66,681.7	1990-01-31	2018-06-30	3,938	358	0.055	0.033	0.046	4.38	2,121,680	6.43
United States	16,810	27,870,503	38.54	4,423,181	88,692.2	1990-01-31	2018-06-30	14,347	1,430	0.027	0.018	0.012	5.61	12,282,071	37.24
Venezuela	83	81,199	0.11	35	13.8										
Aggregate	87,751	72,319,712	100.00	7,665,613	2,007,628.2	1990-01-31	2018-06-30	60,182	6,804	0.033	0.039	0.031	34.70	673,109	100.00

Table 2: **Correlation coefficients**

The table presents the time-series averages of the monthly cross-sectional correlations (in %) of the following variables: (1) Accruals, measured as the annual change in non-cash working capital, less depreciation and amortization expense, divided by average total assets over the last two fiscal years, (2) Net operating assets, denoted as operating assets minus operating liabilities, divided by total assets in the previous fiscal year, (3) Asset growth, defined as the annual growth rate of total assets from the fiscal year that ends in $t-2$ to the fiscal year that ends in $t-1$, (4) Investment-to-Assets, which is the annual change in gross property, plant, and equipment, plus the annual change in inventories, divided by total assets in the previous fiscal year, (5) Gross profitability premium, defined as total revenue minus cost of goods sold, divided by total assets, (6) Return on assets, denoted as income before extraordinary items, divided by total assets in the previous fiscal year, (7) Net stock issues, which equals the annual log change in split-adjusted shares outstanding, (8) Composite equity issuance, defined as the annual log change in the market capitalization of a firm, less the cumulative log stock return over the same time period, (9) Momentum, constructed as the cumulative stock return from month t-11 to month t-1, (10) the quoted bid-ask spread, (11) Amihud's illiquidity, (12) the adjusted high-low spread according to Corwin and Schultz (2012), (13) the FHT spread according to Fong, Holden, and Trzcinka (2017), (14) dollar volume, (15) liquidity shocks, computed as the negative difference between the current quoted spread and its average over the last 12 months, (16) the past 1-month return, (17) the past 3-year return from $t-36$ to $t-13$, (18) the book-to-market ratio, computed as log(B/M), (19) the past 1-month log(ME), (20) beta, calculated from monthly rolling regressions of daily excess stock returns in the previous month on the global market risk premium, with at least 15 non-missing returns required in a given month, and (21) Idiosyncratic volatility (IVOL), defined as the standard deviation of the residual that results from a regression of daily excess returns on a global Fama-French three factor model, with at least 15 non-missing observations of all involved regression variables required in a given month. More detailed definitions of the mispricing-related anomaly variables can be found in Table A6. The liquidity proxies are defined in greater detail in the text. The sample period runs from January 1990 until June 2018. All variables are winsorized per country at the 0.1% and the 99.9% level.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Accruals	(1)	100																				
Net operating assets	(2)	10.4	100																			
Asset growth	(3)	11.5	6.4	100																		
Investment-to-assets	(4)	9.9	32.2	62.3	100																	
Gross profitability premium	(5)	0.9	−0.6	−3.9	−3.2	100																
Return on assets	(6)	8.0	14.4	−4.5	−1.7	13.6	100															
Net stock issues	(7)	0.6	0.6	8.0	6.3	−0.5	−1.9	100														
Composite equity issues	(8)	−0.7	1.8	12.0	9.5	−10.6	−8.7	23.8	100													
Momentum	(9)	−0.3	0.0	1.7	−0.2	3.4	3.1	7.3	0.0	100												
Quoted spread	(10)	−4.6	−0.2	−3.2	−3.0	−6.4	−11.1	−2.4	10.4	−11.6	100											
Illiquidity	(11)	−2.1	−1.4	−2.2	−1.6	−3.0	−3.1	−0.6	1.1	−3.5	31.4	100										
Adj. high-low spread	(12)	−2.6	0.2	−1.2	−0.8	−8.6	−7.3	1.3	8.1	−7.0	45.0	21.7	100									
FHT spread	(13)	−3.4	−1.1	−2.7	−2.3	−8.2	−8.2	−0.4	9.4	−8.7	65.4	25.2	38.9	100								
Dollar volume	(14)	−0.5	−0.1	1.3	0.3	5.0	2.9	−0.1	−1.9	3.6	−10.0	−1.5	−5.0	−5.4	100							
Liquidity shocks	(15)	−0.3	0.0	−1.0	−1.2	0.7	1.6	−2.7	4.3	17.6	−29.9	−9.8	−13.1	−15.5	0.3	100						
$r(t-1)$	(16)	−0.7	−0.1	−1.5	−1.0	0.7	0.8	0.3	−1.4	1.0	−4.1	−0.6	−1.7	−2.0	1.0	9.7	100					
$r(t-36,t-13)$	(17)	5.6	1.5	17.7	11.3	4.6	7.4	6.3	−0.5	−0.4	−9.0	−2.2	−4.7	−6.0	2.2	−1.7	−1.1	100				
log(B/M)	(18)	2.8	−1.6	−11.6	−6.6	−8.7	3.0	−1.4	−6.7	−0.6	−3.1	2.1	3.7	−1.6	−10.1	1.9	0.8	−9.9	100			
log(ME)	(19)	3.0	0.8	4.9	4.3	10.1	10.0	4.9	−7.7	10.1	−53.4	−19.5	−37.2	−42.7	29.2	5.0	2.0	6.5	−8.4	100		
β	(20)	−0.1	0.2	2.7	1.0	2.8	−1.1	−0.2	1.8	2.4	−6.2	−1.7	−3.5	−5.0	6.7	1.2	−0.7	1.1	−14.4	10.9	100	
IVOL	(21)	−2.2	0.0	2.3	0.8	−10.5	−11.3	2.3	16.7	−3.9	45.7	16.4	33.0	39.2	−6.7	−12.4	11.1	−2.5	−3.7	−34.6	3.6	100

Figure 1: **Liquidity costs**
The figure displays the following liquidity cost measures over time: The quoted bid-ask spread (qs), the Fong, Holden, and Trzcinka (2017) FHT spread (fht), the Corwin and Schultz (2012) adjusted high-low spread (adj hls), and the Amihud (2002) measure of illiquidity (illiq). The average daily spreads are calculated for a global sample of 52 countries. The sample period runs from 1990-01 until 2018-06. The ticks in the horizontal axis of the graph illustrate the end of the respective years.

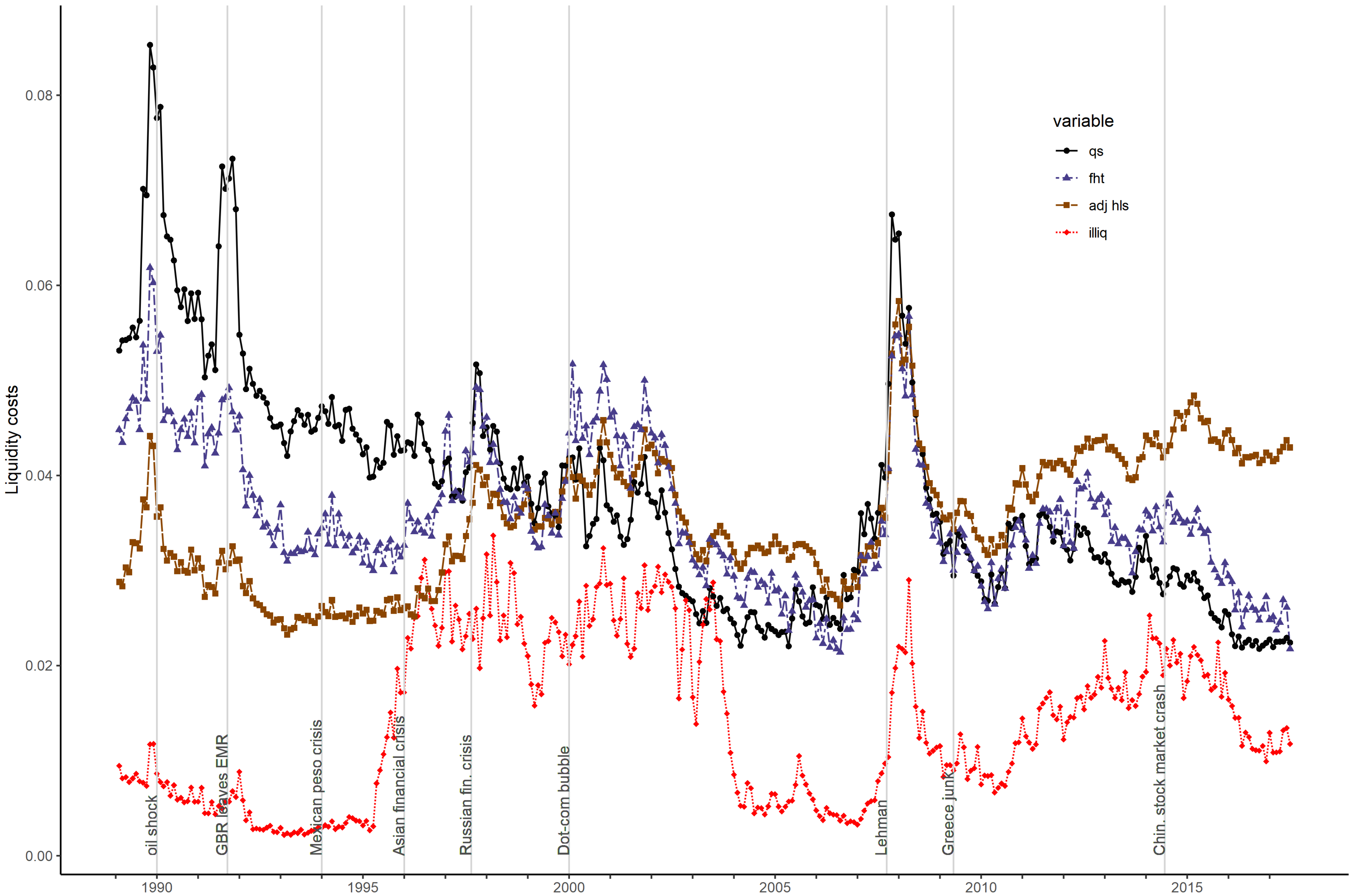

Table 3: **Anomalies in liquid vs. non-liquid markets**
The table reports the average monthly returns of quintile-based long/short portfolios based on accruals, net operating assets, asset growth, investment to assets, gross profitability, return on assets, net stock issues, composite equity issues, momentum, and the international mispricing score for high and low quoted spreads (qs). At the beginning of every month, the median quoted spread is used to separate stocks into liquid (low qs) and non-liquid (high qs) markets. In both panels below, 2x5 portfolios are created based on liquidity and a second anomaly ranking variable stated in column 1. In Panel A, the portfolios are created from the intersections of two liquidity and five anomaly ranking groups. In Panel B, the classification into five anomaly ranking groups is undertaken conditional on the assignment to the liquidity groups. The sample period runs from 1990-01 to 2018-06. T-statistics are given in parentheses.

