Asset pricing anomalies: liquidity-risk hedgers or liquidity-risk spreaders?

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Abstract

We capture two distinct investing preferences – hedging against aggregate liquidity risk or betting on it – in the cross-section of stock returns. A three-factor model underpinned by exposures to changes in market liquidity, isolating two alternating patterns, is developed. Our results can be summarized in the following ways: one, the improved performance of recent asset-pricing models is driven by factors that mimic liquidity risk hedging and are linked to cross-sectional mispricing. Two, our model outperforms competing models in explaining time-series return variation across market states. Three, our parsimonious model enables an understanding of diverging return premia in the cross-section. Four, the estimated risk premiums in our model correspond to theoretical, economic, and statistical restrictions holistically across varied and complex anomaly structures. In this respect, the performance of the proposed model is even better than the risk premiums on factors in the model that have the largest cross-sectional r-squared values.

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1 Introduction

For the reported differences in average returns, asset pricing (AP) literature provides two distinctive stories. One, average returns are compensation for their covariance with known and unknown systematic risks. For example, value stocks earn more than growth stocks not because they are value stocks (a characteristic) but because they all move with a common risk factor i.e., return differentials are risk premiums expected by investors (Ball, Kothari, and Shanken, 1995; Fama and French 1993, 1996; Amihud 2002; Cochrane 2011). Two, the other strand of empirical work labels characteristics such as low BM ratios or winner stocks as proxies to mispricing – link differences in average returns to the departure of markets from efficiency. In doing so, they relate mispricing to liquidity and investor sentiment related explanations (Amihud and Mendelson 1986; DeBondt and Thaler 1985; Haugen, 1995; Jegadeesh 1990).

We note that the changes in aggregate liquidity have peculiary displayed a duality: it has been used to depict both risk and mispricing.[1] To draw a wedge between risk-based and non-risk pricing information that is linked to systematic changes in market liquidity, we follow the Amihud (2002) framework that documents *"ex ante stock excess return is increasing in the expected illiquidity of the stock market"*. His work shows that average returns, and exposures to systematic liquidity changes, are larger for stocks with high illiquidity than low illiquidity. This is best summarized by Acharya and Pedersen (2019) that market liquidity risk is compensation for purchasing illiquid stocks when future market liquidity may suffer. It is likely that return on small stocks i.e., the size effect is one description of liquidity risk compensation (e.g., Banz 1981; Amihud 2002). Implying that if markets are efficient and price illiquidity-risk, we should observe a coherent pricing pattern across stocks/anomalies. However, when we apply this framework to a variety of anomalies, we find that there exists an alternating pattern as well: anomalies that have negative exposures to changes in expected market liquidity have non-negative and significant average returns over time.

Tracking this divergence in return-illiquidity premia, we initiate our work by proposing that a stock's liquidity sensitivity is a unified source to summarize common sources of both, risk and misvaluation. That is, we hypothesize that return variations in anomalies/stock returns depict contrasting preferences for the liquidity-risk taking: anomalies with positive exposures proxy return-illiquidity-risk compensation as proposed in Amihud (2002), whereas the alternating pattern is, absence of liquidity-based pricing framework, perhaps approximating mispricing. If this pattern is prevalent in

[1] For risk-based explanations using liquidity risk see Huberman and Halka (1999), Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Amihud (2002), Acharya and Pederson (2005), Chordia, Subrahmanyam and Tong (2014). For explanations that link investor sentiment using liquidity as a proxy, see Baker and Stein (2004), Campbell, Grossman and Wang (1993), Wang (2001), Chuang and Lee (2006), Kumar and Lee (2006), Tetlock (2007), Ho and Hung (2009), Markus and Weber (2009), Liu (2015).

the cross-section of stocks/anomalies, then sensitivity to changes in expected market liquidity may proxy a unidimensional investing criterion. That is, alternating exposures to systematic liquidity determine investor preferences to bet on aggregate liquidity-risk – compensation for covariance risk – or hedge against i.e., alternating pattern in the cross-section of anomalies. To simplify, we label the latter preference as the liquidity-risk hedging (LH) zero-investment (ZI) strategies while the opposite return-illiquidity-risk pattern for ZIS is labelled as the liquidity-risk spreading (LS) ZI strategies.[2] Our preliminary analysis shows that misvaluation of LH anomalies is aligned to the evidence provided in Stambaugh, Yu and Yuan (2012, 2014 and 2015) and Stambaugh and Yuan (2017). That is, LH ZIS have positive risk-adjusted returns when applied to Fama and French (1996) three-factor (FF3) model and following high sentiment periods LH ZIS post high returns – linked to poor performance of the short legs of these anomalies in low sentiment periods.[3] Finally, as argued in Stambaugh and Yuan (2017), and references therein, mispricing may affect both types of investing patterns.

Our results show that ZIS with alternate systematic liquidity exposures have positive average returns. The average returns of the LH anomalies are higher in comparison to LS anomalies when market liquidity falls contemporaneously, and an opposite return pattern occurs as market liquidity improves. Furthermore, we note that LH based positive average returns are linked to investors' flight-to-liquidity motives: when market illiquidity is low the relative illiquid short (long) portfolios of liquidity-risk hedging (spreading) ZIS are down far more than their long (short) counterparts. Potentially this feature makes LH anomalies attractive to liquidity-risk minimizing investors relative to LS anomalies in periods with falling systematic liquidity. Surprisingly, we note that the mean return on an average LH investment strategy is larger than the mean return on a strategy that combines LS anomalies. This entails that a larger premium is available for liquidity-risk avoidance not just when market liquidity is low, on average than for liquidity-risk-taking across periods and anomalies. Following this, we aggregate the two divergent investor preferences. We categorize ZIS into LH and LS groups given their exposures to unexpected changes in systematic liquidity.[4] From these two sets, we construct LH and LS factors (LHF and LSF, respectively). These two factors are a weighted

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[2] A LH anomaly is depicted by a ZI strategy that is long in the so-called safe "flight-to-liquidity" stocks and that shorts stocks whose prices fall as market liquidity unexpectedly falls.

[3] We note that Stambaugh et al. (2012) differentiate between cross-section of long-short spreads in mispriced anomalies and factor-based anomalies; however, their setting lacks the unified explanation underpinned by investor preference for liquidity as propagated in our work.

[4] We interchangeably refer exposures on the ZIS to unexpected changes in systematic liquidity as liquidity betas, liquidity risk or sensitivity to changes in systematic liquidity. Given our aim to trace mispricing and risk pertaining to abrupt changes in market liquidity, we collect shocks to measure of market illiquidity proposed in Amihud (2002) by applying best fit ARMA structure as determined by Schwartz/Bayesian information criterion (BIC). To transform shocks to market illiquidity into shocks to market liquidity, we multiply the market illiquidity series by minus one: positive (negative) shocks represent unexpected rise (decrease) in market liquidity. Likewise, ZIS' positive (negative) exposures on shocks to market liquidity portray their liquidity risk hedging (spreading) tendencies.

function of ZIS' liquidity betas in each group: LHF (LSF) is the weighted sum of ZIS with negative (positive) liquidity betas.

Contrasting our LHF to mispricing factors of Stambaugh and Yuan (2017) show high pairwise correlations of above 50%. Our LHF is also highly correlated with the profitability and investment factors introduced in Fama and French (2015, FF5) and Hou, Xue and Zhang (2015, HXZ) models as well as to the momentum (WML) factor of Carhart (1997) model.[5] Whereas, our LSF is highly correlated with market and size factors – pairwise correlation of 47% and 80% - available in FF5, HXZ and SY models, respectively. Naturally, we proceed by constructing a factor model that combines market-factor with our factors and names it the "*Market-Hedgers-Spreaders*" (MHS) model. For a broad cross-section of ZIS, our model competes with the SY model and outperforms other factor models.[6] This result is robust when we repeat model comparisons in up- and down-market states. These results do not change when we pit inter-model factors against each other following Barillas and Shanken (2017).

To examine the economic significance of these factors and models, we carry out cross-sectional two-pass regressions (Black, Jensen and Scholes 1972) using different combinations of test portfolios.[7] One, cross-sectional estimations show that most of the factors in the competing models have positive risk premia and are significant even if they do not always correspond to their statistical identification. For LH and LS factor risks, on average the monthly premiums are 0.5% and 0.3%, respectively, across different cross-sectional specifications. These estimated values meet theoretical and statistical idnetifictaion and significance criteria. Whereas the same constraint consistency is not witnessed for the rest of the estimated factor premiums. Here, we observe that a wholesome factor linkage to the cross-sectional return variation leads to improved statistical identification and significance.

Two, the market risk premium is estimated implausibly across all specifications when test portfolios include industry portfolios. The same applies to the RMW of the FF5 model. Three, for the known momentum effect in industry portfolios (Moskowitz and Grinblatt 1999), combining all test portfolios potentially brings a dominant momentum structure that deflates estimated premiums on almost all factors. The estimated premiums on SMB, LRS and WML are exceptions to this deflation.

[5] Furthermore, all positively correlated factors with our LHF factor display comparable return variations: the average returns on positively correlated factors with LHF factor are high (low) as market liquidity falls (rises) unexpectedly. These correlations among model factors endorse our assertion that our LHF approximates mispricing as much as the Stambaugh and Yuan factors aggregate mispricing. Likewise, our LSF mimics risk variations to the extent market and size factors summarize market-wide risks.

[6] We note here that construction of factors based on alternate coefficients using market factor or size factor does not bring similar results: we note that there is a unique pattern in data that is linked to alternate preferences regarding liquidity risk.

[7] We use typical 5×5 size-BM, and 5×5 size-MOM as test portfolios alone and combined and also use specifications that add 43 industry portfolios to test for cross-sectional price of risk premiums.

Unsurprisingly, the Carhart model is the best model for the specification that combines all test portfolios. We confirm Fama and French (2016) findings that for the momentum tilt in the LHS anomaly structure inclusion of the WML factor is vital and this changes the otherwise consistent ranking of models in our work.

Taken together, our model improves on the best performing SY model on two fronts. The first is parsimony – the most valuable part is factor reduction. Second, in contrast to Stambaugh and Yuan's statistical clustering of mispricing factors, we invoke the model on the discerning capacity of market liquidity in the cross-section. Intuitively, this is far more appealing in developing a deep theory to split and aggregate return variations – summarizing risk and mispricing – through a unified source. [8] In sum, our model simplifies discussion on the availability of several new AP factors that are strongly linked to hedging liquidity risk, which potentially spurs mispricing in stock returns.

We conclude that our model leads in capturing the time-series variation across several anomalies and market states. Our model follows the best performing SY model in the cross-sectional tests. We note that we could have enhanced the cross-sectional performance of our model by using a factor that encapsulates investment-related factor variation such as the SY model's MGMT factor, but this compromise would have affected the simplicity of our model. Thus, all models are compromises to capture difficult to explain return patterns both theoretically and empirically. They are bound to miss some part of cross-sectional return variation. In this respect, the MHS model is no exception. Nonetheless, our model presents a unified explanation with the gains of parsimony. An aspect that is missing in competing models.

The paper proceeds as follows. Section 2 discusses the motivation of our work in detail, supplements related literature and testable hypotheses. Sections 3 and 4 describe data and our proposed model, respectively. Section 5 discusses results and section 6 concludes.

2 Motivation, Hypotheses and Literature review

2.1. Anomalies, risk models and mispricing

Both the CAPM (Sharpe 1964, Lintner 1965) and Fama and French (1993, 1996) three-factor models have been undone by Asset Pricing (AP) anomalies. In this respect, the horde of anomalies that fail the FF3 model is unprecedented: Hou Xue, and Zhang (2015) document that the FF3 model is unable to explain average returns on approximately 80 AP anomalies.[9] Summarily, compelling challenges

[8] We also calculate LH and LS factors using systematic liquidity exposures on ZIS while controlling for the market factor. Both set of factors show large correlations between themselves: the LH (LS) factor has a correlation of 0.99 (0.88) with LH (LS) factor that we compute using liquidity risk after controlling for the market factor.

[9] Among many anomalous patterns that leave the FF3 adrift, most mentionable are accruals (Sloan 1996, Richardson, Tuna and Wysocki 2010, ACR), net share issues, (Ikenberry, Lakonishok, and Vermaelen 1995; Loughran and Ritter 1995, NSI), previous month stock volatility (Ang, Hodrick, Xing and Zhang 2006), operating profitability (Novy-Marx 2013, OP), investment (Aharoni, Grundy and Zeng 2013; Haugen and Baker 1996; Titman et al. 2004, and others, INV) and Betting against CAPM beta (Frazzini and Pederson 2014, BETA).

for the FF3 model are posed by profitability and investment-related anomalies along with the momentum anomaly (Carhart 1997, Titman, Wei and Xie 2004, Fama and French 2006, Novy-Marx 2013). In this regard, the vacuum created by the sprawling disorientation of the previously *"good factor models"* has steered the search for new factor models.

Notable additions include the Fama and French (2015) five-factor model and Hou et al.'s q-factor model. Stambaugh and Yuan's (2017) model is another interesting attempt that adds mispricing factors as well as factors describing aggregate risk factors.[10] Across all the latest AP models, the inclusion of factors that are linked to profitability and investment is ubiquitous.[11] Furthermore, evolving evidence shows that each successive model outperforms the predecessor(s) (Stambaugh and Yuan 2017, and Hou, Xue, Mo and Zhang 2019). The byline of Stambaugh and Yuan's (2017) work is fascinating: their model combines narratives that have long divided the asset pricing literature. That is, they merge both rational expectations framework and behavioral finance – the one contentiously questioning the core premise of the former framework. This empirical advancement vindicates Hirshleifer's (2001) assertion that the asset pricing paradigm requires embracing both "*risk and misvaluation"*. Studies have used proxies of investor sentiment (Barberis, Sheleifer and Vishny 1998, Baker and Stein 2004, Shefrin 2005, Baker and Wurgler 2006) to examine the impact of arbitrary investors' decision biases on stock prices.

2.2. Liquidity, risk models and mispricing

Traditionally the risk-based explanation of the returns has predominated in the asset pricing literature (Fama and French 1992, 1993, 1996; Carhart 1997; Lewellen 2010). Among many candidates for risk-based factors, the liquidity-based asset pricing relation has fetched substantial attention (Amihud 2002; Pástor and Stambaugh 2003; Acharya and Pederson 2005; Sadka 2006; and Liu 2006). The success for liquidity factor as the only risk-based explanation of ZIS is mixed for multiple reasons.[12] Nevertheless, we argue that a more important aspect of AP relations, than the debate that which risk factor is better than other, is if the only risk-based explanation is sufficient to rationalize the returns variation and average returns on different ZIS. We conjecture such is not that case as numerous

[10] SY model captures the common mispricing in the famous 11 anomalies (Stambaugh, Yu, and Yuan 2012), that challenge the FF3 model. The commonality in these anomalies is separated with respect to management's investment decision making and firm's profitability. Furthermore, the additional factors in the SY model are constructed using rankings of mispricing (unexplained part of 11 anomalies after fitting a two-factor risk model) in the anomalies than the usual notion of constructing factors on a single anomaly variable. Thus, the sobriquet "Mispricing factors".

[11] All noted models add two new factors to the constrained or unconstrained version of FF3 model. Fama and French (2015) add investment (CMA) and profitability (RMW) factors to their FF3 model and Hou et al's. q-factor model contains investment (IV) and profitability (ROE) factors in addition to the market and size factors. Stambaugh and Yuan add two mispricing factors (notated as MGMT and PERF) – along with market and size factors – constructed from two cluster of anomalies. Unsurprisingly these two clusters are linked to investment (MGMT) and profitability (PERF) of firms.

[12] Goyenko, Holden and Trzcinka (2009) and Fong, Holden and Trzcinka (2017) provide comprehensive evidence on types of liquidity measures such as transaction costs, price impact measure, percent cost measures in general and how literature has proposed numerous proxies within each class.

studies have shown that common mispricing components across stocks persist across stocks and over time (Baker and Wurgler 2006, 2007; Chung, Hung and Yeh 2012; Stambaugh et al. 2012; Stambaugh and Yuan 2017; Engelberg, McLean and Pontiff 2020). Essentially, it indicates that ZIS may have either positive or negative loadings on a particular risk factor, such as liquidity factor, but still earn positive average returns.