	Low qs	High qs	Diff	Low qs	High qs	Diff
	Value-weighted			Equally-weighted		
Panel A: Independent-Sort portfolios						
Accruals	0.0026	0.0061	0.0035	0.0052	0.0068	0.0017
	(2.14)	(4.87)	(2.21)	(7.63)	(8.86)	(1.95)
Net operating assets	0.0048	0.0068	0.0019	0.0075	0.0110	0.0035
	(4.90)	(5.23)	(1.34)	(8.84)	(11.47)	(3.91)
Asset growth	0.0017	0.0049	0.0033	0.0054	0.0122	0.0069
	(1.11)	(3.50)	(1.86)	(5.52)	(11.64)	(6.74)
Investment-to-assets	0.0020	0.0046	0.0026	0.0050	0.0109	0.0058
	(1.65)	(3.54)	(1.67)	(6.01)	(11.42)	(6.65)
Gross profitability premium	0.0038	0.0083	0.0046	0.0038	0.0049	0.0011
	(2.65)	(6.00)	(2.85)	(3.64)	(5.01)	(1.17)
Return on assets	0.0044	0.0033	−0.0011	0.0025	−0.0029	−0.0054
	(2.50)	(1.74)	(−0.56)	(1.51)	(−1.53)	(−4.25)
Net stock issues	0.0027	0.0083	0.0056	0.0065	0.0083	0.0017
	(1.67)	(4.02)	(3.21)	(3.19)	(4.29)	(1.33)
Composite equity issues	0.0034	0.0078	0.0044	0.0071	0.0076	0.0006
	(2.08)	(4.11)	(2.49)	(4.17)	(4.51)	(0.51)
Momentum	0.0089	0.0081	−0.0008	0.0105	0.0071	−0.0035
	(3.19)	(3.22)	(−0.35)	(4.46)	(3.15)	(−2.30)
Mispricing	0.0065	0.0120	0.0055	0.0108	0.0151	0.0043
	(4.27)	(7.05)	(3.48)	(7.87)	(10.48)	(4.52)
Panel B: Dependent-Sort portfolios						
Accruals	0.0025	0.0056	0.0031	0.0049	0.0069	0.0020
	(2.17)	(4.26)	(1.99)	(8.01)	(8.69)	(2.56)
Net operating assets	0.0047	0.0071	0.0024	0.0074	0.0112	0.0039
	(4.87)	(5.69)	(1.78)	(8.56)	(11.84)	(4.39)
Asset growth	0.0024	0.0028	0.0004	0.0058	0.0116	0.0057
	(1.69)	(1.97)	(0.24)	(6.01)	(9.73)	(4.41)
Investment-to-assets	0.0027	0.0034	0.0007	0.0054	0.0100	0.0046
	(2.32)	(2.44)	(0.40)	(6.92)	(9.64)	(4.59)
Gross profitability premium	0.0038	0.0074	0.0037	0.0039	0.0043	0.0004
	(2.83)	(5.14)	(2.22)	(3.79)	(4.32)	(0.40)
Return on assets	0.0031	0.0055	0.0024	0.0010	−0.0018	−0.0029
	(2.03)	(2.84)	(1.13)	(0.82)	(−0.85)	(−1.85)
Net stock issues	0.0023	0.0091	0.0068	0.0061	0.0084	0.0023
	(1.55)	(4.39)	(3.62)	(3.08)	(4.37)	(1.85)
Composite equity issues	0.0030	0.0076	0.0046	0.0065	0.0073	0.0008
	(2.00)	(4.17)	(2.77)	(3.98)	(4.34)	(0.81)
Momentum	0.0073	0.0076	0.0003	0.0104	0.0057	−0.0047
	(2.65)	(3.15)	(0.11)	(4.78)	(2.36)	(−2.64)
Mispricing	0.0065	0.0111	0.0046	0.0114	0.0144	0.0031
	(4.52)	(6.54)	(2.88)	(8.84)	(9.61)	(3.20)

Table 4: **Abnormal returns in liquid vs. non-liquid markets**

The table reports the average monthly abnormal returns (alphas) obtained from regressing quintile-based long/short portfolio returns based on accruals, net operating assets, asset growth, investment to assets, gross profitability, return on assets, net stock issues, composite equity issues, momentum, and the international mispricing index on a global Fama-French three-factor model for high and low quoted spreads (qs). At the beginning of every month, the median quoted spread is used to differentiate stocks into liquid (low qs) and non-liquid (high qs) markets. In both panels below, 2x5 portfolios are created based on liquidity and a second anomaly ranking variable stated in column 1. In Panel A, the portfolios are created from the intersections of two liquidity and five anomaly ranking groups. In Panel B, the classification into five anomaly ranking groups is undertaken conditional on the assignment to the liquidity groups. The sample period runs from 1990-01 to 2018-06. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses.

	Low qs	High qs	Diff	Low qs	High qs	Diff
	Value-weighted			Equally-weighted		
Panel A: Independent-Sort portfolios						
Accruals	0.0031	0.0059	0.0028	0.0053	0.0067	0.0014
	(2.52)	(4.69)	(1.75)	(7.40)	(8.72)	(1.66)
Net operating assets	0.0047	0.0076	0.0029	0.0082	0.0116	0.0034
	(4.75)	(5.67)	(2.03)	(9.13)	(11.83)	(3.54)
Asset growth	0.0005	0.0041	0.0036	0.0047	0.0119	0.0072
	(0.38)	(3.04)	(2.09)	(5.20)	(11.37)	(8.01)
Investment-to-assets	0.0012	0.0042	0.0031	0.0050	0.0110	0.0061
	(1.01)	(3.32)	(1.98)	(5.86)	(11.58)	(7.12)
Gross profitability premium	0.0059	0.0091	0.0032	0.0049	0.0058	0.0009
	(4.60)	(6.76)	(2.09)	(4.82)	(5.91)	(0.93)
Return on assets	0.0067	0.0039	−0.0028	0.0029	−0.0026	−0.0055
	(4.28)	(2.18)	(−1.44)	(2.25)	(−1.52)	(−4.31)
Net stock issues	0.0036	0.0089	0.0053	0.0067	0.0085	0.0018
	(3.16)	(5.38)	(2.98)	(5.28)	(5.66)	(1.39)
Composite equity issues	0.0040	0.0080	0.0040	0.0070	0.0080	0.0010
	(3.38)	(4.84)	(2.14)	(7.07)	(6.46)	(0.94)
Momentum	0.0112	0.0088	−0.0024	0.0125	0.0083	−0.0042
	(4.20)	(3.65)	(−1.17)	(5.59)	(3.85)	(−2.96)
Mispricing	0.0084	0.0124	0.0040	0.0116	0.0158	0.0042
	(6.97)	(8.28)	(2.55)	(11.70)	(13.10)	(4.22)
Panel B: Dependent-Sort portfolios						
Accruals	0.0031	0.0057	0.0026	0.0049	0.0069	0.0019
	(2.63)	(4.27)	(1.66)	(7.80)	(8.44)	(2.47)
Net operating assets	0.0046	0.0077	0.0031	0.0080	0.0119	0.0039
	(4.68)	(6.03)	(2.34)	(8.82)	(12.54)	(4.26)
Asset growth	0.0014	0.0018	0.0005	0.0053	0.0113	0.0060
	(1.16)	(1.40)	(0.29)	(6.29)	(9.77)	(5.90)
Investment-to-assets	0.0021	0.0031	0.0010	0.0055	0.0101	0.0046
	(1.92)	(2.23)	(0.57)	(6.94)	(9.64)	(4.93)
Gross profitability premium	0.0058	0.0084	0.0026	0.0052	0.0050	−0.0002
	(4.86)	(5.94)	(1.60)	(5.29)	(4.99)	(−0.21)
Return on assets	0.0057	0.0060	0.0002	0.0018	−0.0018	−0.0036
	(4.28)	(3.36)	(0.12)	(1.64)	(−0.95)	(−2.44)
Net stock issues	0.0034	0.0096	0.0062	0.0063	0.0086	0.0023
	(3.06)	(5.33)	(3.19)	(5.08)	(5.77)	(1.83)
Composite equity issues	0.0035	0.0078	0.0042	0.0064	0.0077	0.0013
	(3.14)	(4.81)	(2.39)	(7.07)	(6.15)	(1.27)
Momentum	0.0096	0.0081	−0.0015	0.0122	0.0071	−0.0051
	(3.64)	(3.52)	(−0.67)	(5.98)	(3.13)	(−3.22)
Mispricing	0.0084	0.0116	0.0031	0.0123	0.0151	0.0028
	(7.42)	(7.69)	(1.99)	(13.08)	(11.98)	(2.81)

Table 5: **Robustness**

The table reports the average monthly abnormal returns of quintile-based long/short portfolios based on mispricing on liquid vs. non-liquid markets. The abnormal returns are computed by adjusting for exposures to the factors of a global Fama-French three-factor model. At the beginning of every month, stocks are designated into liquid and non-liquid markets based on median liquidity. 2x5 portfolios are formed independently based on liquidity and mispricing. In model (1) to (5), the quoted spread is used to proxy for liquidity. In model (3), mispricing is computed using a six-month lag from the end of the previous year for all anomaly components that are based on yearly accounting data. The next two models display results from alternative breakpoint definitions: Model (4) uses globally computed breakpoints, and model (5) uses breakpoints based on big stocks only. In model (6), (7), and (8), the sorting on liquidity is implemented based on Amihud's illiquidity, the FHT spread, and the adjusted high-low spread, respectively. The sample period runs from 01/1990 until 06/2018, based on data availability. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses.

Model	Description	Liquid markets	Non-liquid markets	Diff	Liquid markets	Non-liquid markets	Diff
		Value-weighted			Equally-weighted		
(1)	U.S. market	0.0077	0.0155	0.0078	0.0094	0.0158	0.0064
		(4.79)	(6.96)	(3.56)	(6.53)	(7.49)	(4.00)
(2)	All except U.S. market	0.0075	0.0108	0.0033	0.0115	0.0148	0.0033
		(5.52)	(6.74)	(1.82)	(12.60)	(13.06)	(3.19)
(3)	Alternative mispricing def.	0.0074	0.0118	0.0044	0.0105	0.0146	0.0042
		(6.07)	(7.87)	(2.79)	(9.98)	(11.38)	(3.99)
(4)	Global breakpoints	0.0084	0.0151	0.0067	0.0112	0.0168	0.0056
		(6.74)	(9.18)	(4.01)	(10.61)	(11.17)	(4.73)
(5)	Big stocks breakpoints	0.0069	0.0088	0.0019	0.0079	0.0133	0.0055
		(5.42)	(7.19)	(1.35)	(6.65)	(10.01)	(4.35)
(6)	Illiquidity	0.0085	0.0107	0.0021	0.0125	0.0143	0.0018
		(7.13)	(11.10)	(1.81)	(11.36)	(10.92)	(1.67)
(7)	FHT spread	0.0081	0.0109	0.0028	0.0121	0.0147	0.0026
		(6.54)	(7.21)	(1.87)	(12.41)	(11.49)	(2.83)
(8)	Adj. high-low spread	0.0070	0.0127	0.0057	0.0115	0.0161	0.0046
		(6.10)	(7.15)	(3.04)	(14.77)	(12.21)	(4.07)

Table 6: **Properties of 5x5 portfolios based on mispricing and liquidity**
Panel A and Panel B present the average quoted spread (qs) and mispricing score for each of the portfolios. In either case, the value of a given portfolio is obtained by first computing the median per month and then averaging the medians across time. Panel C reports the average number of stocks within each of the portfolios. The portfolios are constructed by sorting independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and the quoted spread (qs). The sample period goes from 1990-01 until 2018-06.