For instance, Asness, Moskowitz and Pedersen (2013) document the availability of the premium on value and momentum factors while showing that both have alternating aggregate liquidity-risk exposures. [13]Asness et al. note that this pattern is challenging and is partially explained by alternating liquidity-risk exposures, which is aligned to our proposition in this work. This observation segregates the investors into two groups, one that takes liquidity risk and the other that hedge their investment against liquidity risk. To this effect, in volatile times when market liquidity freezes, investors look for safe securities that offer liquidity. Amihud (2002) notes *"… in times of dire liquidity, there is a flight-to-liquidity that makes large stocks relatively more attractive"*.[14]

Vayanos (2004) develops a model that shows in periods of economic distress, investors' effective risk aversion increases, illiquid assets' contemporaneous riskiness flares and the combined effects are related to flight-to-quality. In the same vein, Baker and Wurgler (2007) argue that the attractiveness of liquid stocks results in an inverse relationship between safe stocks and sentiment changes, increasing the prices of bond-like stocks during episodes of flight-to-quality.

2.3. Motivation and theoretical framework

Stambaugh et al. (2012, 2014 and 2015) show that, due to short sales constraints, overpricing is more prevalent than underpricing in the presence of market-wide sentiment. In such settings, Stambaugh et al. (2012) report that the mispriced ZIS has large risk-adjusted returns and offer large average returns following periods of high investor sentiment that are driven by short side portfolios. They document that the impact of sentiment changes only significantly affects short portfolios of the mispriced anomalies, which are overpriced/weakened during/following high sentiment periods, whereas the long legs of mispriced ZIS have no significant sentiment bearings. These traits are shared by the noted LH anomalies in our work. Taken together the long legs of the mispriced anomalies are not exposed to sentiment related overpricing and bundle so-called safe stocks that are less sensitive to systematic liquidity changes. We argue that either anomaly can offer a hedge against the systematic liquidity or it is an investment bundle to earn an illiquidity premium. In the first case, anomalies

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[13] The presence of positive average returns on both sets of anomalies undertaken in our work – not just value and momentum anomalies/factors – is evidence that misvaluation and risk-based return premia coexist.

[14] It could also be motivated for allowing distortions in investors' liquidity risk assessment: excess avoidance of liquidity risk in the cross-section may make stocks/portfolios that hedge liquidity risk attractive when market liquidity suddenly falls. Arguably investors' flight-to-liquidity motives, with the rise in expected market illiquidity, may cause asset substitution of less liquid stocks/portfolios with stocks/portfolios with better liquidity features to avoid liquidity risk when the former are known for their disproportionality large liquidity exposures than the latter.

provide a hedge against the large drawdowns in illiquid stocks when market liquidity is falling (Amihud 2002) and anomalies that go long (short) in portfolios that have high (low) liquidity-risk.[15] Hence, the liquidity sensitivity of candidate anomalies might vary because of clientele effects to mitigate or enhance liquidity risk in their portfolio choices.

Our motivation is consistent with the evidence in Pástor, Stambaugh and Taylor (2020): they report that small, active funds tend to hold fewer liquid portfolios while large funds' holdings have low transaction costs. Perhaps both type of institutional investors caters for alternating investor risk preferences. For small funds, this may also result from their growth strategy and financial constraints. Second, the multidimensional impact of liquidity can be linked to several patterns in data such as firm capitalization, trading volume, stock turnover, earnings shocks, return volatility etc. (Amihud and Medelson 1986; Bhushan 1994; Amihud 1996; Acharya and Pedersen 2005; Liu 2006; Sadka 2006; Han and Lesmond 2011, among others).[16]

Finally, the role of market liquidity in mispricing spurred on by investor sentiment is another important research question. Reportedly, investor sentiment can increase market liquidity under buying and selling pressures of noise traders in numerous ways, from slow information processing, overconfidence, short sales constraints (Kyle 1985, De Long, Shleifer, Summers and Waldmann 1990, Odean 1998 a&b, Baker and Wurgler 2006). Stambaugh et al. (2012) show how these aspects typically result in overvaluation rather than undervaluation because of short sales constraints. Stambaugh et al. (2012) provide vital guidelines i.e., subject to short sales constraints overpricing is prevalent relative to underpricing.[17] Under this setting, ZI strategies that take advantage of this mispricing should be stronger following high investor sentiment periods and overpriced (more illiquid) stocks in the short portfolios spur this predictive strength. The Stambaugh and Yuan (2017) model is built on the same premise and they show that their mispriced factors are predicted by investor sentiment. For our mispricing factor i.e., LHF, we find the same and even stronger predictability. Further to this, the short portfolio instigates this strong predictability (see Table 3 or discussion in section 4.1).

3 Data: market liquidity and anomalies

[15] The exposures on liquidity risk hedging anomalies may appear straightforward following the work of Stambaugh et al. (2012) i.e., return anomalies that are sentiment driven should have positive alphas after fitting a candidate risk model. To provide a reverse explanation, we observe that an alternate pattern is observed for so-called risk based ZCS in their work. We report that for liquidity risk spreading (LS) anomalies FF3 absolute alphas are highly correlated (0.69) to the estimated liquidity risk exposures on LS anomalies in Table 1.

[16] Because systematic liquidity affects average return in the cross-section in multiple ways, there is a strong chance that the impact of systematic liquidity is subsumed by other factors – which attempts to measure a common source of variation in stock data by the very manner of their construction – in the AP models.

[17] Stambaugh et al. (2012) show that the leading cause of mispricing emanates through the overpricing of their short legs that contain stocks, which are costly to trade and arbitrage, have large information asymmetry, and have diverging views on their value and expectations to earns future returns.

Data for stocks prices, returns and traded volume are obtained from the Center for Research in Security Prices (CRSP) at daily and monthly frequencies. The common stock data for firms with the share code 10 or 11 and listings on NYSE, AMEX and NASDAQ exchanges are retrieved for the period of 1960:01-2016:12. We use the stock data to compute aggregate market liquidity measures for the US market and deciles portfolios based on stock illiquidity.

All the other data series – anomalies and model factors – are retrieved from Kenneth French's database, Robert Stambaugh's homepage, and the AQR website. The factors data for the HXZ model are provided by Lu Zhang. We are grateful to all of them for providing these datasets, without which this research would not have been possible. In case of multiple availabilities of a long-short strategy, we selected the ones available at Kenneth French webpages for consistency of screens employed in our work.

3.1 Market liquidity

We begin our analysis by approximating market liquidity for the US market using the price impact (PI) measure of Amihud (2002).[18] The PI measure is estimated:

$$ILLQ_{i,t} = \frac{1}{n}\sum_{d=1}^{n}\left|R_{i,d,t}\right| / [P_{i,d,t} \times Vol_{i,d,t}]. \quad (1)$$

Where $|R_{i,d,t}|$ is the absolute return on stock i on day d in month *t*, and ($P_{i,d,t} \times Vol_{i,d,t}$) is the daily volume in dollars for stock i on day d in month *t*. The *n* indicates the number of trading days available for month *t*. This ratio gauges the daily price response per unit of dollar volume traded for each stock. These daily price responses are then averaged across months for each stock in month *t* following, among others, Amihud (2002), Avramov, Cheng and Hameed (2015), and Fong et al. (2017). Subsequently, the cross-sectional average of the $ILLQ_{i,d,t}$ ratios across stocks in month *t* provide a measure for market illiquidity. The Amihud market liquidity measure increases in illiquidity: a large aggregated price response across stocks for a given trading volume represents increasing market illiquidity and vice versa.

Following, the motivation of our work we segregate ZIS into two groups, one that is a reward for liquidity-risk taking and two that pick investors' liquidity risk hedging motives. To do so, we invoke Amihud (2002) that proposes anomalies with positive exposures proxy return-illiquidity-risk compensation. Whereas, the alternating pattern as proposed in our work picks the absence of a liquidity-based pricing framework, perhaps capturing mispricing. To pick ZIS that capture return-illiquidity-risk compensation, we use shocks to market illiquidity to estimate systematic illiquidity

[18] The reported trading volume are known to be overstated for NASDAQ (a dealer market) stocks relative to NYSE (an auction market) stocks. As reported in Anderson and Dyl (2005), we divide all reported trading volumes for NASDAQ stocks by an appropriate factor to counter the relative over reporting of the volume.

exposures on anomalies. [19] We transform shocks to market liquidity, following Sadka (2006), by multiplying the shock series by minus one: positive shocks to market liquidity represent an abrupt increase in market liquidity while negative shocks represent an unexpected decrease in market liquidity. Furthermore, we scale the shocks to market liquidity, $s\_liq_{mkt,t}$, to make it simpler to interpret the estimated liquidity risk across ZIS.

3.2 Anomalies – zero cost long-short investment strategies

To collect anomalies that show differentiable and discernable liquidity-risks differences in the cross-section, we take 12 long-short zero short investment strategies. The chosen anomalies are extensively used in AP literature (Stambuagh et al. 2012; Chichernea, Holder and Petkevich 2015, Hou et al. 2015; Fama and French 2015; Stambaugh and Yuan 2017), however, we aspire to maximize on anomalies that display alternating (sizeable) exposures on changes on market liquidity. In them, six represent ZIS that capture investor sentiment sensitivities captured in Stambaugh et al. (2012). In this respect, they correspond to LH ZIS and fit the criterion of mispriced anomalies set in Stambaugh et al. work, however, we maximize the role of sensitivity of anomalies to changes to market liquidity. Therefore, we augment the set of mispriced anomalies examined in Stambaugh et al. and Stambaugh and Yuan (2017) in line with the motivation of our work. The rest of them are more often known as common sources of risk in the asset pricing literature i.e., size, value and liquidity related ZIS.

It is worth mentioning that NYSE breakpoints are used across all ZIS, for yearly sorts the breakpoints are generated at the end of June in year *t-1* to sort stocks across deciles for year *t*. For consistency, we follow screening procedures described in Fama and French (2015) for the data series that we construct in this work. ZIS undertaken in our work are:

Return variance (VAR)

The long-short strategy is monthly formed based on the variance of daily returns. Return variance is estimated using 60 days (minimum 20) of lagged returns. The long portfolio comprises low variance stocks i.e., the bottom decile of the return distribution and the short portfolio has stocks with high variance stocks i.e., top decile.

Quality-minus-Junk (QMJ)

Asness, Frazzini and Pedersen (2019) show that Quality stocks — those of companies that are profitable, growing and well managed — command higher prices on average than those of

[19] The accumulation of shocks is a common practice in the liquidity related asset pricing literature that accounts for the well-reported persistence in systematic liquidity (Amihud 2002, Acharya and Pedersen 2005, Sadka 2006, Acharya et al. 2016, among others). In order to collect shocks, we employed the best fit autoregressive moving average (ARMA) filter using the Bayesian information criterion and is AR3 and MA4 for the sample period in our work. The conventional course in retrieving shocks from aggregate liquidity is to fit an AR2 model (Amihud 2002, Avramov et al. 2015, among others). The reported results are consistent if we adopt that practice. However, we note that approach adopted in our work is superior in terms of model fitting relative to an AR2 model when the underlying purpose is to retrieve innovations from a sticky series.

unprofitable, stagnant or poorly managed companies – Junk stocks. Based on the Quality to Junk scores of stocks, QMJ strategy is long in the quality (top) decile and shorts junk (bottom) decile.

Momentum (MOM)

The momentum anomaly of Jegadeesh and Titman (1993), is one of the most puzzling anomalies in the cross-section of stock returns, goes long in recent winners (in the previous year), and shorts recent losers. This strategy is implemented monthly.

Operating Profitability (OP)

Novy-Marx (2013) discovers that sorting on gross-profit-to-assets creates abnormal returns. Following their observation, this strategy implements yearly sorts on OP at the end of each June. The ZI strategy is long in return distribution decile with firms with high profitability and is short in bottom decile i.e., firms with low profitability.

Net Share Issue (NSI)

Loughran and Ritter (1995) show that firms issuing new equity in the last year underperform matching non-issuing firms with similar characteristics in the following year. Using last year NSI, portfolios are formed on the yearly basis and the ZI strategy goes long by one dollar in non-issuer or low equity issuing firms and shorts one dollar in firms that belong to the top decile for NSI in the last year.

Ohlson-score (OS)

Campbell, Hilscher, and Szilagyi (2008) document that firms with high financial distress (or failure probability) have low future returns and this finding is a challenge to standard models of rational asset pricing. Stambaugh et al. (2012) report that using the Ohlson (1980) O-score as the distress measure, although it is measured by a static model when the failure probability of Campbell et al. is estimated by a dynamic model, provides comparable results. We only use the static O-score based ZIS that is long in decile of stocks representing low distress and shorts the top decile of a portfolio that contains high financial distress.

CAPM beta (BETA)

Sharpe (1964), through his landmark capital asset pricing model (CAPM), said that average stock returns should be linearly linked to the beta sensitivity on the market factor. Using the preceding five years (two minimum) of past monthly returns stocks are divided based on their CAPM-betas, BETA[20] is long in high-beta stocks and short in low-beta stocks and produces significant positive returns.

Firm capitalization (SIZE)

[20] We note that BETA follow CAPM logic and is different from the one proposed in Frazzini and Pedersen (2014) that reported, a BETA reversal strategy using a different construction scheme, betting against beta also has positive average returns.

Banz (1981) identified a pattern linked to firm capitalization: small firms tend to outperform large capitalization firms. SIZE yearly-sorted ZI strategy is long in small-capitalization stocks and shorts decile of stocks with high firm capitalization as measured by the market value of the equity.

Stock illiquidity (ILLQ)

Amihud and Mandelson (1986) show that stock liquidity creates differences in average returns: low liquidity stocks expected returns are higher than the stocks with high liquidity. Despite the slippery nature of liquidity as a concept, numerous studies show the same using various measures for stock liquidity (Amihud 2002, Liu 2006, and Lee 2011, among others). Using the end of June stock-illiquidity measured by Amihud (2002) price impact proxy, the long-short strategy is long in top decile comprising stocks with high illiquidity and shorts the bottom decile that contains stocks with low illiquidity.

Short-term reversal (STR)

Jegadeesh (1990) reports that stock returns are exposed to reversal: winners from the previous month are next month’s losers. Taking this variation into account, STR is a monthly-sorted ZI strategy. Using this rule, an investment strategy, have positive average returns, is long in stocks belonging to a decile with low returns in the earlier period and shorts stocks, previous period gainers, which are in the top decile.

Long-term reversal (LTR)

DeBondt and Thaler (1985) identify that firms with poor past long-term (e.g. three to five years) performance – loser firms – outperform firms with good past long-term performance i.e., winner firms. The monthly-sorted ZI strategy representing LTR is long in losers whose past five years performance assign them to bottom decile in the cross-section and is short past long-term winners’ i.e., top decile.

Book equity-to-Market equity ratio (BM)

The value effect is one of the oldest and best-known patterns in average stock returns discovered by Stattman (1980). More precisely, a ZI strategy investing in decile of stocks representing high BM tend to outperform the bottom decile stocks with low BM.

3.3 Summary statistics

To initiate our analysis, we begin by estimating liquidity betas for all the ZI strategies:

$$ZI_{i,t} = \beta_0 + \beta_{L,i} s\_liq_{mkt,t} + e_{i,t}. \quad (2)$$

ZI_i is a time series of monthly returns on one of the long-short strategies as outlined in section 3.1. $\beta_{L,i}$ is the estimated sensitivity of that *ZI* strategy to unexpected changes in market liquidity. In line with our motivation, we use β_L of the ZIS to identify investors’ preferences for an investment strategy. All ZIS are divided into two categories given their liquidity betas from equation 2: the ZI strategies with liquidity beta<=0 are listed in the LH group and the ones with positive liquidity return sensitivity are kept in the LS group. The summary statistics for both groups are provided in panel A of table 1. In addition to the six ZIS in each panel, we also compute an average strategy that takes equal positions (monthly) in all the long-short strategies in each category. We name them average liquidity-risk hedging (ALH) and average liquidity-risk spreading (ALS) strategies. All the portfolio returns cover the period of 1963:07 to 2016:12.