	Lowest qs	Next 20%	Next 20%	Next 20%	Highest qs	All stocks
Panel A: Quoted spread						
Most underpriced	0.0046	0.0103	0.0174	0.0310	0.0756	0.0167
Next 20%	0.0046	0.0101	0.0175	0.0316	0.0787	0.0168
Next 20%	0.0045	0.0101	0.0176	0.0319	0.0821	0.0169
Next 20%	0.0045	0.0100	0.0176	0.0325	0.0858	0.0176
Most overpriced	0.0046	0.0102	0.0178	0.0338	0.0913	0.0207
All stocks	0.0045	0.0102	0.0176	0.0320	0.0832	0.0176
Panel B: Mispricing						
Most underpriced	0.3302	0.3281	0.3267	0.3263	0.3283	0.3279
Next 20%	0.4123	0.4119	0.4119	0.4119	0.4122	0.4120
Next 20%	0.4777	0.4776	0.4775	0.4775	0.4779	0.4777
Next 20%	0.5495	0.5505	0.5511	0.5516	0.5519	0.5509
Most overpriced	0.6565	0.6597	0.6664	0.6744	0.6814	0.6683
All stocks	0.4710	0.4725	0.4751	0.4799	0.4915	0.4777
Panel C: Number of stocks						
Most underpriced	701	701	703	668	565	3,338
Next 20%	691	705	682	651	606	3,335
Next 20%	694	695	658	638	650	3,335
Next 20%	669	666	655	654	691	3,335
Most overpriced	583	569	637	724	825	3,337
All stocks	3,338	3,335	3,335	3,335	3,337	16,680

Table 7: **Abnormal returns of 5x5 portfolios based on mispricing and liquidity**
The table reports the average monthly abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and the quoted spread (qs). The abnormal returns are computed by adjusting for exposures to the factors of a global Fama-French three-factor model. The table also presents the results of univariate sortings based on mispricing and the quoted spread. The sample period goes from 1990-01 until 2018-06. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses.

	Lowest qs	Next 20%	Next 20%	Next 20%	Highest qs	Highest - lowest	All stocks
Most underpriced	0.0062	0.0043	0.0058	0.0045	0.0058	−0.0004	0.0059
(Bottom 20%)	(5.67)	(3.45)	(4.34)	(3.28)	(3.88)	(−0.27)	(5.87)
Next 20%	0.0032	0.0033	0.0017	0.0035	−0.0005	−0.0037	0.0031
	(2.89)	(2.62)	(1.27)	(2.78)	(−0.32)	(−2.32)	(2.94)
Next 20%	0.0032	−0.0001	0.0009	−0.0002	−0.0022	−0.0054	0.0024
	(2.49)	(−0.07)	(0.55)	(−0.15)	(−1.36)	(−3.16)	(2.06)
Next 20%	0.0001	−0.0004	−0.0017	−0.0035	−0.0058	−0.0059	−0.0003
	(0.07)	(−0.29)	(−1.11)	(−1.98)	(−2.95)	(−2.97)	(−0.33)
Most overpriced	−0.0021	−0.0061	−0.0077	−0.0108	−0.0167	−0.0147	−0.0039
(Top 20%)	(−1.25)	(−3.63)	(−4.52)	(−5.22)	(−8.03)	(−6.48)	(−2.61)
Most overpriced -	−0.0083	−0.0104	−0.0135	−0.0153	−0.0225	−0.0142	−0.0098
most underpriced	(−5.43)	(−7.59)	(−8.94)	(−7.52)	(−11.81)	(−6.37)	(−7.56)
All stocks	0.0030	0.0008	0.0003	−0.0010	−0.0041	−0.0071	
	(2.91)	(0.67)	(0.28)	(−0.79)	(−2.95)	(−5.29)	

Figure 2: **Abnormal returns of portfolios ranked by mispricing and liquidity**
The figure plots the average monthly abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and the quoted spread (qs). The abnormal returns are computed by adjusting for exposures to the factors of a global Fama-French three-factor model. The sample period goes from 1990-01 until 2018-06.

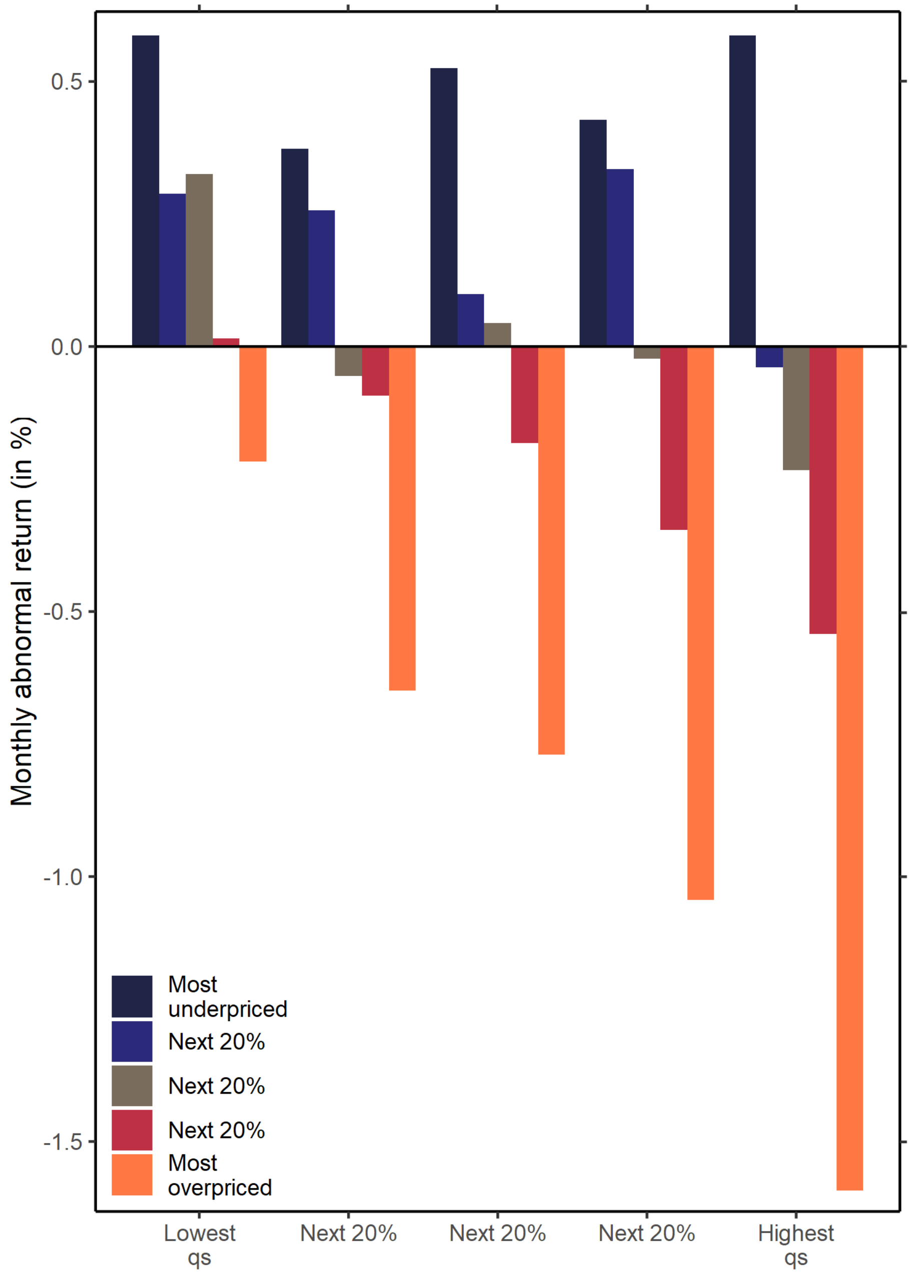

Figure 3: **Illustration of subsamples in the analysis of mispricing and liquidity shocks**
The figure plots the subsample coverage in months analyzed relative to the full sample for the analysis of mispricing and liquidity shocks. I differentiate between three cases: (A) More positive than negative liquidity shocks, (B) approximately equally as many positive as negative liquidity shocks, and (C) more negative than positive liquidity shocks. The bars (or rectangles) illustrate if a given month (or time period) from 1990-01 until 2018-06 is part of a subsample. The analysis is performed in a region-neutral approach, so overlaps in the coverage of the three scenarios are generally possible. Also, because the most extreme scenarios of approximately "only negative shocks" or "only positive shocks" are excluded, it can occur that a short period of time is not part of any of the three scenarios. This applies once in 2008 (only negative shocks) and once in 2009 (only positive shocks). The ticks on the horizontal axis of the graph illustrate the beginning of the years. Liquidity shocks are defined as the negative difference between the quoted spread and its past 12-month average.

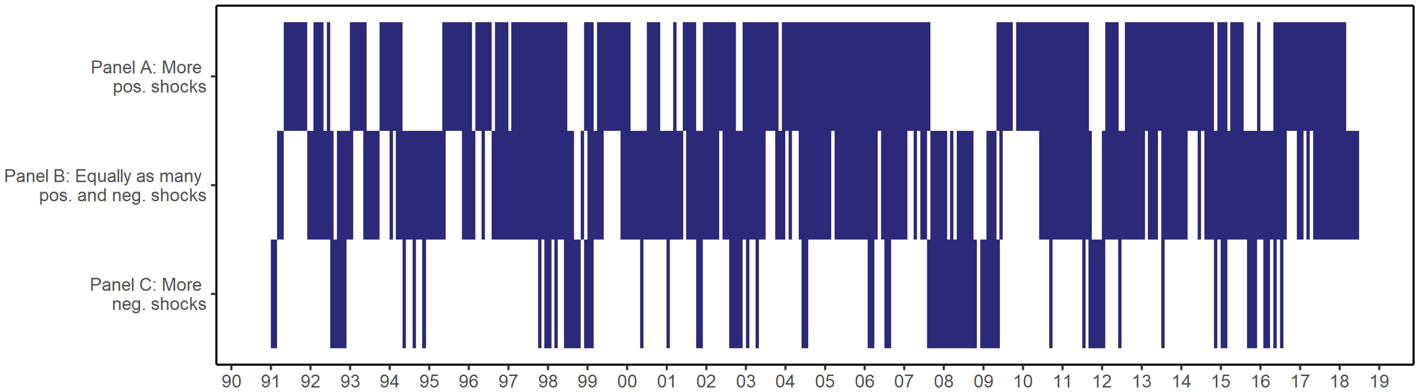

Table 8: **Properties of 5x5 portfolios based on mispricing and liquidity shocks**
The table presents the properties of 5x5 portfolios under three market conditions: More positive than negative liquidity shocks, approximately equally as many positive as negative shocks, and more negative than positive shocks, in panel A, B and C, respectively. For both liquidity shocks and mispricing the value of a given portfolio is obtained by first computing the median per month and then averaging the medians across time. Also shown are the average number of stocks within each of the portfolios. The portfolios are constructed by sorting independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and liquidity shocks. The latter are defined as the negative difference between the quoted spread and its past 12-month average: $liqu_{i,t} = -(qs_{i,t} - avg\_qs_{i|t-12,t-1})$. The sample period runs from 1991-01 until 2018-06, based on data availability.