As we argue, the ZI strategies with negative liquidity betas are liquidity-risk-hedgers, whereas liquidity-risk-spreaders are the ones that yield better returns as market liquidity improves. For example, as panel A of table 1 shows, a liquidity-risk hedger strategy such as MOM, which goes short in a loser portfolio that is relatively less liquid than the long winner portfolio, has a negative liquidity beta of –0.02.[21] Those investors who expect better returns as market liquidity improves invest in liquidity-risk-spreaders e.g., SIZE, ILLQ, BM ZIS. The SIZE long-short strategy goes long in a less liquid portfolio of stocks, such as small firms, and goes short in big capitalization firms whose liquidity credentials are reportedly better. This is evidenced by a liquidity beta of 0.009. The shocks to aggregate liquidity are standardized by its standard deviation, therefore the estimated liquidity betas also describe economic significance.[22]

Overall, the statistics in panel A of table 1 show that all ZIS have positive average returns, regardless of the group they belong to, with highly significant ALH and ALS tendencies. The ZIS with the largest/lowest average returns and standard deviation (Std.) are in the liquidity-risk hedger group. Whereas, on average, the Std. of ALH and ALS strategies show that liquidity-risk hedging ZIS have higher idiosyncratic risk relative to liquidity-risk spreading (long-short) strategies. Nonetheless, the LH are the ones that have a larger Sharpe ratio (SR) of 0.14 relative to liquidity-risk spreaders SR of 0.10, respectively. Based on information ratio (IR) liquidity-risk hedging strategies on average outperform the benchmark index – the average effect is largely driven by a large return difference between momentum anomaly and the market return. However, this is not the case for liquidity-risk spreading strategies: the average IR for the ALS is –0.039, see panel A of table 1. In summary, all LH anomalies are in more ways linked to mispricing as noted in Stambaugh et al. (2012): all of them have positive and large FF3 model alphas. The FF3 model alpha for the LS group, on the contrary, is negative for six of the seven ZIS. Furthermore, the α_{FF3} for ALH is highly significant at 0.9%,

[21] Post transformation of illiquidity measure into a liquidity measure, positive shocks to market liquidity reflect increase in market liquidity and vice a versa. Therefore, a positive liquidity beta for a ZI strategy shows that the returns on ZI strategy are expected to increase by an amount of liquidity beta as market becomes liquid. The negative liquidity betas show a proportional decrease in the expected returns for the strategy as market liquidity improves. However, investors hold these strategies to keep themselves hedged as market liquidity decreases and because of their negative relationship with market liquidity they expect marginal benefits (or lower losses) in these market circumstances.

[22] It is widely established that small firms are less liquid than the large firms. This consensus is to the effect that researchers have widely used firm's size as a proxy for its liquidity e.g., see Amihud (2002) for US stocks, Butt and Virk (2015) for Nordic stocks.

whereas economically the FF3 model alpha of -0.1% (t-value = –2.073) on the ALS strategy is much smaller than the ALH strategy.

Panels B and C of table 1 provide the same summary statistics for long and short portfolios of the ZIS. On average, we document that the long portfolios of LH ZIS tend to outperform their corresponding short portfolios' SR and IR by a large amount. The FF3 alphas of long portfolios across ZIS are larger, in absolute terms than their short portfolios. Whereas the liquidity betas on liquidity-risk hedging ZIS are driven by liquidity risks of short portfolios: the short-legs of the liquidity-risk hedging strategies are more sensitive to abrupt changes in market liquidity than their long counterparts. The long and short portfolios of LS ZIS show an opposite pattern to what we have reported as summary detail for the liquidity-risk hedger ZIS. The only exception is the average returns on long and short LS differentials: mean returns on LS ZIS are also positive. Finally, we highlight that long (short) portfolios of LH (LS) ZIS are less exposed to changes in systematic liquidity than their short (long) legs of them.

The positive time-series returns on liquidity-risk hedger ZIS and the larger liquidity-risk of the short portfolios relative to long portfolios of these strategies affirm our hypotheses. If liquidity risk has a role as a one-dimensional risk aversion parameter, these liquidity betas describe the relative liquidity-risk hedging/investing uptake of each ZI strategy: the ones requiring coverage (compensation) against (for) liquidity-risk provide high (low) returns when market liquidity unexpectedly falls (improves).

3.4 Return variation in the ZIS across varying market liquidity conditions

We segregate monthly returns on both sets of ZIS into five quintiles that are generated by breakpoints of shocks to market liquidity. Table 2 provides the average returns across the five quintiles for LH and LS ZIS in panels A and B, respectively. Given investors' flight to liquidity, we expect that the returns on liquidity-risk hedging ZIS should be higher in Q1 relative to Q5 and vice versa for liquidity-risk spreading ZIS. Furthermore, for the disproportionate effect of exaggerated liquidity-risk avoidance, and excess demand for portfolios with better liquidity when market liquidity falls abruptly, we anticipate that the returns on the short (long) portfolios of LH (LS) ZIS fall far more than long portfolios and an opposite pattern should be present as market liquidity unexpectedly improves. The support for this hypothesis is especially strong. For simplicity, we analyze these results for LH and LS ZIS separately.

In panel A of table 2, long-short differences of LH ZIS are positive (negative) in Q1 (Q5) for all six investment strategies. In all 12 instances, the average returns on LH ZIS in Q1 and Q5 have t-statistics that reject the null of zero mean values at a 0.01 significance level. To sum up these differences, the average return on the combination strategy (ALH) has long-short differences of 2% and -0.9% in Q1 and Q5, respectively and both are statistically highly significant. The absolute average return (increase) of 3.5% on the short portfolios in Q5 is larger than the absolute average return (drop) of 2.8% on them in Q1. The t-statistics for these averages are significant at 1% critical values.

To the extent that unexpected changes in aggregate liquidity capture sentiment changes in the stock returns, our results endorse the evidence in Stambaugh et al. (2012). The contemporaneous implication of their results is that mispriced anomalies – like LH ZIS in our work – are supposed to have large returns on their short portfolios in periods when investor sentiment is high relative to periods when it is low. To this effect panel A of table 2 shows that the short portfolios have larger and statistically significant, average returns for all 12 instances in Q4 and Q5. The averages on both long and short portfolios are positive and highly significant. However, to the extent that changes to market liquidity proxy sentiment effect, the long-short difference on the ALH strategy is only significant in Q5.

The return structure changes in aggregate liquidity, and more prominently in Q2 and Q3, supports our main hypothesis; the effect stemming from excess demand for liquid stocks results in the sizeable increase in return on long portfolios. Essentially, the return on long portfolios is relatively large in comparison to average returns on short portfolios of LH ZIS in Q2 and Q3. Perhaps the persistence in excess demand for liquid stocks/portfolios in Q2 and Q3 (across periods) represent the risk aversive tendency of investors in conditions when market liquidity-risk is high (Vayanos 2004) high i.e., Q2 and/or when its direction is unclear i.e., Q3. These return changes display a flight-to-liquidity effect that keeps liquid (long) portfolios of the LH ZIS attractive and in demand, which results in positive average returns on these anomalies in Q2 and Q3.

Overall, we argue that in conditions when market liquidity risk is extremely high the prices for all portfolios may fall. However, because of the high liquidity-risk exposures of the short portfolios of the LH ZIS, the gains on these ZI strategies stem from the large return declines in the illiquid short portfolios to such an extent that prices of the liquid leg of LH ZIS do not fall to the same levels. Besides the asymmetric return variation, arguably the flight to liquidity regulates the fall in long portfolios even in conditions when shocks to unexpected market illiquidity are relatively high (Q3) or even when they are rather neutral (Q2). If sudden improvements in market liquidity proxy investor sentiment, then the return variation in Q4 and Q5 depict that the sentiment effect applies across the board.

Panel B of table 2 reports the distribution of returns on LS investment strategies that are more commonly employed in mimicking systematic variation in average returns. In Q1, where market liquidity falls abruptly, the long/illiquid portfolios of LS ZIS have lower returns than the short/liquid portfolios of the same ZIS. The average returns on the long portfolio of LS ZIS are significant in all six instances, albeit the average losses on short portfolios are only significant for the reversal investment strategies. This implies that large negative returns on LS ZIS are driven by the drawdowns on the long portfolios, nevertheless, these differences are only significant for BETA, ILLIQ and SIZE zero-cost strategies.

Moving across the quintiles, the long portfolios of LS ZIS have higher returns than the corresponding short portfolios in Q3, Q4 and Q5. The outperformance in Q4 and Q5 is noticeable as it is seen in all 12 instances. Furthermore, the average differentials are significant for ten out of 12 instances in these two quintiles. We note that risk compensation is only missing in Q1 and Q2: the mean values on ALS are economically, as well as statistically, not different from zero. The mixed nature of the reverse pattern for LS ZIS enhances the scope of liquidity risk to describe risk variations as well as the mispricing that the LH anomalies capture.

Consistent with Stambaugh et al. (2012) i.e., factors accounting for systematic risks – to an extent LS ZIS in our work – can also be exposed to mispricing. That is, if mispricing is compelling then we should witness the reverse pattern that is found in panel A of Table 2. However, the long-short differences for ALS are in reverse, sizeable, and significant for the extreme quintiles (and Q4) only when compared to the return variation of ALH. Thus, if abrupt changes in market liquidity reflect changes in arbitrage constraints, the significant return variations in the extreme quintiles for the average tendency in LS ZIS are consistent with Baker and Wurgler (2006) and Stambaugh et al. (2015). Both studies document that mispricing occurs at the extremes of a composite mispricing measure and is stronger for smaller stocks. This in turn can be the inflection point that is linked to the large systematic liquidity sensitivity of relatively illiquid stocks (Amihud 2002).

To establish discernability, we estimate market betas for ALS across five quintiles and see that market risk is not increasing with the increasing returns on ALS across five quintiles. That is, CAPM underpredicts ALS return, which is an opposite pattern to ALH strategy (and anomalies) and shows the presence of potential liquidity risk related compensation to augment the equilibrium model of type CAPM.[23] Nonetheless, the divisive nature of return variation in this category concerning abrupt changes in market liquidity is a clear manifestation of the puzzling, and potentially simultaneous, effects of risk and mispricing.

4 Model

4.1 Factor construction

For the fact that our evidence supports the claim that liquidity-risk avoidance is linked to mispricing in the cross-section as well as the risk variation, we factorize these distinctive return variations. We name them liquidity-risk hedging factor (LHF) and liquidity-risk spreading factor (LSF). Stambaugh et al. (2015) and Stambaugh and Yuan (2017) note that mispricing is more a matter of extremes, in

[23] We are thankful to an anonymous reviewer to check in this direction, and it has helped discernibility especially for liquidity risk spreading anomalies in a succinct and clear manner.

line with this empirical pattern, we maximize weights on anomalies with large sensitivity to unexpected changes to market liquidity. That is anomalies that show large liquidity-risk sensitivity display excessive liquidity-risk avoidance or excessive risk-taking. Therefore, we adopt a weighting function using the absolute values of the liquidity exposures available from equation 2 (as reported in table 1) for each set of ZIS. Under this scheme the weight for i ZIS (in each group) is tied to its liquidity betas:

$$w_i = \frac{|\beta_{L,i}|}{\sum_i |\beta_{L,i}|} \text{ subject to budgetary constraints of } \sum_i w_i = 1.$$

For ease of notation, we refer to the LH anomalies with **A** and the LS anomalies with $\boldsymbol{B}$. That is, we have one factor from each group:

$$LH_t = w_{i,\boldsymbol{A}} r_{i,\boldsymbol{A}} \text{ , and}$$
$$LS_t = w_{i,\boldsymbol{B}} r_{i,\boldsymbol{B}} \text{ ,} \quad (3)$$

where w_i is the weight vector for each group of anomalies and $r_{i,X}$ is the return matrix (set of ZIS) belonging to X group i.e., $\boldsymbol{A}$ *or* $\boldsymbol{B}$. Thus, the two linear combinations of the defined weight structure assimilate cross-sectional commonalities in investor preferences for or against liquidity risk. Our approach follows the Stambaugh and Yuan (2017) procedure to the extent that our factors accumulate information across a group of anomalies. Normally, factor construction follows the procedure pioneered by Fama and French (1996).[24] Nonetheless, the proposed weighting function and factor construction sit well with our motivation. In addition to this, this factorization also validates the empirical evidence in Asness et al. (2013): momentum and value factor have alternating liquidity risks and positive price of risk in the cross-section (see section 5.4 for details).

Table 3 presents the summary statistics of our proposed factors and regression output describing how our factors are linked to investor sentiment. This is especially relevant for our LHF as LHF assimilates return variation from a subset of 11-prominent anomalies examined in Stambaugh et al. (2012) and Stambaugh and Yuan (2017) along with VAR and QMJ ZIS. Results show alternating sentiment exposures to our liquidity-risk factors, where the effect for LHF is similar to the ones noted in Stambaugh and Yuan (2017) for their mispricing factors.

We note that the factor returns on LHF (LSF) are significantly strong (weak) following high sentiment states. The regression outputs describe how the sentiment effects for LHF (LSF) are driven by their short (long) portfolio. The slope coefficients on both the long and short legs are uniformly negative for both factors, however, for LHF (LSF) the sentiments effects on short (long) portfolios are approximately eight (four) times greater in impact relative to their long (short) portfolios. In sum, the

[24] Factors are constructed from a 2×3 double sort portfolios and each factor represents a single anomaly. Almost all models follow this convention in constructing new factors (Carhart 1997; Liu 2006; Asness et al. 2019; Hou et al. 2015; Fama and French 2015; Stambaugh and Yuan 2017).

overall sentiment effect for LHF and LSF are 0.009 and -0.006 with corresponding t-values of 4.625 and -3.547.

This implies that LHF follows the guidelines set in Stambaugh et al. (2012): the short leg of the so-called mispriced anomalies should be significantly less profitable following high investor sentiment. However, a significant reverse sentiment exposure for LSF shows that cross-sectional mispricing influences even the risk-based factor changes. Nonetheless, the average returns on both factors may combine both compensations for systematic risk and mispricing. As Stambaugh et al. (2012) argue, the Baker and Wurgler (2006) sentiment proxy only picks up the mispricing part but does not say it is the only exposition of spread in anomalies.

4.2 A three-factor model

Incorporating LHF and LSF, we develop a three-factor model augmenting the single-factor market model of Sharpe (1964) under the assumptions of the arbitrage pricing theory of Ross (1976). We test our *Market-Hedger-Spreader (MHS)* model:

$$R_{i,t} = \alpha_i + b_i(R_{m,t} - R_{f,t}) + lh_i LHF_t + ls_i LSF_t + \varepsilon_{i,t}, \tag{4}$$

where, $R_{m,t} - R_{f,t}, LHF_t$ and LSF_t are returns on the market portfolio, liquidity-risk-hedger factor and liquidity-risk-spreader factor, respectively. While in the same order, b_i, lh_i and ls_i are the factor sensitivities of the portfolio i on the model factors.

We omit the size factor even though other new factor models (Fama and French 2015; Hou et al. 2015 and Stambaugh and Yuan 2017) keep it. This is because we aim to aggregate variations in returns that are linked to investors' preferences for liquidity-risk hedging and spreading to develop a parsimonious description of average returns. Thus, adding a size factor when the SIZE anomaly is already a proportional part of LSF is likely to be an excess in our case. Furthermore, there is an added consistency in our model's factors: they are all a combination of, although different, linear weighting schemes. However, the factors in all other models (except, of course, the market factor) are usually constructed from two-way portfolio sorts to capture the anomaly eliciting a unique cross-sectional return variation.

Theoretically, our exposition augments existing literature: Stambaugh et al. (2012) link what kind of sentiment spurs (predominantly) mispricing, while our motivation links this mispricing to an agent's preferences for liquidity-risk. It is highly likely, as shown earlier, that mispricing factors and our LHF reinforce each other. However, by our approach, LHF and LSF are primed to capture independent explanations for risk and mispricing. Arguably, this information is left unexplained by other factors as well as by Stambaugh and Yuan mispricing factors.[25]

[25] SY model compute mispricing factors using intercepts from a two-factor risk model. In our case, we aggregate mispricing and risk related return variation left unexplained by market factor through a unified source.

We provide regression outputs of our model for both sets of anomalies in table 4. The results in panel A show our model explains return variations of otherwise hard-to-explain liquidity risk hedging anomalies well. To stress this point, the alpha on the average liquidity-risk hedger portfolio is only 10 bps i.e., it is 9 times lower than what we have with the FF3 model (see Appendix A-II in the supplementary file).[26] The exposures on our LHF are positive and highly significant for the liquidity-risk-hedgers ZIS. The loadings on LSF are significant for four out of six anomalies. On average this relationship for the ALH strategy shows a plausible negative sign given alternating preferences for liquidity-risk, although is insignificant.

Panel B, table 4, reports the results for the so-called liquidity-risk spreaders. The intercept on ALS is economically not different from zero until three decimal points implying that risk variations in stock returns are neatly captured by our model. However, the model performance of FF3 for liquidity-risk spreaders is not poor either: FF3 intercept of ALS is –0.001 with t-values of –2.073 (see Appendix A-II in the supplementary file). We note that LSF influences the average returns of the liquidity-risk spreading ZIS in the same fashion as LHF does for LH ZIS. LHF, on average, positively and significantly influences liquidity-risk spreader ZIS, however. Through this, we entertain the possibility that cross-sectional mispricing also affects the so-called anomalies that are established to capture risk variations and mimic unknown state variables.

The diverging evidence for the two different sets of ZIS by our model is illuminating in many ways. Foremost, this evidence underpins how the latest factor editions, as well as factor models, have outperformed the FF3 model in explaining average returns. As noted in table 4, this is especially true for anomalies with positive risk-adjusted FF3 model returns, as evidenced in Stambaugh et al. (2012). All the latest factor models incorporate this missing common variation in FF3but this is only linked to mispricing in the SY model and our model. The SY model is broad in its development and accommodation for mispricing. Whereas the incorporation of profitability and investment-related factors in the FF5 model and HXZ is, at least theoretically, associated with risk variation although, as noted in Stambaugh and Yuan (2017), the factors in them might also be affected by mispricing.

5 Model comparisons

Our replication exercise using a host of factor models shows that the latest factor models do a remarkable job, on account of model intercepts, relative to the FF3 model. In short, the results show that our model performs the best: the mispricing given by the SY model, HXZ model and FF5 model for the combination liquidity-risk hedging strategy is higher than the MHS model. One striking feature in LS ZIS regressions is the very comparable performance of the FF3 model to that of the

[26] We provide replicate table 4 using other models i.e., Carhart model, FF5 model, HXZ model and SY model. See results provided in Appendix A of the supplementary file. We also produce a discussion therein explaining why FF3 falls short and how latest editions streamline a large cross-section of anomalies.

latest AP models: alpha estimates from all models are equal to zero for up to two significant values for ALS strategy and are statistically super significant.

5.1 AP Models competition to explain liquidity-risk hedging and spreading anomalies

Our results in section 4.2 show that the MHS model is a clear improvement over the FF3 model, especially for LH ZIS. On top of this, the return variation in the LH factor, and the latest factors belonging to the recent AP models, bodes well to our motivation to differentiate investor preferences for liquidity-risk exposures of ZIS yielding anomalous returns. Given there are several AP models that outperform the FF3 model, it is only plausible to assess how the performance of the MHS model matches the improvements attained by the most recent factor models. However, for the sake of completeness and how differences emerge among prior and latest benchmarks, we also include the FF3 model and Carhart model in our model comparison exercise. We compare the model performance of all the models using the 14, including the ALH and ALS ZIS, zero-cost investment strategies.

The model comparison exercises are carried out using multiple metrics displaying the ability of candidate AP models to explain the two sets of anomalies that depict alternating liquidity-risk preferences. Namely, these are Gibbons, Ross and Shanken (GRS, 1986) test, the average of absolute alphas $A|\alpha|$, and the average of adjusted r-squared for each set of ZIS undertaken in our work.[27] Furthermore, we produce all of these evaluation criteria for the full sample period, UP and DOWN market states.[28] We replicate model comparison metrics in UP and DOWN market states. One, Cooper, Gutierrez and Hammed (2004) that momentum profits are different across market states. Two, two sets of anomalies are exposed differently to aggregate liquidity then they might behave differently across these states to capture changes in risk premia and mispricing.

Panel A of table 5 provides evaluation metrics for LH ZIS across the full sample period (1965:07 to 2016:12), DOWN and UP market states. For the full sample period, our results replicate the evidence in Fama and French (2015, 2016), Hou et al. (2015) and Stambaugh and Yuan (2017). That is, all models are incomplete descriptions of expected returns and the p-values for the GRS test are equal to zero for rounding to two decimal points. Whereas our results for the GRS test following DMS show that all the models capture variations in the return premia of LH ZIS: the null of zero mispricing (intercepts) for LH ZIS cannot be rejected for any of the models. This implies that all the models, including the FF3 and Carhart models, capture the return variations following DMS even for LH ZIS.

[27] The GRS test determines the ability of a model to suppress mispricing in the cross-section i.e., if the time-series regression intercepts (alphas) for the set of test assets are jointly zero because if an AP model explains spreads on e.g., ZIS then regression intercepts should not be different from zero.

[28] To define DOWN and UP market states, we follow Cooper et al. (2004). Their study proxy market states by using the last 3-year cumulative excess returns on market index that is, if the lagged 3 years' cumulative excess return is positive, the market is referred to be in an up state and negative cumulative excess return on market index imply the contrary i.e., a market downturn or a down state.

However, the bigger pricing issues for the models, including the latest editions, lay during UP market states: the GRS test statistic reject the null hypothesis of zero mispricing.

Using a simplistic and economically meaningful comparison metric of $A|\alpha|$, the monthly average of absolute alphas, FF3 produces the largest mispricing for LH ZIS of 90 bps and the same for the Carhart model is 60 bps. The $A|\alpha|$ for FF5 and HXZ models are 50 bps and 40 bps, respectively, which are considerably larger than the smallest values of 20 bps that we get from SY and MHS models. However, the MHS model performs the best in DOWN and UP market states: $A|\alpha|$ is 40 and 30 bps, respectively. The SY model shares the performance of the MHS model for LH anomalies in UP states, only. Most importantly, given the challenges posed by LH ZIS, the starkest results are seen for the FF3 model in the DOWN states: FF3 model $A|\alpha|$ of 50 bps is smaller than the same given by Carhart (60 bps), FF5 (70 bps), HXZ and SY (60 bps) models. Whereas $A|\alpha|$ in UP market states reveals where the recent factors models improve relative to the FF3 model: average mispricing given by FF3 model is largest in UP market states.

In terms of competing models' ability to explain the time-series variability in realized returns, the average adjusted r-squared AR^2_{Adj} values for the set LH ZIS shows that the MHS model explains on average 61% of the variance of them. This is the largest value; followed by the SY model (58.8%), Carhart model (58.6%), FF5 model (58.2%), and HXZ model (55.1%). FF3 model explains only 44.8% of the return variance of LH ZIS. In DOWN states MHS (FF3 model) leads (lags) rest of the specifications in explaining return variance of liquidity-risk hedging anomalies. The second-best model is the FF5 model that explains 66.7% of the return variance which is followed by the SY model (65.6%). In UP states MHS model leaders and laggards are the same i.e., MHS and FF3 model, respectively. Our model is followed by the Carhart model (58.5%), SY model (57.8) and FF5 model (57.2%).

Results for LS ZIS are shown in panel B of table 5. When considering the GRS test for the full sample period all models other than the FF3 model are good models. The GRS test yields the lowest value of 0.559 for the MHS model among all factor models. The corresponding p-value is 0.789. In comparison, the p-values for the FF5 model and HXZ model are large and describe their good fit for LS ZIS in the full sample. The GRS test for HXZ and MHS models produce the largest and second-largest p-values (0.431 and 0.207) for LS ZIS following DOWN states. In UP states, more or less, full sample results are repeated: all models are good explanations (at 5% p-value threshold for the GRS test statistic) of average returns except the FF3 model. In terms of power for the GRS test statistic in UP states, the MHS model p-value is the largest and it is followed by FF5, HXZ and SY models, respectively.

When using $A|\alpha|$ to explain spread on LS anomalies, panel B of table 5 shows MHS equals or outperforms the best performing models across all samples. Here, we note that the good fit of the SY model for LH ZIS has not been replicated for the LS ZIS: the SY model $A|\alpha|$ of 20 bps, 60 bps and 20 bps in the full sample, DOWN and UP states are larger than the second-best model in each sample period.

In general, the latest editions of factor models do not explain large parts of the return variation in LS ZIS. In almost every sample period, the FF3, FF5 and Carhart models outperform the HXZ, SY and MHS models in terms of adjusted r-squared values.

The unambiguous conclusion from these results is that the latest factor models, including ours, comfortably outperform FF3 for LH ZIS, whereas for LS ZIS their outperformance is not a massive improvement. Our model leads the pack across all sample periods for $A|\alpha|$ for both types of anomalies but ranking among models to describe return variance of ZIS is less clear-cut: AR^2 places MHS model on the top for LH ZIS in the full sample and DOWN states; Carhart model leads for LH (LS) ZIS in UP (DOWN) states and FF5 (FF3) model leads for LS ZIS in the full sample (UP states). Besides the marked performance of our MHS model, the resultant inference for other factor models relative to FF3 cannot escape attention.

Put simply, the latest editions of AP models expand the FF3 factor structure with potentially omitted factor variation related to investors' liquidity-risk hedging motives that edge out FF3. Therefore, the performance of these models for anomalies that are presumed to proxy established systematic variation in return premia, such as firm capitalization or BM ratios, is not substantially better than the FF3 model. This makes the relative merits of all the latest models debatable for the different sets of test portfolios that describe a different factor structure and emphasizes the salience of our work in deciphering the separation of investors' liquidity-risk preferences.

5.2 Factors explaining factors of other models

Fama and French (2016), Hou et al. (2015, 2019) and Stambaugh and Yuan (2017) have compared models across a range of test portfolios. Results in section 5.1 are a subset of contests performed in these studies. The evidence in these studies shows that models in each succeeding work outperform their predecessors. These comparisons are credible; nevertheless, they do not identify differentiated investor preferences. As our work shows (more robustly in section 5.1), this scheme discerns in which periods, and for what type of anomalies, these models bring improvements relative to the FF3 model. In this context, as Barillas and Shanken (2017, 2018) argue, the ability of AP models to explain competing models' factors exceeds their relative performance for a host of test portfolios and essentially is all that matters in model comparisons. We use spanning regressions to compare the pricing ability of each model for the non-nested factors in other models.

Table 6 breaks down results from these regressions: panel A provides regression alphas for each model factor and panel B populates GRS statistics for each model if the alphas on non-nested factors in the rest of the factor models are jointly zero.[29]

The results in panel A show that HXZ, SY and MHS models invariably explain the factor returns on FF5 factors. All but one of the regression intercepts produced by these three models have t-values that cannot reject the null of indistinguishability from zero. The exception is the CMA factor for our MHS model. Furthermore, on average HXZ model produces the smallest alphas for non-nested factors belonging to the FF5 model. When examining the HXZ model's non-nested factors, the SY model's alphas are, on average, the lowest, followed by the MHS model. FF5 model alphas are the largest for HXZ factors. However, this is driven by their model's inability to explain the HXZ model profitability (ROE) factor which has an intercept estimate of 50 bps and is highly significant. SY and MHS models also fall short of the ROE premium. In general, the inability of our model to explain the investment (IA) factor persists.

The spanning regressions for the SY model show that no competing models capture the SMB_{SY}, MGMT and PERF premiums. The only model for SY factors that deserves merit is the MHS model: spanning alpha of 30bps for the SY model's PERF factor has a t-statistic that is borderline significant at 0.1 significance values. The MHS model does not explain investment and SMB_{SY} factors. Potentially, this inability stems from the evidence in Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018) for large stocks, and the fact that our LH and LS factors do not include investment-related anomalies/factors variation. Finally, we assess our LH and LS factors. FF5 and HXZ models do not fully explain the LHF premium: alpha values of 0.5% and 0.3% are highly significant, respectively. SY model produces a lower alpha of 0.2%. The unexplained returns on LSF are economically small in spanning regressions and have statistically insignificant t-values.

The $A|\alpha_i|$, provided in table 6, for FF5, HXZ, SY and MHS models is 0.24%, 0.13%, 0.08% and 0.14%, respectively. FF5 model has the least success in explaining the returns on the factors belonging to the competing models. HXZ alphas are significant in four instances out of eight runs for the model and this for the SY model occurs only for ROE and LHF premiums in HXZ and MHS models, respectively. MHS model alphas for non-nested factors are also highly significant in five out of 10 instances, where three times the sizeable and significant alphas are on investment-related factors present in FF5, HXZ and SY models. SY model is the most effective model here and, even if we dismiss the fact that the MHS model lacks an investment-related factor, the pricing ability of the MHS model closely matches that of the HXZ model in spanning tests. Furthermore, the large significant

[29] Considering the difference in construction procedures of size factor in SY model and ad hoc SMB factor in FF3, FF5 and HXZ models, we consider SY model SIZE factor (SMB_{SY}) non-nested factor for FF5 and HXZ models and regard SMB (as in FF3 model) nested for FF5 and HXZ models. The size factor, in all AP models is a non-nested factor for our model.

alphas on factors capturing profitability related factor variation, i.e., ROE, PERF and LHF, endorses our assertion that liquidity-risk hedging is pivotal in the cross-section.

Panel B of table 6 reports the pricing ability of each model to jointly suppress alphas on the non-nested factors is contested using the GRS test. Following the results in panel A, the GRS test for HXZ and SY models has large p-values for FF5 model factors. While for the rest of the models, at 5% critical p-values, GRS tests confirm the evidence in Hou et al. (2019) and Stambaugh and Yuan (2017) that neither of the HXZ and SY models explains the non-nested factors of the other. The same holds for the MHS model i.e., none of the other models can jointly explain the premium on LH and LS factors.[30]

5.3 Cross-sectional tests

In this section, we examine if the latest AP models are the cross-sectional determinants of average returns and if their risk premium on them is economically meaningful: is the estimated factor risk premium correspond to the time-series mean of the factor. To do so, we estimate the factor risk-premiums using the two-pass cross-sectional tests following Black, Jensen and Scholes (1972). The corresponding first pass time-series regression is as follows

$$R_{i,t} - R_f = \beta_{i,m}\left(R_{m,t} - R_f\right) + \beta_{i,1}(f_1) + \beta_{i,2}(f_2) + \cdots + \beta_{i,K-1}(f_{K-1}) + \epsilon_{i,t}, \qquad (11)$$

where $\beta_{i,K}$ are factor loadings on K factors contained in the multifactor model. To exemplify, for our MHS model, the first pass time-series regression is $R_{i,t} - R_f = \alpha_i + b_i R_{m,t} - R_{f,t} + lh_i LRH_t + ls_i LRS_t + \varepsilon_{i,t}$. The estimated slope coefficients (b_i, lh_i and ls_i) are estimated on the model factors $R_{m,t} - R_{f,t}, LRH_t$ and LRS_t, respectively, for different combinations of test assets, i.e., excess returns on 25 size-BM, 25 size-MOM and 50 test portfolios combining the first two sets. In the second pass, we estimate a cross-sectional regression using N test portfolios average excess returns on factor sensitives, β_i:

$$\overline{R_{i,t} - R_f} = \hat{b}_{i,m}\lambda_m + \widehat{lh}_i\lambda_{m,LRH} + \widehat{ls}_i\lambda_{LRS} + \zeta_{i,t}. \qquad (12)$$

Likewise, we repeat these two steps for all models to estimate the price of factor (beta) risks i.e., λ_K. [31] We begin our return-beta cross-sectional tests with 25 size-BM portfolios as LHS dependent variables. The results for all the competing models are reported in table 7. The GRS F test shows that all models fail to suppress cross-sectional mispricing. The results show that the latest AP models outperform the FF3 model even for size-BM testing portfolios: the adjusted R^2 value for the FF3 model is the lowest among all. In this respect, our MHS model, despite having a factor less than the

[30] With this, it may also appear interesting to see if our LHF and LSF can be explained by a model containing another liquidity factor. We add Pastor and Stambaugh (2003) factor in the FF3 model and repeat the estimations for LHF and LSF factor. We find large and significant alphas on these factors and GRS-F test also reject the ability of liquidity augmented FF3 model to jointly explain alphas on these factors.

[31] To account for errors in the variables issue, we also computed Shanken (1992) corrected standard errors (unreported results). The significance of estimated premium is unaffected to the extent of discussion in the paper.

SY model, explains almost the same cross-sectional variation in the size-BM portfolios as by the SY model. Both have adjusted R^2 values of 78.4% and 79.75%, respectively.

To examine the meaningfulness of the estimated risk premiums for the factor of the competing AP model, we follow Lewellen et al. (2010) recommendations. They argue that there should be theoretical and empirical constraints on the estimated factor risk premiums in the cross-sectional tests: do the estimated risk premiums correspond to predictions made by theory and by the time-series mean. We evaluate the sign and magnitude of the estimated risk premiums, for all the competing models under these constraints.

The estimated market risk premium is always positive and significant and is around its time-series average of 0.005. The same applies to the size risk premium whose time-series average is 0.003. The risk premium on the size factor in HXZ and SY models is 0.004. Estimated premiums correspond to the time-series averages depending on differences in defining and constructing size factors-Stambaugh and Yuan (2017). The risk premium on the value factor, in all the specifications that contain it, is 10 bps more than its average of 0.003, although is significantly estimated. Whereas the risk premium on the momentum factor is more than half its time-series average of 0.007, although is positive and significantly estimated.

The examination of factor risk premiums of the new factors in the latest AP models show that the estimated risk premiums on RMW and CMA factors in the FF5 model are 0.004 and 0.001, where the former is statistically significant but is 10 bps more than its time-series average. Whereas the CMA risk premium is lower than its time-series average of 0.003 by 20bps and is estimated insignificantly.

The risk premium on the IA factor of the HXZ model corresponds to its mean value, whereas the estimated risk premium on ROE is less than 10 bps to its mean value. The estimated risk premiums on MGMT and PERF factors in the SY model are 10 bps and 42 bps more than their factor mean levels. The risk premiums on LHF and LHS more closely correspond to their mean levels: inflation in the estimated risk premiums is less than 10 bps relative to their mean level.