	Neg. liqu. shocks	Next 20%	Next 20%	Next 20%	Pos. liqu. shocks	All stocks
Panel A: More positive than negative shocks						
Liquidity shocks						
Most underpriced	-0.0067	-0.0002	0.0015	0.0049	0.0177	0.0019
Next 20%	-0.0070	-0.0002	0.0015	0.0048	0.0178	0.0016
Next 20%	-0.0076	-0.0002	0.0015	0.0048	0.0181	0.0015
Next 20%	-0.0079	-0.0002	0.0015	0.0049	0.0188	0.0014
Most overpriced	-0.0090	-0.0003	0.0015	0.0049	0.0198	0.0013
All stocks	-0.0076	-0.0002	0.0015	0.0049	0.0184	0.0015
Mispricing						
Most underpriced	0.3294	0.3300	0.3277	0.3270	0.3260	0.3280
Next 20%	0.4097	0.4095	0.4092	0.4088	0.4090	0.4093
Next 20%	0.4748	0.4742	0.4738	0.4737	0.4735	0.4740
Next 20%	0.5462	0.5448	0.5448	0.5454	0.5461	0.5455
Most overpriced	0.6678	0.6527	0.6514	0.6571	0.6640	0.6594
All stocks	0.4940	0.4728	0.4661	0.4686	0.4715	0.4740
Number of stocks						
Most underpriced	294	362	391	370	340	1,691
Next 20%	317	364	374	361	340	1,690
Next 20%	338	360	362	351	346	1,690
Next 20%	373	354	338	345	348	1,690
Most overpriced	438	314	294	327	385	1,691
All stocks	1,692	1,690	1,690	1,690	1,691	8,453
Panel B: Equally as many positive as negative shocks						
Liquidity shocks						
Most underpriced	-0.0126	-0.0021	0.0004	0.0033	0.0145	0.0010
Next 20%	-0.0135	-0.0021	0.0004	0.0033	0.0147	0.0006
Next 20%	-0.0141	-0.0022	0.0004	0.0033	0.0150	0.0004
Next 20%	-0.0144	-0.0022	0.0004	0.0033	0.0154	0.0002
Most overpriced	-0.0159	-0.0024	0.0004	0.0034	0.0166	-0.0002
All stocks	-0.0141	-0.0022	0.0004	0.0033	0.0152	0.0004
Mispricing						
Most underpriced	0.3305	0.3304	0.3291	0.3275	0.3254	0.3284
Next 20%	0.4125	0.4122	0.4120	0.4117	0.4118	0.4121
Next 20%	0.4780	0.4776	0.4774	0.4770	0.4768	0.4774
Next 20%	0.5514	0.5500	0.5494	0.5497	0.5501	0.5501
Most overpriced	0.6776	0.6632	0.6581	0.6608	0.6687	0.6666
All stocks	0.4997	0.4803	0.4689	0.4686	0.4710	0.4772
Number of stocks						
Most underpriced	511	612	679	679	638	3,118
Next 20%	562	630	661	652	611	3,116
Next 20%	604	634	644	629	605	3,116
Next 20%	660	636	605	606	609	3,116
Most overpriced	783	604	525	551	655	3,117
All stocks	3,119	3,116	3,115	3,116	3,117	15,583
Panel C: More negative than positive shocks						
Liquidity shocks						
Most underpriced	-0.0258	-0.0069	-0.0019	0.0001	0.0061	-0.0013
Next 20%	-0.0275	-0.0071	-0.0020	0.0001	0.0061	-0.0018
Next 20%	-0.0283	-0.0071	-0.0020	0.0002	0.0066	-0.0020
Next 20%	-0.0282	-0.0070	-0.0021	0.0002	0.0065	-0.0025
Most overpriced	-0.0300	-0.0072	-0.0021	0.0002	0.0076	-0.0036
All stocks	-0.0281	-0.0071	-0.0020	0.0002	0.0063	-0.0020
Mispricing						
Most underpriced	0.3261	0.3234	0.3235	0.3223	0.3209	0.3231
Next 20%	0.4107	0.4104	0.4099	0.4096	0.4086	0.4098
Next 20%	0.4775	0.4770	0.4762	0.4772	0.4767	0.4768
Next 20%	0.5532	0.5524	0.5517	0.5492	0.5526	0.5520
Most overpriced	0.6813	0.6738	0.6620	0.6609	0.6721	0.6720
All stocks	0.4987	0.4866	0.4722	0.4628	0.4698	0.4766
Number of stocks						
Most underpriced	216	258	299	339	290	1,324
Next 20%	241	279	297	311	274	1,323
Next 20%	271	286	294	288	273	1,323
Next 20%	303	296	277	266	277	1,323
Most overpriced	375	300	237	208	290	1,323
All stocks	1,324	1,323	1,323	1,323	1,323	6,616

Table 9: **Abnormal returns of 5x5 portfolios based on mispricing and liquidity shocks**

The table reports the average monthly abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and liquidity shocks, defined as the negative difference between the quoted spread and its past 12-month average: $liqu_{i,t} = -(qs_{i,t} - avg\_qs_{i|t-12,t-1})$. The analysis is performed under three market conditions: More positive than negative liquidity shocks, approximately equally as many positive as negative shocks, and more negative than positive shocks, in panel A, B and C, respectively. The abnormal returns are computed by adjusting for exposures to the factors of a global Fama-French three-factor model. The table also presents the results of univariate sortings based on mispricing and liquidity shocks. The sample period goes from 1991-01 until 2018-06, based on data availability. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses.

	Neg. liqu. shocks	Zero shocks	Next 20%	Next 20%	Pos. liqu. shocks	Pos. - neg. shocks	All stocks
Panel A: More positive than negative shocks							
Baseline analysis							
Most underpriced	0.0108	0.0066	0.0052	0.0065	0.0109	0.0001	0.0070
(Bottom 20%)	(4.76)	(3.63)	(2.97)	(3.40)	(5.02)	(0.04)	(4.64)
Next 20%	0.0042	0.0028	0.0062	0.0068	0.0128	0.0086	0.0043
	(2.28)	(1.31)	(3.44)	(3.25)	(2.91)	(1.80)	(2.13)
Next 20%	0.0020	0.0022	0.0054	0.0031	0.0074	0.0054	0.0031
	(0.86)	(1.28)	(3.05)	(1.17)	(2.06)	(1.36)	(1.81)
Next 20%	−0.0026	−0.0009	0.0007	0.0023	0.0052	0.0079	0.0001
	(−0.99)	(−0.50)	(0.34)	(0.99)	(1.80)	(2.17)	(0.07)
Most overpriced	−0.0120	−0.0032	−0.0018	−0.0038	−0.0042	0.0078	−0.0027
(Top 20%)	(−4.16)	(−1.21)	(−0.85)	(−1.64)	(−1.53)	(2.41)	(−1.16)
Most overpriced -	−0.0228	−0.0099	−0.0070	−0.0104	−0.0151	0.0077	−0.0097
most underpriced	(−7.43)	(−3.55)	(−3.68)	(−5.20)	(−5.72)	(2.09)	(−5.42)
All stocks	0.0004	0.0014	0.0036	0.0039	0.0080	0.0077	
	(0.16)	(0.83)	(2.11)	(1.65)	(3.12)	(2.66)	
Abnormal returns relative to second quintile (i.e. zero shock) portfolio							
Most underpriced	0.0042	0	−0.0015	−0.0001	0.0043		
(Bottom 20%)	(1.44)		(−0.66)	(−0.05)	(1.71)		
Next 20%	0.0014	0	0.0034	0.0040	0.0100		
	(0.60)		(1.52)	(1.45)	(1.88)		
Next 20%	−0.0002	0	0.0031	0.0009	0.0052		
	(−0.10)		(1.93)	(0.36)	(1.43)		
Next 20%	−0.0017	0	0.0016	0.0032	0.0061		
	(−0.68)		(0.74)	(1.24)	(1.82)		
Most overpriced	−0.0088	0	0.0014	−0.0006	−0.0009		
(Top 20%)	(−3.32)		(0.54)	(−0.19)	(−0.30)		
Most overpriced -	−0.0129	0	0.0029	−0.0005	−0.0052		
most underpriced	(−3.37)		(1.00)	(−0.15)	(−1.47)		
All stocks	−0.0011	0	0.0022	0.0025	0.0066		
	(−0.67)		(1.58)	(1.27)	(2.46)		

	Neg. liqu. shocks	Next 20%	Zero shocks	Next 20%	Pos. liqu. shocks	Pos. - neg. shocks	All stocks
Panel B: Equally as many positive as negative shocks							
Baseline analysis							
Most underpriced	0.0039	0.0036	0.0060	0.0047	0.0117	0.0078	0.0060
(Bottom 20%)	(2.50)	(2.79)	(4.82)	(3.49)	(6.87)	(3.89)	(5.98)
Next 20%	0.0009	0.0006	0.0038	0.0046	0.0097	0.0088	0.0035
	(0.59)	(0.41)	(2.92)	(3.45)	(5.27)	(3.80)	(3.12)
Next 20%	-0.0008	0.0011	0.0024	0.0042	0.0063	0.0070	0.0024
	(-0.44)	(0.80)	(1.92)	(2.65)	(3.44)	(3.39)	(2.18)
Next 20%	-0.0023	−0.0016	0.0004	0.0031	0.0028	0.0051	−0.0001
	(-1.27)	(−1.08)	(0.32)	(1.84)	(1.58)	(2.22)	(−0.08)
Most overpriced	-0.0102	−0.0056	−0.0027	−0.0008	−0.0031	0.0071	−0.0036
(Top 20%)	(-4.65)	(−2.89)	(−1.42)	(−0.45)	(−1.29)	(2.40)	(−2.35)
Most overpriced -	-0.0141	−0.0092	−0.0088	−0.0055	−0.0148	−0.0007	−0.0096
most underpriced	(-6.24)	(−5.04)	(−4.97)	(−3.25)	(−6.49)	(−0.24)	(−7.09)
All stocks	-0.0012	0.0003	0.0030	0.0033	0.0063	0.0074	
	(-0.86)	(0.23)	(2.52)	(2.69)	(4.11)	(4.30)	
Abnormal returns relative to medium 20% (i.e. zero shock) portfolio							
Most underpriced	-0.0022	−0.0025	0	−0.0013	0.0056		
(Bottom 20%)	(-1.18)	(−1.73)		(−0.84)	(3.22)		
Next 20%	-0.0029	−0.0031	0	0.0008	0.0059		
	(-1.65)	(−2.19)		(0.63)	(3.45)		
Next 20%	-0.0031	−0.0013	0	0.0018	0.0039		
	(-1.75)	(−0.97)		(1.18)	(2.24)		
Next 20%	-0.0027	−0.0021	0	0.0027	0.0024		
	(-1.48)	(−1.40)		(1.87)	(1.22)		
Most overpriced	-0.0074	−0.0029	0	0.0019	−0.0003		
(Top 20%)	(-3.50)	(−1.70)		(1.16)	(−0.15)		
Most overpriced -	-0.0053	−0.0004	0	0.0033	−0.0060		
most underpriced	(-2.13)	(−0.20)		(1.53)	(−2.29)		
All stocks	-0.0042	−0.0027	0	0.0003	0.0033		
	(-3.16)	(−2.53)		(0.33)	(2.38)		