Harvey, Liu, Zhu (2016) note that with an abundance of factors (and factor models) and p-hacking concerns a test statistic above 3 should be used as a threshold in empirical testing. Using this threshold, we find RMW of the FF5 model and ROE of the HXZ model lose ground. CMA factor premium is not different from zero even at conventional t-values.

The results using size-MOM test portfolios are presented in Table 8. Comparisons based on the GRS test are not different for summary findings in Table 7. In terms of adjusted R^2 value, HXZ, Carhart, SY and FF5 models have explanatory power of >80% and our MHS model explains almost 75% of the spread variation in the 25 size-MOM portfolios. However, the strength of the MHS model is displayed by the consistency of estimated risk premiums on LHF and LHS factors that more closely correspond to their mean values. In this respect, we note that estimated risk premiums on market and size factors are inflated by, on average, 10 bps across all competing models. The value factor is implausibly estimated in the FF3 and FF5 model and the Carhart model, it is inflated by 30 bps from its mean value. When it comes to WML, RMW, CMA, IA, ROE, and MGMT factors, we find that their risk premiums deviate by +10 bps, -20 bps, +70bps, -20 bps, +20 bps, and +30 bps. Besides LHF and LSF, the only risk premium that closely matches its mean levels from the rest of the AP models is PERF from the SY model. When it comes to statistical significance SMB and HML for FF3 model, HML, and CMA of FF5 model, and MGMT of SY model do not meet >3 t-stat hurdle rate. However, RMW and IA factor premiums of FF5 and HXZ models are insignificant for size-MOM portfolios at conventional t-values. Overall, the FF3 model lacks explanatory power for momentum structure underpinned by investors' liquidity-risk hedging motives.

Following Lewellen et al. (2010), we raise the bar for all the competing models and use 50 test portfolios i.e., we combine 25 size-BM and 25 size-MOM portfolios. This is followed by adding 48 industry portfolios.[32] This test aims to penalise a model's ability to pick a particularly strong factor structure of the LHS dependent variables. We provide results for these estimations in tables 9 and 10.

When we combine size-BM and size-MOM factor structures, the SY model leads explaining of cross-sectional spread variation followed by HXZ and MHS models. The checks on the theoretical and empirical consistency of estimated risk premiums show that, among all factors, LHF and LSF meet the criteria efficiently; however, we note the deviations in the rest of the factor risk premiums are reduced when we combine both two different factor structures.

The inclusion industry portfolio together with size-BM and size-MOM portfolios presumably brings a dominating momentum structure on the LHS anomaly portfolios: for the first time, the momentum factor premium performs nearest to its average. However, the best performance is displayed by SMB and LRS factor premiums. The rest of the factor risk premiums, across competing models, are highly deflated relative to their time-series means. The largest difficulty to explain LHS anomaly portfolios is observed for market factor: it is negatively estimated in all instances which is theoretically counterintuitive. We note that deflation in factor risk premiums is ubiquitous, except SMB, LRS and WML factors. Perhaps, this consistent deflation stems from not capturing the momentum effect fully when assumingly we have 73 momentum related LHS test portfolios in the cross-section. To this extent, our results conform Fama and French (2015, 2016) findings: the presence of WML is vital when a robust momentum related factor structure is present in the LHS anomaly portfolios.

[32] Moskowitz and Grinblatt (1999) document that there is a robust and common momentum effect in industry returns that explains much of the individual stock momentum anomaly. This implies that inclusion of 48 industry portfolios together with 25 size-MOM portfolios may bring a strong momentum structure in the LHS portfolios.

For statistical significance on the estimated premiums, we note that the value factor does not meet >3 t-value threshold across all models. CMA and RMW factor premiums also fall short where the premium on the CMA factor is implausibly estimated in the FF5 model. The deflated IA and ROE premiums in the HXZ model also do not meet the >3 t-value hurdle. Other victims of this threshold are MGMT and LHF premiums in SY and MHS models although both are plausibly estimated. For the noted issues on estimated factor risk premiums, in the order of explanation of cross-sectional variation in 98 test assets, we presume the meaningful r-squared (and adjusted r-squared) values are limited to the Carhart model, SY model and MHS models only.

Overall, the persistent consistency of estimated risk premiums of the factors in the MHS model, across different anomaly structures, underpins their ability to explain return spreads on alternating liquidity investing preferences. This results in the MHS model's price of risk estimations meeting several crucial theoretical, economic, and statistical assumptions. In this vein, even the tightest statistical constraint of >3 t-value results in significant estimated risk premiums for LHF and LSF premiums, with one exception, that are nicely tied to their mean values. A feat that is not achieved consistently, across different portfolio sets or their combinations, by the rest of the competing AP models or the factors therein.

5.4 Additional tests

We replicate the results reported in table 3 for all the competing factor models to gauge how factors are linked to investor sentiment. These results show that most factors are influenced by mispricing: increasing sentiment in the prior periods predict high returns for nine out of 12 factors analyzed in our work.[33] In sum, we note that the latest factors, together with the value factor, describe the type of mispricing outlined in Stambaugh et al. (2012) i.e., common return variation that could be linked with mispricing i.e., LH investing motives motivated in this work. Furthermore, we note that pervasive mispricing affects the risk-based factors as well.

As we noted in section 5.2, the MHS model lacks factor variation coming from investment anomalies. To incorporate this factor variation, we estimate liquidity betas for anomalies that are linked to investment-related return variation (for details see Hou et al. 2019 and Stambaugh and Yuan 2017). We find liquidity betas on these anomalies are non-trivial and are insignificantly estimated. This insensitivity to market liquidity changes scuppers the possibility of factorizing investment-related return variation in our model: creating a third factor that is neutral to market liquidity will be spurious and add random variation in the model. This result also underpins the need for factorizing return sensitivity that is significant in the time-series and cross-section for a persistent and/or systematic pattern.

[33] We populate these results in Table A-VII of Appendix A in the supplementary file.

Considering that our results in Table 5 only account for LH and LS ZIS and not for investment-related factor variation, we expand the cross-section of investment anomalies, mainly, that are employed in constructing the MGMT factor in Stambaugh and Yuan (2017). These estimations retain the robustness of our main results in the full sample and across market states.

6 Conclusion

We invoke an intuitive relationship between asset pricing anomalies, return variation in them, and their sensitivity to changes in market liquidity. We split anomalies into two categories given the distinctiveness of anomalies' sensitivity to unexpected changes in systematic liquidity. Using this split two distinctive investing patterns in the cross-section are factorized and a parsimonious three-factor model is developed that includes a broad-based market factor. Results from time-series regressions show that our model performs better than or equal to the best performing model among competing models in the full sample as well as UP and DOWN market states. That is, our model describes time-series risk shifts across varying market periods. Furthermore, our results show that the better performance of all models, including our three-factor model, is driven by the inclusion of common variation – mispricing – of liquidity-risk hedging. To this extent, earlier elucidations and especially the FF3 model failed on this frontier and as per our classification is only a good descriptor of liquidity risk spreading anomalies. Thus, the performance of these models is deemed inconclusive explanations for a wide set of anomalies that mimic investors' liquidity-risk hedging tendency. Our motivation, the resultant factor model and model comparisons explain numerous stylized facts such as designing of anomalies/ZIS, distortions in liquidity-risk assessment and consequent systematic presence of persistent mispricing in the cross-section.

Our evidence shows factors in our model not only explain the time-series return variability across anomalies but also have sizeable and significant cross-sectional risk premiums. This observation is robust for using several LHS anomaly portfolios. None of the other factor models and factors therein meets the imposed constraints in Lewellen et al. (2010) and Harvey et al. (2016) as consistently and coherently as is the MHS model (and factors). On a separate note, we observe that the estimated risk premium on the market factor suffers the most when several anomaly structures are combined and the significance of HML factor premium is sensitive to the presence of the WML factor in the model when LHS test portfolios contain momentum structure.

Our results are crucial in understanding numerous AP artefacts. The first is the simultaneous presence of premia for value factor and momentum in the cross-section (Asness et al. 2013) when both are negatively correlated between themselves and have alternating factor exposures to systematic liquidity. To highlight this differentiation, empirical results enforce our motivation: average returns and model-adjusted returns on prominent ZIS are explained by alternate preferences for liquidity investing. With these distinctive liquidity preferences, investors show their appetite to hedge against liquidity risk or place bets on portfolios whose returns rise with increasing market liquidity. The differentiating return variation, when accommodated through our liquidity-risk spreading and hedging factors, describes the simultaneous presence of compensation for risk and misvaluation, respectively. Thus, we infer that excessive risk aversion or liquidity-risk hedging is pivotal in summarizing misvaluation in the cross-section. The latest models, with different orientations to ours, essentially incorporate omitted variables that describe investors' liquidity-risk hedging motives and resultantly provide better explanations for anomalies challenging models that only include risk-based factors e.g., the FF3 model.

The second artefact is that we utilize the fuzziness of aggregate liquidity in segregating risk-based variations from pervasive return variations coming from mispricing in the cross-section. Nonetheless, both these components may not perfectly describe risk variations and mispricing in stock returns: both LHF and LSF are significantly predicted by investor sentiment. But then all other factors are contaminated by mispricing in one way or another. Overall, this illustrates that systematic risks may also reflect at least partially, sentiment-driven mispricing. We conclude that the bifurcation of anomalies as in our work is central when the presence of anomalies plague convention rational expectation frameworks. Here, the averaging of patterns in stock returns given their liquidity-risk sensitivity is an effective tool to develop parsimonious models as well as an examination of several well-performing AP models. Implying that the unified nature of our approach is intuitively meaningful.

Overall, the crux of our findings is that the MHS model, with gains of unified coherent explanation through changes in market liquidity, meets several theoretical, economic, and statistical constraints. This aspect is missing in other models that bring distinctive risk or non-risk factor variations. With this methodological and empirical simplification, our model outperforms all in time-series regressions and performs coherently to the imposed constraints in the cross-sectional estimations. Even better than the best model in explaining cross-sectional return variation. The second-best result for the MHS model, in terms of cross-sectional r-squared values, is the *"cost of coherence"* of the proposed model. Adding an investment factor in an ad-hoc manner may improve the gains of our model but that will not be an ideal outcome to the simplification and purpose of our model.

Following, famous British statistician (1913-2013), we note that there are no perfect models, and a strong test of type GRS-F test surely captures this aspect in full. In the context of this work, each model is a compromise in the manner it is developed and examined empirically. All are bound to miss some part of cross-sectional return variation. Thus, explaining return variation across the cross-section of stocks and with the presence of anomalies is still an open field.

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Table 1 Descriptive statistics

The table reports summary statistics for two groups of zero investment strategies (ZIS) viz. liquidity-risk hedgers and liquidity-risk spreaders. This grouping is established based on the exposures of the undertaken ZIS to shocks to aggregate liquidity. These exposures are estimated using a univariate model: $ZI_{i,t} = \beta_0 + \beta_L s\_liq_{mkt,t} + \varepsilon_{i,t}$. Here $s\_liq_{mkt,t}$ are shocks to aggregate liquidity, estimated using Amihud (2002) price impact measure, and these shocks to market liquidity are standardized to have zero mean and unit variance. Furthermore, systematic liquidity measure is transformed following Sadka (2006) and increases in liquidity. All ZIS are subsequently assigned to two groups in consideration of the sign of each ZIS: the negative (positive) market liquidity beta ZIS are referred to as liquidity-risk hedgers (spreaders). Each group of ZIS contain an aggregated liquidity-risk hedging/spreading strategy that is the cross-sectional average of all ZIS available in that group across months. We name them aggregate liquidity hedgers (ALH) and aggregate liquidity spreaders (ALS), respectively. All portfolios are based on NYSE/AMEX/NASDAQ stocks with CRSP share codes 10 and 11. To this effect, panel A reports monthly summary stats for all ZIS, i.e., the long and short difference portfolios, panels B and C repeat the same stats for the long and short portfolios of these ZIS accordingly. To explain, Avg. reports the monthly value-weighted average of each portfolio, Std. provides standard deviation for these portfolios. The Sharpe ratio (SR) is computed as the average monthly excess portfolio return divided by the portfolio's standard deviation whereas the Information ratio (IR) is computed: $\frac{E(R_p - R_m)}{\sqrt{\sigma(R_p - R_m))}}$ where $E(R_p - R_m)$ is the expected active return relative to benchmark market return divided by the tracking error i.e., the standard deviation of the active return. The third moment of each portfolio is provided against Skewness and a non-zero value describes which side of the distribution is heavier relative to the other. The CAPM and FF3 model alphas are presented in rows titled α_{CAPM} and α_{FF3}, respectively. Finally, β_L is the systematic exposure of each portfolio to shocks to systematic market liquidity. T-stats for Avg. and regression estimates are presented in ().

		Liquidity-risk hedgers							Liquidity-risk spreaders					
Panel A: ZIS	**VAR**	**QMJ**	**MOM**	**OP**	**NSI**	**OS**	**ALH**	**BETA**	**ILLLIQ**	**SIZE**	**STR**	**LTR**	**BM**	**ALS**
Mean	0.005	0.005	0.013	0.002	0.005	0.0004	0.005	0.001	0.004	0.003	0.003	0.004	0.005	0.003
	(1.62)	(2.91)	(4.68)	(1.47)	(3.64)	(0.29)	(3.52)	(0.384)	(2.50)	(1.63)	(1.60)	(2.21)	(2.61)	(2.54)
Std.	0.078	0.045	0.070	0.041	0.034	0.037	0.037	0.066	0.038	0.048	0.053	0.050	0.047	0.034
SR	0.060	0.115	0.185	0.058	0.144	0.011	0.139	0.011	0.099	0.064	0.063	0.087	0.103	0.100
IR	-0.003	0.000	0.088	-0.038	-0.003	-0.071	0.000	-0.090	-0.024	-0.034	-0.030	-0.010	-0.004	-0.039
Skewness	-0.308	0.083	-1.412	0.245	0.012	0.161	-0.313	0.177	0.820	0.733	0.222	0.985	0.446	0.935
α_{FF3}	0.010	0.010	0.017	0.005	0.005	0.004	0.009	-0.004	-0.000	-0.001	0.001	-0.001	-0.003	-0.001
	(5.094)	(8.423)	(6.159)	(4.081)	(4.558)	(4.104)	(8.807)	(-2.682)	(-0.335)	(-1.222)	(0.431)	(-0.472)	(-2.922)	(-2.073)
β_L	-0.020	-0.008	-0.008	-0.008	-0.004	-0.007	-0.009	0.012	0.004	0.009	0.003	0.003	0.005	0.006
	(-6.655)	(-4.864)	(-2.891)	(-4.697)	(-2.989)	(-4.889)	(-6.513)	(4.502)	(2.973)	(4.746)	(1.237)	(1.698)	(2.958)	(4.640)

Panel B: Long Portfolios	LVAR	HQMJ	WINNER	HOP	LNSI	LOS	LALH	HBETA	ILL	SMALL	LSTR	LLTR	HBM	LALS
Mean	0.008	0.006	0.015	0.010	0.011	0.009	0.010	0.010	0.012	0.011	0.010	0.013	0.013	0.012
	(1.06)	(3.56)	(6.16)	(5.41)	(6.49)	(4.72)	(6.054)	(3.22)	(5.50)	(4.61)	(3.46)	(4.94)	(5.41)	(4.78)
Std.	0.033	0.043	0.061	0.046	0.043	0.048	0.041	0.079	0.056	0.063	0.072	0.066	0.061	0.061
SR	0.256	0.140	0.243	0.214	0.256	0.186	0.239	0.127	0.217	0.182	0.137	0.195	0.213	0.189
IR	0.121	0.063	0.292	0.275	0.260	0.202	0.501	0.113	0.217	0.159	0.120	0.195	0.224	0.226
Skewness	-0.264	-0.384	-0.395	-0.417	-0.189	-0.256	-0.476	-0.209	0.025	-0.152	-0.253	0.276	-0.157	-0.206
α_{FF3}	0.004	0.003	0.010	0.006	0.005	0.006	0.006	0.001	0.004	0.003	0.002	0.003	0.002	0.003
	(6.274)	(5.918)	(8.191)	(8.466)	(6.638)	(9.122)	(16.210)	(1.303)	(5.548)	(4.759)	(1.466)	(2.826)	(2.785)	(5.083)
β_L	0.005	0.009	0.013	0.010	0.009	0.009	0.009	0.017	0.013	0.017	0.016	0.016	0.015	0.016
	(3.660)	(5.343)	(5.596)	(5.441)	(5.211)	(5.042)	(5.720)	(5.602)	(5.999)	(7.296)	(5.697)	(6.263)	(6.599)	(6.731)
Panel C: Short Portfolios	**HVAR**	**LQMJ**	**LOSER**	**LOP**	**HNSI**	**SOS**	**SALH**	**LBETA**	**LIQ**	**BIG**	**HSTR**	**HLTR**	**LBH**	**SALS**
Mean	0.004	0.001	0.002	0.007	0.006	0.009	0.005	0.009	0.008	0.008	0.007	0.009	0.008	0.008
	(6.49)	(0.36)	(0.64)	(2.86)	(2.72)	(3.47)	(1.821)	(6.83)	(5.02)	(5.07)	(3.03)	(3.70)	(4.10)	(4.79)
Std.	0.088	0.070	0.080	0.065	0.056	0.063	0.067	0.035	0.042	0.042	0.055	0.059	0.050	0.043
SR	0.042	0.014	0.025	0.113	0.107	0.137	0.072	0.270	0.198	0.200	0.120	0.146	0.162	0.189
IR	-0.025	-0.114	-0.058	0.070	0.047	0.119	-0.010	0.152	0.227	0.317	0.051	0.142	0.161	0.347
skewness	-0.072	-0.492	0.602	-0.595	-0.361	-0.628	-0.365	-0.269	-0.282	-0.333	-0.233	-0.344	-0.213	-0.399
α_{FF3}	-0.005	-0.007	-0.007	0.000	0.000	0.002	-0.003	0.006	0.004	0.004	0.001	0.004	0.005	0.004
	(-3.530)	(-7.315)	(-3.667)	(0.114)	(0.067)	(2.205)	(-3.800)	(7.140)	(9.535)	(19.771)	(0.993)	(5.367)	(9.574)	(13.434)
β_L	0.025	0.017	0.021	0.017	0.013	0.016	0.018	0.006	0.008	0.009	0.013	0.013	0.010	0.010
	(7.354)	(6.497)	(6.908)	(6.890)	(5.824)	(6.843)	(7.200)	(4.107)	(5.166)	(5.319)	(6.367)	(5.558)	(5.078)	(5.815)

Table 2 Quintiles with contemporaneous shocks

Panel A of the table presents monthly average excess returns for the period July 1963-December 2016 for six so-called liquidity-risk hedging zero investment strategies (ZIS) and the aggregate liquidity-risk hedging (ALH) strategy that is the cross-sectional average of all ZIS available in the group across months. Namely, these strategies are VAR, QML, MOM, OP, NSI, OS and ALH. The sample average returns on these strategies along with the average returns on them across five quintiles subjected to shocks to market liquidity are shown under headings Avg., L1, L2, L3, L4 and L5, respectively. These illiquidity related quintiles are defined using the shocks to systematic market liquidity that is estimated by Amihud (2002) price impact measure: L1 is the first quintile that accumulates the most illiquid (negative) shocks to market liquidity and L5 gathers data points across these ZI strategies when the market liquidity witnesses most liquid (positive) shocks. Panel B repeats the same for liquidity-risk spreaders. Namely, these ZIS are BETA, ILLQ, SIZE, STR, LTR BM and the aggregate liquidity-risk spreading (ALS) strategy that is the cross-sectional average of all ZIS available in the liquidity-risk spreaders group across months. The underlined, bold and bold & italic mean returns have t-values that are significant at 0.1, 0.05 and 0.01 significance levels.

Panel A: Liquidity hedging ZIS						Panel B: Liquidity spreading ZIS					
	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VAR	***0.034***	***0.017***	0.008	-0.006	***-0.029***	BETA	***-0.020***	***-0.011***	0.000	0.007	***0.028***
LVAR	-0.003	***0.010***	***0.008***	***0.012***	***0.016***	HBETA	***-0.022***	-0.001	0.008	***0.019***	***0.045***
HVAR	***-0.037***	-0.008	0.000	***0.018***	***0.045***	LBETA	-0.001	***0.01***	***0.008***	***0.012***	***0.017***
QMJ	***0.023***	***0.009***	0.005	-0.004	-0.008	ILLLIQ	***-0.009***	-0.002	0.002	***0.012***	***0.016***
HQMJ	-0.009	***0.005***	0.004	***0.009***	***0.021***	ILL	***-0.015***	0.005	***0.009***	***0.023***	***0.038***
LQMJ	***-0.032***	-0.004	-0.001	***0.013***	***0.029***	LIQ	-0.005	0.007	***0.007***	***0.011***	***0.022***
MOM	***0.017***	***0.017***	***0.016***	0.010	0.004	SIZE	***-0.014***	-0.005	0.001	***0.012***	***0.022***
WINNER	-0.012	**0.011**	***0.012***	***0.024***	***0.040***	SMALL	***-0.02***	0.002	0.007	***0.024***	***0.044***
LOSER	***-0.030***	-0.006	-0.004	***0.014***	***0.035***	BIG	-0.006	0.007	***0.006***	***0.012***	***0.022***
OP	***0.017***	0.004	0.001	-0.002	***-0.009***	STR	-0.002	0.003	-0.003	***0.009***	***0.008***
HOP	-0.007	0.007	***0.009***	***0.014***	***0.026***	LSTR	**-0.019**	0.006	0.003	***0.022***	***0.037***
LOP	***-0.024***	0.002	0.008	***0.016***	***0.035***	HSTR	***-0.017***	0.002	0.005	***0.012***	***0.029***
NSI	***0.012***	***0.008***	0.003	0.004	-0.004	LTR	-0.003	0.005	0.003	0.005	***0.013***
LNSI	-0.007	***0.009***	***0.009***	***0.018***	***0.025***	LLTR	***-0.016***	0.008	0.009	***0.021***	***0.043***
HNSI	***-0.020***	0.001	0.005	***0.014***	***0.029***	HLTR	-0.013	0.003	0.006	***0.015***	***0.03***
OS	**0.018**	0.004	-0.001	***-0.009***	***-0.009***	BM	-0.007	0.002	0.007	***0.01***	***0.011***
LOS	-0.008	**0.008**	0.006	***0.012***	***0.025***	HBM	***-0.015***	0.007	***0.012***	***0.023***	***0.037***
SOS	***-0.025***	0.004	0.007	***0.022***	***0.035***	LBH	-0.008	0.005	0.005	***0.013***	***0.026***
ALH	***0.020***	***0.010***	0.005	-0.001	***-0.009***	ALS	***-0.009***	-0.002	0.002	***0.009***	***0.016***
LALH	-0.008	***0.008***	***0.008***	***0.015***	***0.025***	LALS	***-0.018***	0.004	0.008	***0.022***	***0.041***
SALH	***-0.028***	-0.002	0.003	***0.016***	***0.035***	SALS	-0.009	0.006	0.006	***0.013***	***0.025***

Table 3 Liquidity factors and investor sentiment

The table reports the mean and standard deviation of the liquidity-risk factors LHF and LSF along with market factors (Rm-Rf). Furthermore, the table presents estimates of θ from the following regression:

$$R_{i,t} = \mu_i + \theta_i S_{t-1} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly excess return the long, the short, or the long-short difference for each of the factors ($R_m - R_f$, LHF, LSF), and S_{t-1} is the previous month's level of the investor-sentiment index of Baker and Wurgler (2006). T-stats are reported in (). The sample period is 196307-201509. The underlined, bold and bold & italic mean returns are significant at 0.1, 0.05 and 0.01 significance levels.

Factor	Mean	Std.	SR	Long Portfolio		Short Portfolio		Long-Short	
				$\hat{\theta}$	*t-stat*	$\hat{\theta}$	*t-stat*	$\hat{\theta}$	*t-stat*
Rm-Rf	***0.005***	0.044	0.115	-	-	-	-	-0.003	-1.536
LHF	***0.005***	0.046	0.112	-0.001	-0.703	-0.010	-3.283	0.009	4.625
LSF	<u>0.003</u>	0.038	0.074	-0.007	-2.696	-0.002	-0.917	-0.006	-3.547

Table 4 Liquidity-risk hedging/spreading ZIS and MHS

We report regression estimates for the model proposed in our work that contains excess returns on the market factor (Rm – Rf), liquidity-risk hedging factor (LHF) and liquidity-risk spreading factor (LSF) for all the ZIS undertaken in our study:

$$ZIS_{i,t} = \alpha_i + b_i R_{m,t} - R_{f,t} + lh_i LHF_t + ls_i LSF_t + \varepsilon_{i,t}$$

Panel A reports regressions estimates (t-stats) for the model alpha and the model factors for the liquidity-risk hedging ZIS. The last column provides the r-squared (adjusted r-squared) for each time-series regression. Panel B repeats the same for liquidity-risk spreaders accordingly.

Panel A: Liquidity-risk hedgers

ZIS	Constant	$R_m - R_f$	LHF	LSF	r-squared
VAR	-0.003	-0.122	1.583	0.054	0.898
	(-2.733)	(-4.340)	(38.005)	(1.191)	(0.897)
QMJ	0.003	0.020	0.609	-0.334	0.752
	(3.006)	(0.808)	(16.526)	(-8.278)	(0.751)
MOM	0.004	0.244	1.189	0.548	0.238
	(1.552)	(3.587)	(11.741)	(4.932)	(0.235)
OP	-0.002	0.117	0.731	-0.050	0.617
	(-1.678)	(4.117)	(17.289)	(-1.072)	(0.615)
NSI	0.003	-0.168	0.485	0.238	0.370
	(2.267)	(-5.527)	(10.731)	(4.795)	(0.367)
OS	0.001	0.0162	0.171	-0.462	0.437
	(0.660)	(-0.529)	(3.748)	(-9.265)	(0.434)
ALH	0.001	0.018	0.794	-0.001	0.969
	(3.366)	(2.505)	(74.321)	(-0.094)	(0.968)

Panel B: Liquidity-risk spreaders

ZIS	Constant	$R_m - R_f$	LHF	LSF	r-squared
	-0.002	0.419	-0.391	0.811	0.807
BETA	(-1.398)	(12.967)	(-8.139)	(15.402)	(0.806)
	-0.000	-0.178	0.280	1.161	0.705
ILLLIQ	(-0.008)	(-7.621.)	(8.075)	(30.540)	(0.704)
	0.001	-0.318	0.040	1.271	0.779
SIZE	(0.941)	(-12.610)	(1.073)	(30.949)	(0.778)
	0.001	0.228	-0.0217	0.322	0.144
STR	(0.671)	(4.149)	(-0.266)	(3.596)	(0.139)
	0.001	-0.297	0.347	1.204	0.395
LTR	(0.446)	(-6.773)	(5.310)	(16.810)	(0.392)
	0.001	-0.148	0.325	1.024	0.320
BM	(0.636)	(-3.413)	(5.048)	(14.496)	(0.317)
ALS	0.000	-0.049	0.097	0.964	0.934
	(1.084)	(-5.123)	(6.789)	(61.886)	(0.934)

Table 5 Overall performance of the AP models.

We present a model comparison of the tested model specifications in our study. The first metric is Gibbons, Ross and Shanken (1986, GRS) F-test, which tests if the model alphas are jointly zero, and is reported in the first column. Respective p-values are reported in [] under column heading p-values. Next, we present the absolute average of model-alphas for each model under the column heading of $A|\alpha_i|$. Lastly AR^2_{Adj} averages the adjusted R^2 for each type of test asset. All model statistics are calculated for the FF3 model, Carhart model, FF5 model, q4 model and SY model. Panel A produces these stats for liquidity-risk hedgers and panel B repeats them for liquidity-risk spreaders.

	Full Sample				DOWN				UP			
	GRS-test	p-values	$A\|\alpha_i\|$	AR^2_{Adj}	GRS-test	p-values	$A\|\alpha_i\|$	AR^2_{Adj}	GRS-test	p-values	$A\|\alpha_i\|$	AR^2_{Adj}
Panel A: Liquidity-risk hedgers												
FF-3 Model	14.095	[0.000]	0.009	0.448	1.252	[0.285]	0.005	0.489	14.841	[0.000]	0.008	0.455
Carhart Model	9.545	[0.000]	0.006	0.586	1.274	[0.274]	0.006	0.634	8.780	[0.000]	0.006	0.585
FF5 Model	9.786	[0.000]	0.005	0.582	1.752	[0.109]	0.007	0.667	12.104	[0.000]	0.006	0.572
HXZ Model	6.207	[0.000]	0.004	0.551	6.207	[0.000]	0.006	0.551	6.262	[0.000]	0.004	0.543
SY Model	2.308	[0.025]	0.002	0.588	1.697	[0.122]	0.006	0.656	2.938	[0.005]	0.003	0.578
MHS Model	4.405	[0.000]	0.002	0.610	1.514	[0.175]	0.004	0.715	3.998	[0.000]	0.003	0.585
Panel B: liquidity-risk spreaders												
FF-3 Model	2.050	[0.047]	0.002	0.629	1.646	[0.135]	0.005	0.686	2.108	[0.041]	0.002	0.611
Carhart Model	1.593	[0.135]	0.001	0.650	1.652	[0.133]	0.005	0.702	1.677	[0.112]	0.002	0.634
FF5 Model	0.803	[0.585]	0.001	0.653	1.706	[0.120]	0.006	0.713	1.014	[0.420]	0.001	0.637
HXZ Model	0.872	[0.603]	0.001	0.593	1.025	[0.431]	0.007	0.630	1.168	[0.320]	0.001	0.573
SY Model	1.786	[0.087]	0.002	0.577	1.726	[0.115]	0.005	0.616	1.217	[0.291]	0.002	0.566
MHS Model	0.559	[0.789]	0.001	0.581	1.425	[0.207]	0.004	0.663	0.594	[0.761]	0.001	0.560

Table 6 Factor spanning

Panel A presents alpha estimates for the non-overlapping factor among the competing models. The underlined, bold and bold & italic alpha estimates are significant at 0.1, 0.05 and 0.01 significance levels, respectively. For example, we estimate the unexplained return for the value factor for all the models except the FF5 model: HML is not contained by HXZ, SY and MHS models. The alpha for the size factors of FF5 and HXZ are estimated even for the SY model because the size factor in the SY model is constructed with different breakpoints relative to breakpoints taken in the computation of size factors in FF5 and HXZ models. In Panel B, the Gibbons-Ross-Shanken (1989) based F-statistics signifying the join test of zero alphas for the factors of one model on another model is shown, with the p-value are shown below in the parenthesis. The model included is the five-factor model of Fama and French (2015), shown as FF5, with the factors such as SMB, HML, RMW and CMA. The four-factor model of Hou, Xue and Zhang (2015a), shown as HXZ with the factors such as SMB, IA and ROE. The four-factor mispricing model of Stambaugh and Yuan (2017), shown as SY with the factors such as SMB, MGMT and PERF. The construction of the size factor of SY is particularly different from other models. Lastly, the factors included in the model MHS are LHF and LSF. The sample period is from July 1963 to December 2016.

	Model-Based Alphas for Factors			
Panel A: Dependent variables	FF5	HXZ	SY	MHS
Factors in FF5				
SMB	-	-	0.001	0.001
HML	-	0.001	0.000	0.001
RMW	-	0.000	0.001	0.000
CMA	-	0.000	-0.001	***0.002***
Factors in HXZ model				
SMB	-	-	-0.000	0.001
IA	***0.001***	-	0.001	***0.003***
ROE	***0.005***	-	***0.003***	***0.003***
Factors in SY model				
SMB	***0.002***	***0.002***	-	***0.002***
MGMT	***0.003***	***0.004***	-	***0.004***
PERF	***0.007***	***0.003***	-	<u>0.003</u>
Factors in MHS				
LHF	***0.005***	***0.003***	<u>0.002</u>	-
LSF	-0.001	0.001	0.000	-
Panel B: Average alphas from factor spanning regressions				
$A\|\alpha_i\|$	0.002	0.001	0.001	0.001
Panel C: GRS F-Statistics (p-value)				
SMB, HML, RMW, CMW	-	0.986	0.846	2.183
		(0.466)	(0.619)	(0.007)
SMB, IA, ROE	15.419	-	5.560	11.399
	(0.000)		(0.000)	(0.002)
SMB, MGMT, PERF	24.691	13.933	-	14.797
	(0.000)	(0.003)		(0.003)
LHF, LSF	19.116	8.517	2.269	-
	(0.000)	(0.000)	(0.005)	

Table 7 Cross-sectional risk premiums using size-BM test portfolios

This table presents the risk premiums related estimates using the two-pass methodology proposed by Black, Jensen, and Scholes (1972) using 25- size and book-to-market (SBM) test portfolios. Under GRS, the Gibbons-Ross-Shanken (1989) based F-statistics signifying the join test of zero alphas for the factors various models are shown, with the p-value are shown below in the parenthesis. The risk premium associated with market beta is shown as λ_M, whereas the risk premiums associated with other betas factors of SMB, HML, WML, CMA, IA, ROE, MGMT, PFRF, LHF and LSF are shown as λ_{SMB}, λ_{HML}, λ_{UMD}, λ_{RMW}, λ_{CMA}, λ_{IA}, λ_{ROE}, λ_{MGMT}, λ_{PERF}, λ_{LRH}, and λ_{LRS} respectively. In the last column, the r-squared (R^2) and adjusted r-squared (AR^2) are shown.