Table 9: **(continued)**

	Neg. liqu. shocks	Next 20%	Next 20%	Zero shocks	Pos. liqu. shocks	Pos. - neg. shocks	All stocks
	Panel C: More negative than positive shocks						
				Baseline analysis			
Most underpriced	−0.0042	0.0006	−0.0012	−0.0002	−0.0036	0.0007	−0.0069
(Bottom 20%)	(−1.03)	(0.12)	(−0.27)	(−0.05)	(−0.92)	(0.16)	(−1.26)
Next 20%	−0.0035	0.0047	−0.0017	−0.0018	0.0018	0.0052	−0.0092
	(−0.69)	(0.98)	(−0.39)	(−0.44)	(0.33)	(0.73)	(−1.73)
Next 20%	−0.0085	0.0004	0.0044	0.0052	0.0002	0.0087	−0.0053
	(−1.57)	(0.07)	(0.96)	(1.10)	(0.04)	(1.63)	(−0.89)
Next 20%	−0.0077	0.0053	0.0051	0.0074	−0.0028	0.0049	−0.0076
	(−1.41)	(0.99)	(0.95)	(1.44)	(−0.66)	(0.87)	(−1.02)
Most overpriced	−0.0076	0.0084	−0.0023	0.0017	−0.0051	0.0025	−0.0125
(Top 20%)	(−0.99)	(1.08)	(−0.31)	(0.25)	(−0.80)	(0.29)	(−1.44)
Most overpriced -	−0.0034	0.0079	−0.0010	0.0018	−0.0015	0.0019	−0.0056
most underpriced	(−0.44)	(1.11)	(−0.15)	(0.23)	(−0.22)	(0.20)	(−0.85)
All stocks	−0.0150	−0.0049	−0.0101	−0.0051	−0.0121	0.0029	
	(−2.22)	(−0.72)	(−1.59)	(−0.87)	(−1.67)	(0.72)	
	Abnormal returns relative to fourth quintile (i.e. zero shock) portfolio						
Most underpriced	−0.0041	0.0008	−0.0010	0	−0.0034		
(Bottom 20%)	(−0.85)	(0.16)	(−0.24)		(−0.88)		
Next 20%	−0.0017	0.0064	0.0001	0	0.0035		
	(−0.32)	(1.45)	(0.01)		(0.68)		
Next 20%	−0.0137	−0.0048	−0.0008	0	−0.0050		
	(−2.09)	(−0.78)	(−0.16)		(−1.00)		
Next 20%	−0.0151	−0.0021	−0.0023	0	−0.0102		
	(−3.17)	(−0.47)	(−0.66)		(−1.85)		
Most overpriced	−0.0093	0.0068	−0.0039	0	−0.0067		
(Top 20%)	(−1.15)	(1.14)	(−0.74)		(−0.96)		
Most overpriced -	−0.0052	0.0060	−0.0029	0	−0.0033		
most underpriced	(−0.57)	(0.89)	(−0.43)		(−0.41)		
All stocks	−0.0099	0.0002	−0.0050	0	−0.0071		
	(−2.45)	(0.06)	(−1.86)		(−1.87)		

Figure 4: **Abnormal returns of portfolios ranked by mispricing and liquidity shocks**
The figure plots the average abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and liquidity shocks. The analysis is performed under three market conditions: More positive than negative liquidity shocks, approximately equally as many positive and negative shocks, and more negative than positive shocks, in panel A, B and C, respectively. The abnormal returns are computed by adjusting for exposures to the factors of a global Fama-French three-factor model. The sample period goes from 1991-01 until 2018-06, based on data availability.

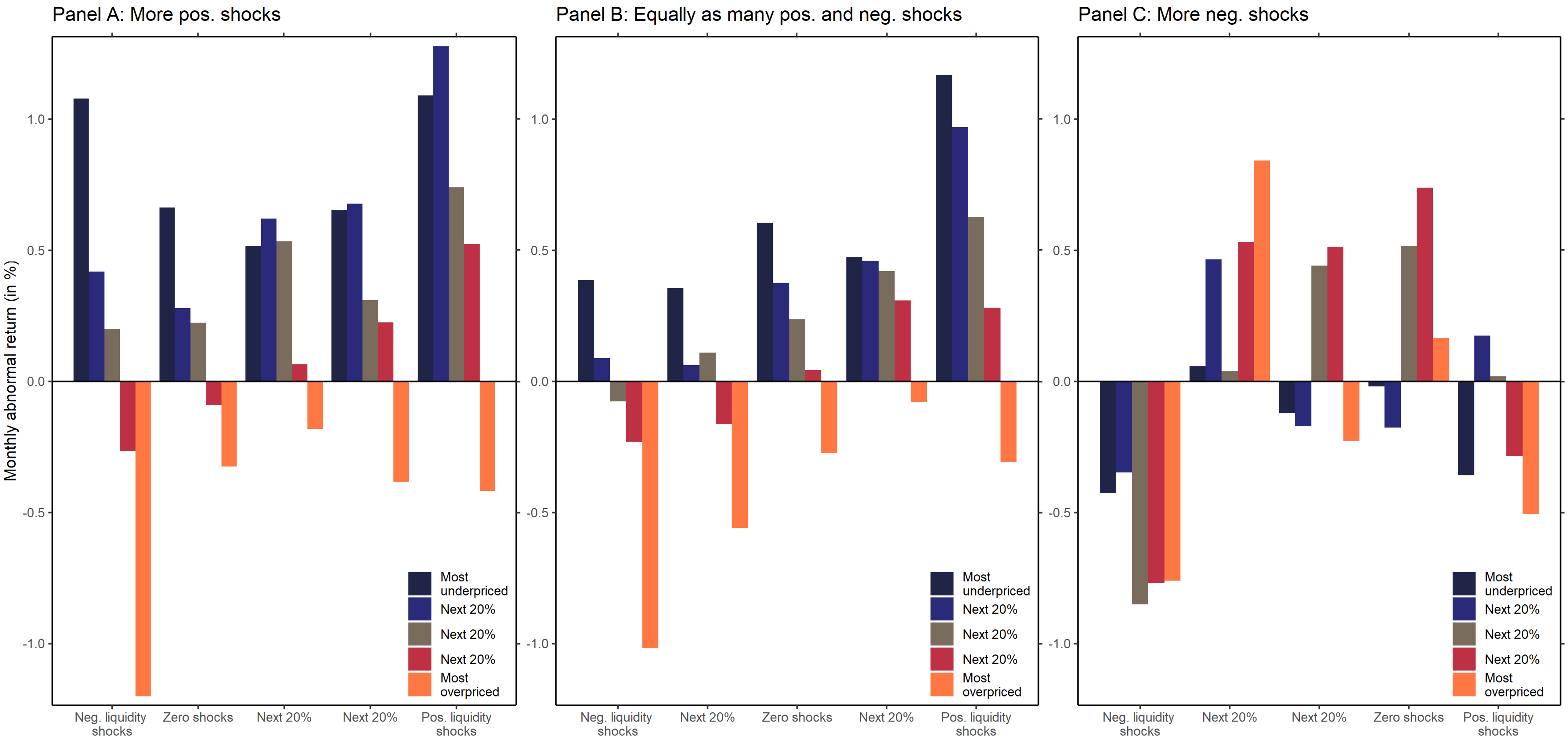

Table 10: **Abnormal returns of 5x5 portfolios based on mispricing and liquidity shocks in the full sample**
The table reports the average monthly abnormal returns of negative liquidity shock and positive liquidity shock difference portfolios for each mispricing group, calculated: (i) with global breakpoints; and (ii) with regional breakpoints. In (i), every month, I first compute the cross-sectional zero-shock quantile and assign it to the associated liquidity shock quintile portfolio (i.e. the "zero-shock" portfolio). The returns of the difference portfolios are then calculated for each of the mispricing groups as the differences between the returns of the liquidity shock quintile portfolios and the return of the zero-shock portfolio. I only analyze the difference portfolios with the largest positive and negative deviations from the zero-shock portfolio and label them in the table as "positive liquidity shocks" and "negative liquidity shocks", respectively. For instance, if in a given month the zero shock quantile falls in the range of the first liquidity shock quintile portfolio, for any mispricing group, the negative difference portfolio has a return of zero, and the positive difference portfolio has a return computed as the difference in returns between liquidity shock portfolio five and one. In (ii), the computation principally follows the same approach, but it is performed for every region separately. The returns of the difference portfolios are then averaged across regions to obtain a global estimate. In both cases, the computation of abnormal returns is based on a Fama-French three-factor model, with a global version used in (i) and a regional version used in (ii). The 5x5 portfolios underlying the analysis are formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and liquidity shocks defined as the negative difference between the quoted spread and its past 12-month average: $liqu_{i,t} = -(qs_{i,t} - avg\_qs_{i|t-12,t-1})$.