	GRS F-test (p-value)	λ_M	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{RMW}	λ_{CMA}	λ_{IA}	λ_{ROE}	λ_{MGMT}	λ_{PERF}	λ_{LRH}	λ_{LRS}	R^2 AR^2
FF3	3.936	0.005	0.003	0.004										55.750
	0.000	(9.462)	(4.001)	(5.727)										(49.429)
Carhart	3.298	0.006	0.003	0.004	0.033									76.589
	0.000	(13.108)	(5.243)	(7.721)	(4.024)									(71.907)
FF5	3.236	0.004	0.003	0.004		0.004	0.001							71.877
	0.000	(9.473)	(5.342)	(5.248)		(1.936)	(0.532)							(64.476)
HXZ	3.451	0.005	0.004					0.004	0.004					65.995
	0.000	(9.642)	(5.300)					(6.853)	(1.863)					(59.194)
SY	2.003	0.005	0.004							0.007	0.012			83.127
	0.003	(16.144)	(8.421)							(8.633)	(3.765)			(79.752)
MHS	2.506	0.005										0.006	0.004	81.096
	0.000	(14.654)										(6.430)	(7.810)	(78.395)

Table 8 Cross-sectional risk premiums using size-MOM test portfolios

This table presents the risk premiums related estimates using the two-pass methodology proposed by Black, Jensen, and Scholes (1972) using 25- size and momentum (SMOM) test portfolios. Under GRS, the Gibbons-Ross-Shanken (1989) based F-statistics signifying the join test of zero alphas for the factors various models are shown, with the p-value are shown below in the parenthesis. The risk premium associated with market beta is shown as λ_M, whereas the risk premiums associated with other betas factors of SMB, HML, WML, CMA, IA, ROE, MGMT, PFRF, LHF and LSF are shown as λ_{SMB}, λ_{HML}, λ_{UMD}, λ_{RMW}, λ_{CMA}, λ_{IA}, λ_{ROE}, λ_{MGMT}, λ_{PERF}, λ_{LRH}, and λ_{LRS} respectively. In the last column,, the r-squared (R^2) and adjusted r-squared (AR^2) are shown.

	GRS F-test (p-value)	λ_M	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{RMW}	λ_{CMA}	λ_{IA}	λ_{ROE}	λ_{MGMT}	λ_{PERF}	λ_{LRH}	λ_{LRS}	R^2 AR^2
FF3	5.248	0.006	0.004	-0.007										-2.319
	0.000	(4.595)	(2.148)	(-1.853)										(-16.936)
Carhart	3.974	0.006	0.002	0.006	0.008									85.110
	0.000	(12.094)	(3.471)	(3.192)	(10.244)									(82.132)
FF5	4.424	0.006	0.004	-0.005		0.001	0.010							88.560
	0.000	(10.436)	(5.890)	(-2.548)		(0.403)	(2.126)							(85.550)
HXZ	2.762	0.005	0.005					0.002	0.007					88.196
	0.000	(12.930)	(8.129)					(1.331)	(10.215)					(85.836)
SY	2.859	0.006	0.004							0.003	0.007			85.919
	0.000	(13.473]	(5.972)							(2.006)	(7.546)			(83.103)
MHS	3.028	0.006										0.006	0.004	78.768
	0.000	(10.977)										(5.385)	(4.236)	(75.735)

Table 9 Cross-sectional risk premiums using size-BM and size-MOM test portfolios

This table presents the risk premiums related estimates using the two-pass methodology proposed by Black, Jensen, and Scholes (1972) using 25- size and book-to-market (SBM), 25-size and momentum (SMOM) test portfolios. Under GRS, the Gibbons-Ross-Shanken (1989) based F-statistics signifying the join test of zero alphas for the factors various models are shown, with the p-value are shown below in the parenthesis. The risk premium associated with market beta is shown as λ_M, whereas the risk premiums associated with other betas factors of SMB, HML, WML, CMA, IA, ROE, MGMT, PFRF, LHF and LSF are shown as λ_{SMB}, λ_{HML}, λ_{UMD}, λ_{RMW}, λ_{CMA}, λ_{IA}, λ_{ROE}, λ_{MGMT}, λ_{PERF}, λ_{LRH}, and λ_{LRS} respectively. In the last column, the r-squared (R^2) and adjusted r-squared (AR^2) are shown.

	GRS F-test (p-value)	λ_M	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{RMW}	λ_{CMA}	λ_{IA}	λ_{ROE}	λ_{MGMT}	λ_{PERF}	λ_{LRH}	λ_{LRS}	R^2 (AR^2)
FF3	4.495	0.005	0.003	0.003										-12.149
	0.000	(6.552)	(2.873)	(1.831)										(-19.463)
Carhart	3.798	0.006	0.002	0.004	0.008									77.526
	0.000	(16.644)	(5.636)	(6.816)	(10.540)									(75.528)
FF5	3.924	0.005	0.003	0.002		0.001	0.011							59.361
	0.000	(9.801)	(4.841)	(1.714)		(0.493)	(4.387)							(57.227)
HXZ	3.373	0.005	0.005					0.004	0.006					78.992
	0.000	(15.614)	(10.117)					(7.754)	(9.662)					(77.125)
SY	2.991	0.006	0.004							0.005	0.006			81.516
	0.000	(18.931)	(9.161)							(7.987)	(8.644)			(79.873)
MHS	3.249	0.005										0.006	0.004	78.206
	0.000	(17.237)										(7.892)	(7.567)	(76.784)

Table 10 Cross-sectional risk premiums using size-BM, size-MOM and industry portfolios

This table presents the risk premiums related estimates using the two-pass methodology proposed by Black, Jensen, and Scholes (1972) using 25- size and book-to-market (SBM), 25-size and momentum (SMOM) test portfolios and 48 Fama and French industry portfolios. Under GRS, the Gibbons-Ross-Shanken (1989) based F-statistics signifying the join test of zero alphas for the factors various models are shown, with the p-value are shown below in the parenthesis. The risk premium associated with market beta is shown as λ_M, whereas the risk premiums associated with other betas factors of SMB, HML, WML, CMA, IA, ROE, MGMT, PFRF, LHF and LSF are shown as λ_{SMB}, λ_{HML}, λ_{UMD}, λ_{RMW}, λ_{CMA}, λ_{IA}, λ_{ROE}, λ_{MGMT}, λ_{PERF}, λ_{LRH}, and λ_{LRS} respectively. In the last column, the r-squared (R^2) and adjusted r-squared (AR^2) are shown.

	GRS F-test (p-value)	λ_M	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{RMW}	λ_{CMA}	λ_{IA}	λ_{ROE}	λ_{MGMT}	λ_{PERF}	λ_{LRH}	λ_{LRS}	R^2 (AR^2)
FF3	10.75	-0.007	0.003	0.001										0.234
	(0.00)	(-3.33)	(4.59)	(1.39)										(0.21)
Carhart	9.93	-0.002	0.003	0.002	0.006									0.367
	(0.00)	(-0.99)	(4.99)	(2.54)	(4.81)									(0.34)
FF5	10.63	-0.006	0.003	0.002		-0.002	0.004							0.260
	(0.00)	(-2.17)	(4.39)	(1.46)		(-1.93)	(2.14)							(0.22)
HXZ	8.13	-0.005	0.004					0.001	0.001					0.290
	(0.00)	(-2.29)	(5.42)					(1.52)	(1.33)					(0.26)
SY	8.49	-0.002	0.004							0.003	0.004			0.313
	(0.00)	(-0.96)	(5.70)							(2.96)	(3.10)			(0.28)
MHS	9.52	-0.005										0.002	0.003	0.238
	(0.00)	(-1.79)										(1.71)	(3.36)	(0.21)

Supplementary results for "Asset pricing anomalies – liquidity risk spreaders or liquidity risk hedgers?"

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This appendix discusses the robustness tests for sections 3.4 and 4.2, wherein the results of tables 2 and 4 are replicated for factors in the competing asset pricing models and models as well, respectively. These models are Fama and French (1996) three-factor model, Carhart (1997) four-factor model, the five-factor model of Fama and French (2015), Hou, Xue, and Zhang (2015) q-factor model, and lastly the Stambaugh and Yuan (2017) SY model. To keep the consistency with the paper, there are two sets of anomalies that are tested in this appendix. One set is composed of liquidity risk-hedgers such as Return Variance (VAR), Quality-minus-Junk (QMJ), Momentum (MOM), Operating Profitability (OP), Net Share Issue (NSI) and Ohlson-score (OS). The second set is composed of liquidity-risk spreaders CAPM beta (BETA), Firm capitalization (SIZE), Stock illiquidity (ILLQ), Short-term reversal (STR), Long-term reversal (LTR), Book-to-Market equity ratio (BM).

Factor return variation across varying market liquidity conditions

We examine the return variation in prominent factors, in the competing factor models, across the aggregate liquidity risk quintiles. These results are presented in table A-I. The reported liquidity betas for the factors show a discernible division among factors: only Rm-Rf, SMB and LSF have positive liquidity betas. Furthermore, the return variation of these risk factors resembles what we saw for LS ZIS.

All remaining risk factors describe liquidity risk hedging motives in line with the sign on their liquidity betas: exposures to changes to market liquidity are highly significant except for HML, WML and CMA. Nonetheless, the return variation in these factors is rather aligned to the return variation seen for LH ZIS: average returns on these risk factors are large in Q1 and small in Q5. Only divergence is seen for the return variation, across quintiles, for value anomaly and value factor. This result describes the confounding and conflicted nature of return variation linked to the value anomaly and support Daniel and Titman (2006) assertion that BM is a "catch-all" variable; one that will proxy for numerous aggregate shocks resulting in distinctive sensitivities on high and low BM stocks. This is further supported by the fact that the value factor liquidity beta is positive yet is insignificantly estimated.

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Performance of competing models for Liquidity risk hedging and liquidity risk spreading anomalies

Table A-II summarizes the results for the Fama and French (1993) three-factor model. The main reason for the failure of FF3 models is its inability to price the liquidity risk-hedgers as is indicated in panel A of table A-II. As shown in table A-I in this appendix that the market factor, R_m – R_f and the size factor, SMB are positively exposed to market liquidity. Therefore, the liquidity risk-hedgers are negatively exposed to these factors and these results in significant alphas associated with the FF3 model for liquidity risk hedgers. The ALH strategy, which is the average of liquidity risk-hedgers, related returns portray this effect succinctly: alpha is economically meaningful and statistically reliable. The exposure of ALH towards market and size factors is negative and significant, whereas for HML it is insignificant. In panel B, for the liquidity risk-spreaders, the performance of FF3 significantly improves and for most liquidity risk-spreading strategies FF3 model alphas are small and insignificant. We see no reason that the performance of the FF3 model for any spreader strategy may be adversely affected, as the FF3 model summarizes factor variations that are required to price these strategies.

Any model that includes the factors that have negative exposure towards market liquidity, as is indicated in table A-I, is destined to perform better than the FF3 model for liquidity risk-hedger strategies. Accordingly, Carhart (1997) model has performed better than the FF3 model. The pricing error of ALH reduces from 0.009 (given by the FF3 model) to .006 (given by the Carhart model) as per panel A of table A-III. On the other hand, the FF5 (2015) model includes two factors RMW and CMW in addition to three factors of FF3, whereas both newly included factors are negatively exposed to market liquidity. Similarly, the performance of the FF5 model is better than FF3, and the pricing errors have been reduced to 0.005 for ALH as per panel A of table A-IV. Although these pricing errors are still significant. The model proposed by Hou, Xue and Zhang (2015) the q-factor model has two factors IA and ROE in addition to market and size that have a significant and negative relationship with market liquidity. This model has further reduced the pricing errors for liquidity risk-hedgers and the ALH has pricing errors of .004 as per panel A of table IV. Lastly, the model purported by Stambaugh and Yuan (2017), the SY model also has two factors MGMT and PREF in addition to market and size that are negatively and significantly related to market liquidity. Resultantly, most liquidity risk-hedgers are positively exposed to these mispriced factors and this positive exposure has reduced the pricing errors for the liquidity risk-hedgers.

The SY has reduced the pricing errors as per panel A of table VI, in the most prominent way in comparison to the models such as FF5, q-factor that also have two factors which are negatively exposed to market liquidity. It is not mainly because of the higher positive exposure of these liquidity risk-hedgers towards MGMT and PREF factors of the SY model. Instead, the average returns on these factors are pertinently higher than RMW, CMW of FF5 and IA, ROE of q-factor, this helps in reducing the pricing errors for the SY model. Lastly, the performance of all these models in comparison to FF3 for liquidity risk-spreaders is not that high as is in the case of liquidity risk-hedgers. These results are shown in panel B of the respective tables. The slight improvement in the performance is because of the overpricing of spreaders by FF3 model. As these spreaders are now mostly negatively exposed to additional factors that are included in other models, therefore, the overall pricing errors are small.

Factors and investor sentiment – Summary discussion

These results, reported in table A.VII, show that most factors are influenced by mispricing: increasing sentiment in the prior periods predict high returns for nine out of 12 factors analyzed in our work. The positive sign on the WML factor is insignificant, otherwise, the remaining eight (leaving aside market, size and LS factors) have precise positive sentiment predictions that are significant at 0.1 or below critical t-values. Here, we note that size and LSF i.e., risk factors, to the extent that investor sentiment describes mispricing, are negatively influenced by investor sentiment. Market factor also has negative prediction but the coefficient on investor sentiment is imprecise. The negative slopes on investor sentiment imply that these factors are expected to have high returns following low levels of sentiment, compared to the opposite sentiment prediction for factors that are positively influenced by investor sentiment.

A-I Factor aggregate liquidity sensitivities and return dispersion across market liquidity quintiles

The table presents the relationship between AP factors from different models and time-varying market liquidity by estimating the following equation,

$$F_{i,t} = \beta_0 + \beta_L s\_liq_{mkt,t} + e_{i,t}$$

where $F_{i,t}$ is the excess return on a particular factor. The results are reported for $R_m - R_f$, *SMB* and *HML* belong to FF-3 model, WML is taken from Carhart (1996) model, *RMW* and *ROE* are coming from FF5 model, *IA* and *ROE* factors are from the q-model of Hou et al. (2015) and *MGMT* and *PREF* are the mispricing based factors coming from the Stambaugh and Yuan's (2017) model. $s\_liq_{mkt,t}$ are shocks to market liquidity estimated using Amihud (2002) price impact measure. The coefficients on changes to market liquidity are reported under β_L(first column) and t-statistics are presented below in (). The second column under heading Avg. provides sample average returns for each ZIS. Headings Q1, Q2, Q3, Q4 and Q5 present excess average returns for each factor across market liquidity related quintiles, which increase in liquidity: Q1 is the first quintile, which accumulates the most illiquid (negative) shocks to market liquidity and Q5, gathers data points when the market has witnessed the most liquid (positive) shocks. Each succeeding quintile is 20% less risky in terms of unexpected changes in estimated market liquidity.

	β_L	Avg.	Q1	Q2	Q3	Q4	Q5
Rm – Rf	0.011 (6.251)	0.005	***-0.015***	***0.003***	0.004	***0.011***	***0.023***
SMB	0.006 (4.782)	0.003	***-0.010***	-0.001	0.002	***0.007***	***0.015***
HML	-0.001 (-0.497)	0.004	0.004	0.004	0.005	***0.006***	-0.001
WML	-0.003 (-1.567)	0.007	***0.005***	***0.009***	***0.009***	***0.007***	0.002
RMW	-0.002 (-2.413)	0.002	***0.006***	0.001	0.002	0.002	0.001
CMA	-0.001 (-1.242)	0.003	***0.005***	***0.005***	0.003	***0.004***	-0.001
IA	-0.002 (-2.025)	0.004	***0.006***	***0.005***	***0.004***	***0.004***	0.001
ROE	-0.003 (-3.134)	0.005	***0.009***	***0.007***	***0.006***	0.002	0.003
MGMT	-0.003 (-2.981)	0.006	***0.013***	***0.008***	0.005	0.004	-0.002
PERF	-0.004 (-2.469)	0.007	***0.011***	***0.007***	***0.009***	0.003	0.004
LHF	-0.012 (-6.800)	0.005	***0.024***	***0.012***	0.006	-0.002	***-0.014***

LSF	0.008 (5.201)	0.003	***-0.012***	-0.004	0.002	***0.009***	***0.020***

A-II Liquidity risk hedging/spreading ZIS and FF3 Model

This table replicates table 4 in the paper using the FF3 model of Fama and French (1996) for all the ZIS undertaken in our study:

$$ZI_{i,t} = \alpha_i + b_i R_{m,t} - R_{f,t} + s_i SMB_t + h_i HML_t + \varepsilon_{i,t}$$

Panel A reports regressions estimates (t-stats) for the model alpha and factors for the liquidity risk-hedging ZIS. The last column provides the r-squared (adjusted r-squared) for each time series regression. Panel B repeats the same for liquidity risk spreaders accordingly.