	Global breakpoints		Region average	
	Neg. liqu. shocks	Pos. liqu. shocks	Neg. liqu. shocks	Pos. liqu. shocks
Most underpriced	−0.0025	0.0050	−0.0014	0.0040
(Bottom 20%)	(−1.46)	(2.46)	(−0.97)	(2.60)
Next 20%	−0.0037	0.0060	−0.0059	0.0062
	(−2.17)	(3.22)	(−4.19)	(3.35)
Next 20%	−0.0034	0.0026	−0.0057	0.0007
	(−1.89)	(1.31)	(−3.49)	(0.43)
Next 20%	−0.0065	0.0027	−0.0063	0.0019
	(−3.11)	(1.42)	(−3.55)	(1.15)
Most overpriced	−0.0074	0.0037	−0.0083	0.0010
(Top 20%)	(−3.32)	(1.68)	(−5.15)	(0.55)
Most overpriced -	−0.0049	−0.0013	−0.0070	−0.0029
most underpriced	(−1.91)	(−0.48)	(−3.52)	(−1.36)

Table 11: **VWLS Fama-MacBeth regressions**

Panel A reports the coefficients (multiplied by 100) from monthly firm-level VWLS Fama-MacBeth regressions of stock returns on liquidity and nine individual mispricing-related anomaly variables as well as composite mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017). Standard return predictors comprise the past 1-month return, the past 1-year return from $t-12$ to $t-2$ (i.e. momentum), the past 3-year return from $t-36$ to $t-13$, the past 1-month $log(ME)$, $log(B/M)$ computed with book equity from the previous fiscal year end and market equity from the previous end of the year, and β calculated from monthly rolling regressions of daily excess stock returns in the previous month on a global market risk premium. At least 15 non-missing returns are required for beta to be calculated in a given month. T-statistics based on Newey-West corrected standard errors with six lags are given in parantheses. The sample period goes from 1990-01 until 2018-06, based on data availability. The independent variables are winsorized at the top and bottom 1% level and standardized to have a mean of zero and unit standard deviation.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Quoted spread	−0.386				−0.368	−0.362	−0.380	−0.359	−0.352	−0.377	−0.354	−0.344	−0.382	−0.322	−0.440	−0.440
	(−4.36)				(−3.81)	(−4.11)	(−4.33)	(−3.92)	(−4.16)	(−4.29)	(−4.01)	(−3.95)	(−4.34)	(−3.73)	(−4.49)	(−4.16)
Illiquidity		−0.146														
		(−1.99)														
FHT spread			−0.392													
			(−4.67)													
High-low spread				0.024												
				(0.24)												
Accruals					−0.154									−0.126		
					(−3.31)									(−3.01)		
Net operating assets						−0.160								−0.195		
						(−5.09)								(−3.93)		
Asset growth							−0.121							0.122		
							(−3.23)							(2.18)		
Investment-to-assets								−0.119						−0.070		
								(−3.81)						(−1.59)		
Gross profitability premium									0.206					0.162		
									(5.09)					(3.56)		
Net stock issues										−0.053				0.008		
										(−2.70)				(0.41)		
Composite equity issues											−0.165			−0.065		
											(−4.70)			(−2.29)		
Return on assets												0.292		0.171		
												(4.05)		(2.80)		
Momentum													0.297	0.324		
													(2.76)	(2.87)		
Mispricing															−0.228	−0.314
															(−5.50)	(−6.59)
Quoted spread x mispricing																−0.095
																(−0.26)
$r(t-1)$	−0.340	−0.332	−0.330	−0.333	−0.323	−0.338	−0.352	−0.321	−0.357	−0.340	−0.345	−0.344	−0.340	−0.354	−0.326	−0.328
	(−4.37)	(−4.17)	(−4.13)	(−4.19)	(−4.04)	(−4.24)	(−4.51)	(−4.07)	(−4.54)	(−4.38)	(−4.43)	(−4.43)	(−4.35)	(−4.49)	(−4.09)	(−4.12)
$r(t-12,t-2)$	0.297	0.249	0.249	0.241	0.342	0.318	0.304	0.346	0.329	0.304	0.313	0.291				
	(2.76)	(2.26)	(2.25)	(2.20)	(3.07)	(2.87)	(2.84)	(3.00)	(2.82)	(2.82)	(2.92)	(2.73)				
$r(t-36,t-13)$	−0.146	−0.115	−0.117	−0.116	−0.138	−0.142	−0.092	−0.128	−0.122	−0.138	−0.132	−0.159	−0.145	−0.114	−0.073	−0.073
	(−2.12)	(−1.80)	(−1.83)	(−1.81)	(−1.95)	(−2.05)	(−1.52)	(−1.99)	(−1.93)	(−2.03)	(−1.97)	(−2.39)	(−2.13)	(−1.95)	(−1.12)	(−1.11)
log(ME)	−0.123	−0.109	−0.134	−0.105	−0.115	−0.116	−0.126	−0.121	−0.095	−0.123	−0.132	−0.133	−0.124	−0.127	−0.162	−0.161
	(−1.67)	(−1.52)	(−1.83)	(−1.50)	(−1.36)	(−1.53)	(−1.72)	(−1.49)	(−1.24)	(−1.66)	(−1.81)	(−1.82)	(−1.67)	(−1.61)	(−2.19)	(−2.17)
log(B/M)	0.082	0.139	0.139	0.136	0.146	0.109	0.075	0.098	0.373	0.077	0.080	0.188	0.072	0.500	0.194	0.190
	(0.53)	(0.80)	(0.79)	(0.79)	(1.12)	(0.75)	(0.48)	(0.76)	(2.99)	(0.50)	(0.53)	(1.25)	(0.47)	(3.77)	(1.27)	(1.25)
β	−0.005	0.022	0.019	0.023	0.028	−0.012	0.002	0.006	0.003	−0.002	0.003	0.003	−0.004	0.030	0.071	0.070
	(−0.05)	(0.24)	(0.21)	(0.26)	(0.28)	(−0.12)	(0.02)	(0.06)	(0.03)	(−0.02)	(0.03)	(0.03)	(−0.04)	(0.31)	(0.67)	(0.66)
Number of obs	5,045,620	5,758,626	5,746,998	5,453,089	4,213,393	4,667,623	4,970,500	4,176,215	4,589,599	4,984,094	4,984,257	4,982,689	4,984,284	3,813,935	4,986,128	4,986,128
Adjusted R^2	18.91%	21.55%	21.61%	21.62%	18.66%	18.51%	19.13%	18.51%	18.74%	19.03%	19.11%	19.22%	18.93%	20.50%	18.23%	18.27%

Table 11: **(continued)**
Panel B reports the coefficients (multiplied by 100) from monthly firm-level VWLS Fama-MacBeth regressions, if the previous analysis is repeated with liquidity being replaced by liquidity shocks. Liquidity shocks (1) are defined as the negative difference between the quoted spread (qs) and its past 12-month average: $liqu_{i,t} = -(qs_{i,t} - avg\_qs_{i|t-12,t-1})$. Liquidity shocks (2) are defined accordingly, with Amihud's illiquidity instead of the quoted spread being used as liquidity proxy.

Panel B	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Liquidity shocks (1)	0.363		0.367	0.378	0.361	0.362	0.369	0.367	0.381	0.362	0.360	0.369	0.449	0.455
	(6.79)		(6.36)	(6.86)	(6.89)	(6.42)	(6.51)	(6.89)	(7.29)	(6.88)	(6.76)	(6.30)	(7.15)	(6.78)
Liquidity shocks (2)		0.350												
		(5.96)												
Accruals			−0.126									−0.100		
			(−2.64)									(−2.42)		
Net operating assets				−0.162								−0.191		
				(−4.98)								(−3.53)		
Asset growth					−0.113							0.132		
					(−2.71)							(2.15)		
Investment-to-assets						−0.120						−0.078		
						(−3.82)						(−1.69)		
Gross profitability premium							0.197					0.168		
							(4.92)					(3.57)		
Net stock issues								−0.047				0.023		
								(−2.18)				(1.04)		
Composite equity issues									−0.166			−0.086		
									(−4.48)			(−2.84)		
Return on assets										0.289		0.171		
										(4.02)		(2.68)		
Momentum											0.277	0.278		
											(2.46)	(2.46)		
Mispricing													−0.217	−0.196
													(−4.87)	(−4.12)
Liquidity shocks (1) x mispricing														−0.057
														(−0.15)
$r(t-1)$	−0.349	−0.337	−0.329	−0.347	−0.359	−0.332	−0.357	−0.349	−0.355	−0.351	−0.349	−0.366	−0.344	−0.346
	(−4.57)	(−4.39)	(−4.11)	(−4.35)	(−4.63)	(−4.22)	(−4.52)	(−4.55)	(−4.61)	(−4.57)	(−4.53)	(−4.56)	(−4.35)	(−4.36)
$r(t-12,t-2)$	0.277	0.247	0.318	0.281	0.280	0.312	0.294	0.282	0.289	0.270				
	(2.46)	(2.18)	(2.81)	(2.52)	(2.51)	(2.70)	(2.51)	(2.50)	(2.58)	(2.42)				
$r(t-36,t-13)$	−0.137	−0.120	−0.134	−0.133	−0.083	−0.120	−0.117	−0.130	−0.122	−0.152	−0.135	−0.109	−0.064	−0.065
	(−1.93)	(−1.82)	(−1.80)	(−1.84)	(−1.32)	(−1.78)	(−1.79)	(−1.85)	(−1.77)	(−2.23)	(−1.93)	(−1.77)	(−0.95)	(−0.95)
log(ME)	−0.100	−0.128	−0.093	−0.102	−0.102	−0.105	−0.080	−0.102	−0.111	−0.116	−0.101	−0.111	−0.118	−0.117
	(−1.34)	(−1.78)	(−1.10)	(−1.33)	(−1.38)	(−1.28)	(−1.04)	(−1.36)	(−1.51)	(−1.58)	(−1.35)	(−1.41)	(−1.56)	(−1.55)
log(B/M)	0.070	0.157	0.116	0.092	0.063	0.064	0.351	0.063	0.068	0.176	0.060	0.478	0.177	0.176
	(0.45)	(0.88)	(0.88)	(0.64)	(0.41)	(0.50)	(2.76)	(0.41)	(0.45)	(1.17)	(0.39)	(3.55)	(1.16)	(1.16)
β	−0.004	0.032	0.029	−0.013	0.002	−0.002	0.001	−0.005	0.003	0.005	−0.004	0.026	0.068	0.067
	(−0.04)	(0.33)	(0.27)	(−0.12)	(0.02)	(−0.02)	(0.01)	(−0.04)	(0.03)	(0.05)	(−0.04)	(0.26)	(0.62)	(0.61)
Number of obs	4,729,800	5,508,131	3,968,177	4,389,764	4,665,591	3,941,374	4,318,505	4,677,661	4,677,815	4,676,416	4,677,837	3,605,430	4,678,788	4,678,788
Adjusted R^2	18.65%	21.39%	18.43%	18.26%	18.85%	18.25%	18.48%	18.76%	18.85%	18.97%	18.66%	20.25%	17.96%	17.99%

Appendix

Table A1: **Mispricing and other effects**

The table reports the average monthly abnormal returns of quintile-based long/short portfolios based on mispricing for a low and high state of each of the second sorting variables stated in column 2. At the beginning of every month, stocks are classified into "Low" and "High" groups based on the median of the second sorting variable. Independently, stocks are assigned to five mispricing groups. The abnormal returns are computed by adjusting for exposures to the factors of a global Fama-French three-factor model. The sample period runs from 01/1990 until 06/2018. Leverage is defined as the book value of total assets divided by book equity. Co-skewness according to Harvey and Siddique (2000) is the slope on the squared market factor in a regression of daily excess returns on a global market factor and its squared version, with at least 15 non-missing observations of all the involved regression variables required in a given month. Idiosyncratic volatility according to Ang et al. (2006) is defined as the standard deviation of the residual that results from a regression of daily excess returns on the factors of a global Fama-French three factor model, with at least 15 non-missing observations of all the involved regression variables required in a given month. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses.

Model	Description	Low	High	Diff	Low	High	Diff
		Value-weighted			Equally-weighted		
(1)	Size	−0.0102	−0.0096	0.0006	−0.0121	−0.0119	0.0002
		(−10.68)	(−8.40)	(0.42)	(−10.70)	(−15.47)	(0.26)
(2)	Book-to-market	−0.0100	−0.0079	0.0021	−0.0120	−0.0102	0.0018
		(−7.72)	(−6.05)	(1.40)	(−11.55)	(−12.90)	(2.15)
(3)	Leverage	−0.0096	−0.0090	0.0006	−0.0106	−0.0126	−0.0020
		(−6.84)	(−7.44)	(0.42)	(−9.46)	(−15.72)	(−2.20)
(4)	Co-skewness	−0.0095	−0.0088	0.0007	−0.0120	−0.0116	0.0004
		(−8.35)	(−6.85)	(0.60)	(−12.74)	(−13.02)	(0.76)
(5)	Idiosyncratic volatility	−0.0081	−0.0098	−0.0017	−0.0089	−0.0148	−0.0059
		(−7.49)	(−6.79)	(−1.12)	(−16.46)	(−13.13)	(−5.87)

Table A2: **Average abnormal returns of 5x5 portfolios based on mispricing and liquidity in the U.S.**
The table reports the average abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and the quoted spread (qs). The abnormal returns are computed by adjusting for exposures to the factors of a Fama-French three-factor model in the U.S. The table also presents the results of univariate sortings based on mispricing and the quoted spread. The sample period goes from 1990-01 until 2018-06. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses.

	Lowest qs	Next 20%	Next 20%	Next 20%	Highest qs	Highest - lowest	All stocks
Most underpriced	0.0031	0.0023	0.0031	0.0034	0.0080	0.0049	0.0033
(Bottom 20%)	(3.92)	(2.00)	(2.13)	(2.32)	(4.98)	(2.62)	(4.65)
Next 20%	0.0008	0.0015	−0.0008	0.0025	0.0044	0.0036	0.0010
	(0.85)	(1.23)	(−0.52)	(1.82)	(2.38)	(1.72)	(1.26)
Next 20%	0.0017	−0.0007	0.0012	−0.0001	−0.0002	−0.0019	0.0011
	(1.69)	(−0.55)	(0.77)	(−0.07)	(−0.10)	(−0.79)	(1.41)
Next 20%	−0.0030	−0.0020	−0.0037	−0.0032	−0.0039	−0.0008	−0.0029
	(−2.28)	(−1.52)	(−1.96)	(−1.52)	(−1.57)	(−0.30)	(−3.43)
Most overpriced	−0.0049	−0.0097	−0.0115	−0.0124	−0.0166	−0.0117	−0.0069
(Top 20%)	(−3.08)	(−5.45)	(−5.52)	(−4.85)	(−5.07)	(−3.27)	(−5.41)
Most overpriced -	−0.0080	−0.0120	−0.0146	−0.0157	−0.0247	−0.0166	−0.0102
most underpriced	(−4.55)	(−6.01)	(−5.95)	(−5.76)	(−8.48)	(−5.33)	(−6.43)
All stocks	0.0005	−0.0009	−0.0023	−0.0026	−0.0015	−0.0020	
	(0.87)	(−0.99)	(−2.02)	(−1.88)	(−0.80)	(−1.01)	

Table A3: **Average abnormal returns of 5x5 portfolios based on mispricing and liquidity in developed markets**
The table reports the average abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and the quoted spread (qs). The abnormal returns are computed by adjusting for exposures to the factors of a Fama-French three-factor model in developed markets. The table also presents the results of univariate sortings based on mispricing and the quoted spread. The sample period goes from 1990-01 until 2018-06. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses. Following Jacobs (2016), I use the market classification framework by Morgan Stanley Capital International to define developed markets.

	Lowest qs	Next 20%	Next 20%	Next 20%	Highest qs	Highest - lowest	All stocks
Most underpriced	0.0039	0.0040	0.0086	0.0058	0.0090	0.0051	0.0043
(Bottom 20%)	(4.45)	(3.26)	(5.56)	(3.99)	(4.80)	(2.78)	(5.12)
Next 20%	0.0020	0.0034	0.0045	0.0027	0.0030	0.0010	0.0023
	(2.28)	(2.51)	(2.88)	(1.90)	(1.48)	(0.49)	(2.63)
Next 20%	0.0007	0.0003	0.0019	0.0012	0.0005	−0.0001	0.0007
	(0.70)	(0.22)	(1.25)	(0.71)	(0.30)	(−0.06)	(0.79)
Next 20%	−0.0016	−0.0011	−0.0014	−0.0028	−0.0046	−0.0030	−0.0017
	(−1.75)	(−0.76)	(−0.87)	(−1.58)	(−2.09)	(−1.34)	(−1.88)
Most overpriced	−0.0051	−0.0054	−0.0083	−0.0131	−0.0165	−0.0114	−0.0060
(Top 20%)	(−3.79)	(−3.20)	(−4.10)	(−5.93)	(−6.68)	(−4.67)	(−4.82)
Most overpriced -	−0.0089	−0.0094	−0.0169	−0.0190	−0.0255	−0.0165	−0.0103
most underpriced	(−6.26)	(−5.93)	(−9.06)	(−9.02)	(−11.56)	(−7.33)	(−7.92)
All stocks	0.0009	0.0008	0.0017	−0.0011	−0.0024	−0.0033	
	(1.33)	(0.68)	(1.25)	(−0.82)	(−1.36)	(−1.91)	

Table A4: **Average abnormal returns of 5x5 portfolios based on mispricing and liquidity in emerging markets**
The table reports the average abnormal returns of 5x5 portfolios formed by sorting stocks independently on mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017), and the quoted spread (qs). The abnormal returns are computed by adjusting for exposures to the factors of a Fama-French three-factor model in emerging markets. The table also presents the results of univariate sortings based on mispricing and the quoted spread. The sample period goes from 1990-01 until 2018-06. T-statistics based on heteroskedasticity-consistent standard errors according to White (1980) are given in parentheses. Following Jacobs (2016), I use the market classification framework by Morgan Stanley Capital International to define emerging markets.

	Lowest qs	Next 20%	Next 20%	Next 20%	Highest qs	Highest - lowest	All stocks
Most underpriced	0.0040	−0.0015	0.0008	0.0041	0.0030	−0.0010	0.0022
(Bottom 20%)	(1.35)	(−0.65)	(0.31)	(1.33)	(1.00)	(−0.23)	(1.10)
Next 20%	0.0002	−0.0005	−0.0010	0.0007	−0.0007	−0.0009	−0.0005
	(0.06)	(−0.20)	(−0.38)	(0.25)	(−0.18)	(−0.18)	(−0.22)
Next 20%	−0.0043	0.0006	−0.0041	−0.0012	−0.0105	−0.0063	−0.0024
	(−1.34)	(0.19)	(−1.42)	(−0.32)	(−2.42)	(−1.26)	(−0.95)
Next 20%	−0.0021	−0.0030	−0.0039	−0.0091	−0.0116	−0.0095	−0.0021
	(−0.71)	(−1.12)	(−0.86)	(−2.33)	(−3.47)	(−1.89)	(−0.96)
Most overpriced	−0.0053	−0.0081	−0.0068	−0.0095	−0.0185	−0.0132	−0.0072
(Top 20%)	(−1.16)	(−1.94)	(−1.34)	(−1.82)	(−3.76)	(−2.33)	(−1.73)
Most overpriced -	−0.0094	−0.0066	−0.0076	−0.0136	−0.0215	−0.0122	−0.0093
most underpriced	(−1.94)	(−1.54)	(−1.62)	(−3.23)	(−5.34)	(−2.43)	(−2.41)
All stocks	−0.0009	−0.0017	−0.0039	−0.0027	−0.0082	−0.0073	
	(−0.33)	(−0.75)	(−1.51)	(−0.93)	(−2.75)	(−1.86)	

Table A5: **OLS Fama-MacBeth regressions**

Panel A reports the coefficients (multiplied by 100) from monthly firm-level Fama-MacBeth regressions of stock returns on liquidity and nine individual mispricing-related anomaly variables as well as composite mispricing according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017). Standard return predictors comprise the past 1-month return, the past 1-year return from $t-12$ to $t-2$ (i.e. momentum), the past 3-year return from $t-36$ to $t-13$, the past 1-month $log(ME)$, $log(B/M)$ computed with book equity from the previous fiscal year end and market equity from the previous end of the year, and β calculated from monthly rolling regressions of daily excess stock returns in the previous month on a global market risk premium. At least 15 non-missing returns are required for beta to be calculated in a given month. T-statistics based on Newey-West corrected standard errors with six lags are given in parantheses. The sample period goes from 1990-01 until 2018-06, based on data availability. The independent variables are winsorized at the top and bottom 1% level and standardized to have a mean of zero and unit standard deviation.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Quoted spread	0.234				0.213	0.215	0.224	0.176	0.232	0.236	0.248	0.242	0.232	0.201	0.194	0.203
	(5.13)				(4.48)	(4.54)	(4.79)	(3.46)	(4.51)	(5.02)	(5.25)	(4.99)	(4.93)	(3.90)	(3.99)	(4.10)
Illiquidity		0.190														
		(8.43)														
FHT spread			0.176													
			(4.41)													
High-low spread				0.310												
				(8.09)												
Accruals					−0.151									−0.083		
					(−5.24)									(−2.57)		
Net operating assets						−0.280								−0.325		
						(−8.56)								(−5.46)		
Asset growth							−0.222							0.065		
							(−9.45)							(1.66)		
Investment-to-assets								−0.189						0.000		
								(−6.59)						(−0.01)		
Gross profitability premium									0.230					0.171		
									(6.23)					(4.30)		
Net stock issues										−0.074				−0.024		
										(−3.82)				(−1.16)		
Composite equity issues											−0.283			−0.198		
											(−7.94)			(−6.49)		
Return on assets												0.103		0.060		
												(1.70)		(0.96)		
Momentum													0.270	0.265		
													(3.27)	(3.20)		
Mispricing															−0.463	−0.461
															(−10.50)	(−10.51)
Quoted spread x mispricing																−0.039
																(−0.10)
$r(t-1)$	−0.592	−0.571	−0.573	−0.558	−0.589	−0.592	−0.601	−0.561	−0.599	−0.595	−0.603	−0.607	−0.594	−0.603	−0.599	−0.600
	(−7.94)	(−7.95)	(−7.97)	(−7.83)	(−7.53)	(−7.73)	(−7.99)	(−7.25)	(−7.94)	(−7.91)	(−8.03)	(−8.35)	(−7.89)	(−7.94)	(−8.00)	(−8.02)
$r(t-12,t-2)$	0.273	0.238	0.234	0.248	0.292	0.280	0.273	0.293	0.274	0.277	0.283	0.264				
	(3.31)	(2.94)	(2.90)	(3.10)	(3.51)	(3.35)	(3.30)	(3.43)	(3.20)	(3.36)	(3.43)	(3.26)				
$r(t-36,t-13)$	−0.183	−0.174	−0.174	−0.162	−0.174	−0.153	−0.132	−0.159	−0.193	−0.185	−0.191	−0.196	−0.189	−0.142	−0.150	−0.151
	(−4.46)	(−4.72)	(−4.81)	(−4.44)	(−4.40)	(−3.85)	(−3.27)	(−4.04)	(−4.75)	(−4.43)	(−4.69)	(−5.88)	(−4.55)	(−4.75)	(−3.45)	(−3.49)
log(ME)	−0.154	−0.269	−0.254	−0.211	−0.159	−0.147	−0.155	−0.149	−0.137	−0.150	−0.182	−0.176	−0.151	−0.154	−0.192	−0.188
	(−1.94)	(−3.83)	(−3.88)	(−3.27)	(−1.88)	(−1.82)	(−1.91)	(−1.70)	(−1.61)	(−1.83)	(−2.27)	(−2.38)	(−1.85)	(−2.14)	(−2.26)	(−2.21)
log(B/M)	0.532	0.585	0.600	0.587	0.522	0.568	0.467	0.466	0.634	0.511	0.448	0.476	0.521	0.656	0.461	0.454
	(3.07)	(3.22)	(3.33)	(3.21)	(2.97)	(3.28)	(2.74)	(2.69)	(3.63)	(3.00)	(2.71)	(3.06)	(3.03)	(5.13)	(2.67)	(2.63)
β	−0.003	0.002	0.004	0.002	0.005	0.002	0.002	−0.001	0.005	−0.001	0.007	0.006	−0.002	0.019	0.032	0.033
	(−0.07)	(0.05)	(0.09)	(0.05)	(0.11)	(0.04)	(0.05)	(−0.03)	(0.11)	(−0.03)	(0.16)	(0.15)	(−0.04)	(0.41)	(0.70)	(0.71)
Number of obs	5,046,882	5,761,240	5,749,612	5,724,812	4,214,383	4,668,692	4,971,628	4,177,204	4,590,762	4,985,278	4,985,441	4,983,987	4,985,468	3,814,817	4,987,312	4,987,312
Adjusted R^2	10.42%	12.43%	12.51%	12.47%	10.30%	10.41%	10.47%	10.55%	10.57%	10.43%	10.53%	10.59%	10.41%	11.20%	10.29%	10.35%