Panel A: Liquidity risk hedgers					
ZIS	Alpha	$R_m – R_f$	SMB	HML	r-squared
VAR	0.010	-0.746	-1.262	0.581	0.638
	(5.094)	(-16.471)	(-19.790)	(8.473)	(0.636)
QMJ	0.010	-0.399	-0.776	-0.304	0.536
	(8.423)	(-13.689)	(-18.908)	(-6.893)	(0.534)
MOM	0.017	-0.348	-0.036	-0.534	0.072
	(6.159)	(-5.385)	(-0.393)	(-5.451)	(0.068)
OP	0.005	-0.240	-0.643	-0.032	0.358
	(4.081)	(-7.593)	(-14.432)	(-0.669)	(0.355)
NSI	0.005	-0.236	-0.221	0.563	0.467
	(4.558)	(-9.834)	(-6.528)	(15.467)	(0.464)
OS	0.004	-0.179	-0.750	-0.247	0.509
	(4.104)	(-7.296)	(-21.685)	(-6.656)	(0.507)
ALH	0.009	-0.358	-0.614	0.004	0.573
	(8.807)	(-15.590)	(-18.998)	(0.128)	(0.571)
Panel B: Liquidity risk spreaders					
ZIS	Alpha	$R_m – R_f$	SMB	HML	r-squared
BETA	-0.004	0.748	0.959	-0.406	0.663
	(-2.682)	(20.402)	(18.582)	(-7.306)	(0.661)
ILLLIQ	0.000	-0.039	1.152	0.310	0.835
	(-0.335)	(-2.605)	(54.566)	(13.659)	(0.834)
SIZE	-0.001	-0.084	1.498	0.104	0.870
	(-1.222)	(-5.091)	(64.140)	(4.125)	(0.869)
STR	0.001	0.359	0.144	0.073	0.105
	(0.431)	(7.445)	(2.117)	(1.001)	(0.101)
LTR	-0.001	-0.015	0.752	0.866	0.404
	(-0.472)	(-0.413)	(14.275)	(15.281)	(0.401)

BM	-0.003 (-2.922)	0.195 (8.705)	0.555 (17.657)	1.377 (40.711)	0.755 (0.754)
ALS	-0.001 (-2.073)	0.194 (12.968)	0.843 (40.099)	0.387 (17.127)	0.784 (0.783)

A-III Liquidity risk hedging/spreading ZIS and Carhart Model

This table replicates table 4 in the paper using the Carhart (1997) model:

$$ZI_{i,t} = \alpha_i + b_i R_{m,t} - R_{f,t} + s_i SMB_t + h_i HML_t + w_i WML_t + \varepsilon_{i,t}$$

Panel A reports regressions estimates (t-stats) for the model alpha and factors for the liquidity risk hedging ZIS. The last column provides the r-squared (adjusted r-squared) for each time series regression. Panel B repeats the same for liquidity risk spreaders accordingly.

Panel A: Liquidity risk hedgers						
ZIS	Alpha	$R_m - R_f$	SMB	HML	WML	r-squared
VAR	0.007	-0.691	-1.266	0.685	0.294	0.661
	(3.763)	(-15.490)	(-20.508)	(10.045)	(6.627)	(0.659)
QMJ	0.009	-0.371	-0.778	-0.250	0.152	0.555
	(7.311)	(-12.754)	(-19.347)	(-5.636)	(5.249)	(0.552)
MOM	0.003	-0.065	-0.056	0.003	1.515	0.852
	(2.969)	(-2.481)	(-1.549)	(0.086)	(57.997)	(0.851)
OP	0.005	-0.223	-0.644	0.000	0.090	0.366
	(3.420)	(-6.976)	(-14.538)	(-0.001)	(2.836)	(0.362)
NSI	0.005	-0.237	-0.221	0.561	-0.005	0.467
	(4.494)	(-9.691)	(-6.521)	(14.996)	(-0.190)	(0.463)
OS	0.005	-0.187	-0.749	-0.262	-0.041	0.511
	(4.367)	(-7.489)	(-21.698)	(-6.870)	(-1.668)	(0.508)
ALH	0.006	-0.296	-0.619	0.123	0.334	0.711
	(6.817)	(-15.373)	(-23.258)	(4.179)	(17.474)	(0.709)
Panel B: Liquidity risk spreaders						
ZIS	Alpha	$R_m - R_f$	SMB	HML	WML	r-squared
BETA	-0.002	0.701	0.963	-0.495	-0.251	0.687
	(-1.252)	(19.489)	(19.341)	(-8.994)	(-7.028)	(0.685)
ILLLIQ	0.000	-0.037	1.151	0.313	0.009	0.835
	(-0.453)	(-2.447)	(54.530)	(13.422)	(0.599)	(0.834)
SIZE	-0.001	-0.086	1.498	0.102	-0.005	0.870
	(-1.126)	(-5.060)	(64.095)	(3.935)	(-0.327)	(0.869)
STR	0.004	0.290	0.149	-0.059	-0.371	0.186
	(2.108)	(6.185)	(2.296)	(-0.818)	(-7.976)	(0.181)
LTR	0.000	-0.041	0.754	0.817	-0.137	0.416
	(0.296)	(-1.088)	(14.447)	(14.171)	(-3.649)	(0.413)

	-0.002	0.180	0.557	1.349	-0.078	0.760
BM	(-2.151)	(7.979)	(17.846)	(39.156)	(-3.500)	(0.758)
	0.000	0.168	0.845	0.338	-0.139	0.813
ALS	(-0.114)	(11.838)	(43.115)	(15.606)	(-9.868)	(0.812)

A-IV Liquidity risk hedging/spreading ZIS and FF5 Model

This table replicates table 4 using the FF5 model of Fama and French (2015):

$$ZI_{i,t} = \alpha_i + b_i R_{m,t} - R_{f,t} + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{i,t}$$

Panel A reports regressions estimates (t-stats) for the model alpha and factors for the liquidity risk hedging ZIS. The last column provides the r-squared (adjusted r-squared) for each time series regression. Panel B repeats the same for liquidity risk spreaders accordingly.

Panel A: Liquidity risk hedgers

ZIS	Alpha	$R_m - R_f$	SMB	HML	RMW	CMA	r-squared
VAR	0.004	-0.561	-1.008	0.114	1.144	1.010	0.738
	(2.364)	(-13.643)	(-17.638)	(1.447)	(14.551)	(8.617)	(0.736)
QMJ	0.007	-0.305	-0.563	-0.428	0.936	0.255	0.717
	(6.795)	(-12.553)	(-16.664)	(-9.165)	(20.129)	(3.673)	(0.714)
MOM	0.014	-0.244	0.072	-0.843	0.492	0.674	0.103
	(5.022)	(-3.597)	(0.759)	(-6.468)	(3.786)	(3.484)	(0.096)
OP	0.001	-0.132	-0.352	-0.114	1.275	0.156	0.758
	(1.011)	(-6.355)	(-12.200)	(-2.871)	(32.141)	(2.636)	(0.756)
NSI	0.003	-0.171	-0.178	0.337	0.205	0.495	0.512
	(2.988)	(-6.975)	(-5.206)	(7.153)	(4.372)	(7.076)	(0.508)
OS	0.004	-0.197	-0.704	-0.108	0.188	-0.312	0.540
	(4.087)	(-7.769)	(-19.955)	(-2.220)	(3.862)	(-4.310)	(0.536)
ALH	0.005	-0.268	-0.455	-0.174	0.707	0.380	0.729
	(6.836)	(-13.737)	(-16.771)	(-4.629)	(18.907)	(6.815)	(0.727)

Panel B: 5-Liquidity risk spreaders

ZIS	Alpha	$R_m - R_f$	SMB	HML	RMW	CMA	r-squared
	-0.002	0.655	0.865	-0.126	-0.431	-0.610	0.690
BETA	(-1.002)	(17.465)	(16.592)	(-1.752)	(-6.012)	(-5.700)	(0.688)
	-0.001	-0.031	1.171	0.300	0.085	0.020	0.837
ILLLIQ	(-0.831)	(-1.939)	(52.950)	(9.828)	(2.798)	(0.441)	(0.836)
	0.000	-0.098	1.440	0.084	-0.251	0.048	0.882
SIZE	(-0.150)	(-5.809)	(61.522)	(2.608)	(-7.780)	(0.997)	(0.881)
	0.002	0.323	0.143	0.227	-0.013	-0.342	0.113
STR	(0.755)	(6.310)	(2.013)	(2.313)	(-0.129)	(-2.340)	(0.106)
	-0.001	0.026	0.655	0.554	-0.401	0.698	0.481
LTR	(-0.482)	(0.704)	(12.630)	(7.739)	(-5.626)	(6.565)	(0.477)

	-0.002	0.167	0.472	1.383	-0.366	-0.005	0.781
BM	(-1.647)	(7.421)	(15.034)	(31.923)	(-8.490)	(-0.080)	(0.779)
ALS	0.000	0.174	0.791	0.404	-0.230	-0.032	0.804
	(-0.765)	(11.429)	(37.401)	(13.825)	(-7.888)	(-0.731)	(0.802)

A-V Liquidity risk hedging/spreading ZIS and q-factor model

This table repeats estimations in table 4 using the q-model of Hou, Xue, and Zhang (2014):

$$ZI_{i,t} = \alpha_i + b_i R_{m,t} - R_{f,t} + m_i ME_t + i_i IV_t + r_i ROE_t + \varepsilon_{i,t}$$

Panel A reports regressions estimates (t-stats) for the model alpha and factors for the liquidity risk hedging ZIS. The last column provides the r-squared (adjusted r-squared) for each time series regression. Panel B repeats the same for liquidity risk spreaders accordingly.

Panel A: Liquidity risk hedgers

ZIS	Alpha	$R_m - R_f$	ME	I/V	ROE	r-squared
VAR	0.002	-0.655	-0.883	1.120	0.914	0.702
	(1.050)	(-14.799)	(-14.178)	(10.891)	(12.306)	(0.700)
QMJ	0.006	-0.347	-0.568	-0.191	0.768	0.663
	(4.862)	(-12.858)	(-14.957)	(-3.038)	(16.963)	(0.661)
MOM	0.004	-0.173	0.338	0.012	1.495	0.285
	(1.569)	(-2.799)	(3.891)	(0.084)	(14.439)	(0.280)
OP	0.001	-0.188	-0.441	0.026	0.764	0.539
	(0.504)	(-6.496)	(-10.817)	(0.381)	(15.701)	(0.536)
NSI	0.005	-0.239	-0.210	0.730	-0.118	0.421
	(4.060)	(-8.876)	(-5.547)	(11.673)	(-2.618)	(0.417)
OS	0.004	-0.200	-0.700	-0.406	0.220	0.529
	(3.691)	(-7.641)	(-19.012)	(-6.677)	(5.002)	(0.526)
ALH	0.004	-0.300	-0.411	0.215	0.674	0.741
	(4.224)	(-15.379)	(-14.948)	(4.743)	(20.561)	(0.739)

Panel B: Liquidity risk spreaders

ZIS	Alpha	$R_m - R_f$	ME	I/V	ROE	r-squared
BETA	0.000	0.699	0.717	-0.760	-0.493	0.681
	(0.075)	(18.192)	(13.263)	(-8.513)	(-7.652)	(0.679)
ILLLIQ	0.000	-0.043	1.113	0.264	-0.093	0.784
	(-0.241)	(-2.332)	(42.938)	(6.169)	(-2.994)	(0.783)
SIZE	0.001	-0.101	1.357	0.029	-0.355	0.840
	(1.068)	(-5.112)	(48.753)	(0.624)	(-10.699)	(0.839)
STR	0.003	0.319	0.116	-0.081	-0.265	0.128
	(1.295)	(6.190)	(1.596)	(-0.672)	(-3.060)	(0.122)
LTR	0.002	-0.036	0.623	1.163	-0.734	0.480
	(1.076)	(-0.955)	(11.698)	(13.221)	(-11.547)	(0.476)

	0.000	0.130	0.471	1.350	-0.588	0.470
BM	(0.293)	(3.637)	(9.397)	(16.298)	(-9.835)	(0.467)
ALS	0.001	0.161	0.733	0.328	-0.421	0.789
	(1.438)	(10.118)	(32.682)	(8.845)	(-15.753)	(0.788)

A-VI Liquidity risk hedging/spreading ZIS and mispricing-factor SY-model

This table repeats table 4 in the paper using the SY-model of Stambaugh and Yuan (2017):

$$ZI_{i,t} = \alpha_i + b_i R_{m,t} - R_{f,t} + s_i SMB_t + m_i MGMT_t + p_i PREF_t + \varepsilon_{i,t}$$

Panel A reports regressions estimates (t-stats) for the model alpha and factors for the liquidity risk hedging ZIS. The last column provides the r-squared (adjusted r-squared) for each time series regression. Panel B repeats the same for liquidity risk spreaders accordingly.

Panel A: Liquidity risk hedgers						
ZIS	Alpha	$R_m - R_f$	SMB	MGMT	PERF	r-squared
VAR	0.002	-0.444	-0.974	1.115	0.456	0.672
	(0.905)	(-8.910)	(-14.842)	(14.624)	(9.264)	(0.670)
QMJ	0.004	-0.191	-0.645	0.246	0.539	0.615
	(3.214)	(-6.222)	(-15.962)	(5.245)	(17.779)	(0.613)
MOM	0.001	0.088	0.146	0.286	1.347	0.515
	(0.471)	(1.632)	(2.046)	(3.457)	(25.221)	(0.512)
OP	0.000	-0.065	-0.542	0.308	0.456	0.477
	(0.200)	(-1.975)	(-12.477)	(6.111)	(13.994)	(0.474)
NSI	0.001	-0.064	-0.089	0.843	0.035	0.594
	(0.525)	(-2.636)	(-2.800)	(22.722)	(1.468)	(0.592)
OS	0.003	-0.125	-0.718	-0.045	0.238	0.464
	(2.501)	(-4.201)	(-18.381)	(-0.993)	(8.115)	(0.460)
ALH	0.002	-0.133	-0.470	0.459	0.512	0.797
	(2.393)	(-7.293)	(-19.533)	(16.395)	(28.319)	(0.796)
Panel B: Liquidity risk spreaders						
ZIS	Alpha	$R_m - R_f$	SMB	MGMT	PERF	r-squared
BETA	0.000	0.562	0.821	-0.742	-0.220	0.681
	(-0.018)	(13.623)	(15.126)	(-11.775)	(-5.391)	(0.679)
ILLLIQ	-0.001	-0.049	1.203	0.146	-0.115	0.760
	(-1.730)	(-2.349)	(43.707)	(4.570)	(-5.545)	(0.759)
SIZE	-0.001	-0.138	1.445	-0.119	-0.176	0.758
	(-0.797)	(-5.292)	(42.000)	(-2.986)	(-6.813)	(0.757)
STR	0.006	0.183	0.142	-0.225	-0.431	0.194
	(2.886)	(3.466)	(2.042)	(-2.785)	(-8.251)	(0.189)
LTR	-0.002	0.028	0.851	0.778	-0.362	0.390
	(-0.952)	(0.641)	(14.757)	(11.615)	(-8.355)	(0.386)

BM	-0.001 (-0.855)	0.160 (4.434)	0.713 (15.017)	0.912 (16.526)	-0.481 (-13.498)	0.522 (0.519)
ALS	0.000 (0.199)	0.124 (6.662)	0.863 (35.138)	0.125 (4.380)	-0.297 (-16.137)	0.749 (0.747)

A.VII Factors and investor sentiment

The table reports the estimates of θ from the following regression:

$$R_{i,t} = \mu_i + \theta_i S_{t-1} + \epsilon_{i,t}$$

where $R_{i,t}$ is the monthly excess return the market factor (Rm-Rf) and the long-short difference for each of the factors (SMB, HML, WML, RMW, CMA, IA, ROE, MGMT, PERF, LRH and LRS) and S_{t-1} is the previous month's level of the investor-sentiment index of Baker and Wurgler (2006). The sample period is 196307-20109.

	Rm-Rf	SMB	HML	WML	RMW	CMA	IA	ROE	MGMT	PERF	LRH	LRS
$\hat{\theta}$	-0.003	-0.004	0.002	0.000	0.003	0.002	0.001	0.002	0.005	0.003	0.009	-0.006
t-stat	-1.536	-2.939	1.767	0.131	3.495	2.170	1.878	1.881	4.011	1.939	4.625	-3.547

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