Table A5: **(continued)**
Panel B reports the coefficients (multiplied by 100) from monthly firm-level Fama-MacBeth regressions, if the previous analysis is repeated with liquidity being replaced by liquidity shocks. Liquidity shocks (1) are defined as the negative difference between the quoted spread (qs) and its past 12-month average: $liqu_{i,t} = -(qs_{i,t} - avg\_qs_{i|t-12,t-1})$. Liquidity shocks (2) are defined accordingly, with Amihud's illiquidity instead of the quoted spread being used as liquidity proxy.

Panel B	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Liquidity shocks (1)	0.144		0.155	0.149	0.145	0.165	0.152	0.146	0.160	0.146	0.146	0.171	0.183	0.190
	(4.91)		(5.02)	(4.87)	(4.93)	(5.39)	(5.03)	(4.94)	(5.50)	(5.02)	(4.95)	(5.64)	(4.93)	(5.04)
Liquidity shocks (2)		0.083												
		(4.38)												
Accruals			−0.137									−0.071		
			(−4.43)									(−2.04)		
Net operating assets				−0.270								−0.308		
				(−8.13)								(−5.11)		
Asset growth					−0.211							0.061		
					(−9.08)							(1.47)		
Investment-to-assets						−0.169						0.009		
						(−6.38)						(0.33)		
Gross profitability premium							0.221					0.184		
							(6.02)					(4.71)		
Net stock issues								−0.065				0.011		
								(−3.24)				(0.63)		
Composite equity issues									−0.292			−0.231		
									(−7.88)			(−7.74)		
Return on assets										0.082		0.035		
										(1.28)		(0.54)		
Momentum											0.227	0.216		
											(2.71)	(2.59)		
Mispricing													−0.434	−0.435
													(−9.66)	(−9.68)
Liquidity shocks (1) x mispricing														0.020
														(0.05)
$r(t-1)$	−0.576	−0.552	−0.574	−0.579	−0.582	−0.552	−0.586	−0.579	−0.591	−0.592	−0.578	−0.594	−0.587	−0.587
	(−7.50)	(−7.45)	(−7.21)	(−7.37)	(−7.54)	(−7.04)	(−7.64)	(−7.49)	(−7.64)	(−7.89)	(−7.48)	(−7.81)	(−7.66)	(−7.68)
$r(t-12,t-2)$	0.230	0.221	0.245	0.230	0.230	0.251	0.223	0.232	0.234	0.220				
	(2.74)	(2.65)	(2.91)	(2.74)	(2.73)	(2.90)	(2.59)	(2.78)	(2.80)	(2.67)				
$r(t-36,t-13)$	−0.189	−0.174	−0.182	−0.159	−0.138	−0.170	−0.198	−0.190	−0.195	−0.194	−0.193	−0.149	−0.151	−0.151
	(−4.45)	(−4.65)	(−4.45)	(−3.86)	(−3.36)	(−4.21)	(−4.68)	(−4.40)	(−4.63)	(−5.57)	(−4.49)	(−5.04)	(−3.36)	(−3.36)
log(ME)	−0.241	−0.259	−0.265	−0.232	−0.236	−0.255	−0.230	−0.238	−0.277	−0.263	−0.237	−0.270	−0.255	−0.256
	(−2.93)	(−3.70)	(−3.05)	(−2.77)	(−2.83)	(−2.88)	(−2.75)	(−2.85)	(−3.43)	(−3.59)	(−2.85)	(−3.90)	(−3.00)	(−3.00)
log(B/M)	0.529	0.637	0.510	0.556	0.462	0.444	0.628	0.506	0.438	0.473	0.514	0.625	0.460	0.462
	(2.95)	(3.41)	(2.80)	(3.12)	(2.65)	(2.48)	(3.49)	(2.90)	(2.59)	(2.95)	(2.91)	(4.66)	(2.60)	(2.61)
β	0.000	0.019	0.011	0.005	0.007	0.006	0.008	0.003	0.012	0.010	0.002	0.028	0.034	0.036
	(0.00)	(0.50)	(0.21)	(0.09)	(0.15)	(0.11)	(0.16)	(0.06)	(0.25)	(0.22)	(0.04)	(0.55)	(0.67)	(0.70)
Number of obs	4,730,923	5,510,515	3,969,035	4,390,722	4,666,620	3,942,237	4,319,529	4,678,729	4,678,883	4,677,582	4,678,905	3,606,178	4,679,856	4,679,856
Adjusted R^2	10.35%	12.75%	10.21%	10.31%	10.39%	10.40%	10.44%	10.34%	10.46%	10.52%	10.32%	11.07%	10.21%	10.25%

Table A6: **Anomaly construction**
The table reports the nine anomaly definitions as part of the mispricing score according to Stambaugh, Yu, and Yuan (2015) and Lu, Stambaugh, and Yuan (2017).

Anomaly name	Relation of increase in anomaly variable with future exp. returns	Implementation	Holding period	References
Net stock issues	–	Net stock issues equal the annual log change in split-adjusted shares outstanding, measured as shares outstanding (Compustat annual item CSHO, Datastream item NOSH) multiplied by the adjustment factor (Compustat item cfacshr, Datastream item AF). The annual change is calculated from $t-13$ to $t-1$.	One month	Ritter (1991), Loughran and Ritter (1995), Fama and French (2008)
Composite Equity Issues	–	Composite equity issuance is defined as the annual log change in the market capitalization of a firm less the cumulative log stock return over the same time period. The anomaly variable is calculated from $t-13$ to $t-1$.	One month	Daniel and Titman (2006)
Accruals	–	According to the balance sheet approach of Sloan (1996), accruals are measured as the annual change in non-cash working capital, less depreciation and amortization expense (DP, WC01151), divided by average total assets (AT, WC02999) over the last two fiscal years. Non-cash working capital is defined as the change in current assets (ACT, WC02201), less the change in total cash and short-term investments (CHE, WC02001), less the change in current liabilities (LCT, WC03101), plus the change in short term debt (DLC, WC03051), plus the change in income taxes payable (item TXP, WC03063). In the construction of the anomaly, I use a publishing lag (according to datadate, WC05350) of at least four months before the end of month t.	One year	Sloan (1996)

Table A6: **(continued)**

Anomaly name	Relation of increase in anomaly variable with future exp. returns	Implementation	Holding period	References
Net operating assets	–	Net operation assets are defined as operating assets minus operating liabilities, divided by total assets in the previous fiscal year. Operating assets are total assets (AT, WC02999), less cash and short-term investments (CHE, WC02001). Operating liabilities are total assets less debt included in current liabilities (DLC, WC03051), less long-term debt (DLTT, WC03251), less common equity (CEQ, WC03501), less minority interests (MIB, WC04055), less preferred stock (PSTK, WC03451). In the construction of the anomaly, I use a publishing lag (according to datadate, WC05350) of at least four months before the end of month t.	One year	Hirshleifer et al. (2004)
Asset growth	–	Asset growth is defined as the annual growth rate of total assets (AT, WC02999) from the fiscal year that ends in $t-2$ to the fiscal year that ends in $t-1$. In the construction of the anomaly, I use a publishing lag (according to datadate, WC05350) of at least four months before the end of month t.	One year	Cooper, Gulen, and Schill (2008)
Investment-to-Assets	–	Investment-to-assets are defined as the annual change in gross property, plant, and equipment (PPEGT, WC02301), plus the annual change in inventories (INVT, WC02101), divided by total assets in the previous fiscal year. In the construction of the anomaly, I use a publishing lag (according to datadate, WC05350) of at least four months before the end of month t.	One year	Titman, Wei, and Xie (2004), Xing (2008)

Table A6: **(continued)**

Anomaly name	Relation of increase in anomaly variable with future exp. returns	Implementation	Holding period	References
Momentum	+	The anomaly variable of momentum is the cumulative stock return from month $t-11$ to month $t-1$ (Carhart, 1997).	One month	Jegadeesh and Titman (1993), Carhart (1997)
Gross profitability	+	Gross profitability is defined as total revenue (REVT, WC01001) minus cost of goods sold (COGS, WC01051), divided by total assets (AT, WC02999). In the construction of the anomaly, I use a publishing lag (according to datadate, WC05350) of at least four months before the end of month t.	One year	Novy-Marx (2013)
Return on assets	+	Return on assets is defined as income before extraordinary items (IB, WC01551) divided by total assets (AT, WC02999) in the previous fiscal year. In the construction of the anomaly, I use a publishing lag (according to datadate, WC05350) of at least four months before the end of month t.	One year	Fama and French (2006), Chen, Novy-Marx, and Zhang (2011)