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Illiquidity, Investor Sentiment and Stock Returns: Evidence from Malaysia

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ABSTRACT

Market illiquidity (ILQ) and investor sentiment (IS) show a significant role in Malaysian capital market, the variation of average stock returns left unexplained by capital asset pricing model is covered effectively by ILQ and sentiment risks. Our IS measure consists of six market proxies. This study tests pricing implications using size, liquidity and BM ranked portfolios. It finds that small and illiquid stocks are exposed more to sentiment risk. ILQ and sentiment factors jointly explain the variations explained by size and value effects. Furthermore, quantile regressions reveal an asymmetric influence of IS, a large (small) effect is observed on stocks with high (low) returns. A three factor model directed at capturing ILQ and IS risks is apparently persuasive in this market.

Keywords: Asset Pricing, Investor Sentiment, Illiquidity
JEL Classifications: G10, G12

1. INTRODUCTION

Instead of being left behind, we observe a replicating pattern of outperforming large firms in Malaysian market during post-2000 period. More importantly, while the small premium has been reversed, size effect persists. One could explain a reversal through change in fundamentals, yet a potential argument is the change in investor behavior. Prior evidence of small premium would have contributed to the inversion, indicating a role of irrationality in markets. An inversion may read investor behavior, and perhaps, may be explained by the pricing effects of herding and sentiment. Literature on behavioral asset pricing argues that sentiment risk limits arbitrage activity of rational traders (DeLong et al., 1990). Hence, not only the systematic risk, the irrational component of sentiment risk should show a link to asset prices. One of the limitations in understanding pricing implications of investor sentiment (IS) in emerging markets is unavailability of definitive sentiment measures. In their influential papers, Baker and Wurgler (2006; 2007) present an aggregate sentiment index following an indirect approach. However, the indices aroused in US markets may impound their applications in emerging context due to inherent limitations. For instance, volumes and activity of derivatives market serves proxy of sentiment changes efficiently in developed markets than the under-developed. Similarly, low trading frequency may cause proxies inefficient in capturing investor behavior. For instance, closed end fund discount used by Baker and Wurgler (2007) is less appropriate in Malaysian stock market because trading by closed end funds are in an early stage. Practitioners in emerging markets also suffer from limited empirical evidence problem. Yang and Li (2013) point that sentiment based asset pricing models are still in the exploratory stage. Yet, expectation of a completely rational measurement for irrational human decisions is unreasonable, as evident in many studies including that of Feldman (2010) and Li and Yu (2012) who demonstrate different methods of sentiment measures.

Size effect (Banz, 1981) has received empirical support and the three factor pricing model of Fama and French (1993) accommodates the effect in small minus big (SMB). However, Fama and French (2015) recognize that three factor model (1993) misses much of the variation of the average returns and introduce two more factors, profitability and investment. According to Agarwal (2010) size factor of Fama and French (1993) is indeed a proxy for financial distress risk. Liu (2006) argue that the association of smaller stocks with higher returns is due to liquidity risk in small firms. Small stocks are relatively illiquid, thus small premium's source is illiquidity (ILQ). Meanwhile, Malaysian evidence (Jais and Gunathilaka, 2016) suggests a primacy in ILQ risk factor in multiple factor pricing models. Size is exposed to ILQ characteristics of the asset. Moreover, while there is no "best practice" asset valuation suggestion (Foong and Goh, 2010), investor biasness is strong (Jarita and Salina, 2009) in Malaysian market.

Our attept in this paper is to show the role and pricing implications of IS, ILQ changes, and the popular size and value patterns. We test the performance of an alternative three factor model directed at capturing return variations due to IS and ILQ risks. In this effort, a six-variable composite sentiment index is used, and this unique index demonstrates robustness in multiple factor arbitrage pricing theory (APT, Ross, 1976) models. Results of pricing model tests are sensitive to risk characteristics of the test assets. Thus, we apply the models to assets formed on size and liquidity independently, and also on SBM double sorted assets. This procedure ensures that the effect of individual risk characteristics do represent well in the portfolios formed. The idea of this article is to demonstrate pricing consequences of ILQ and IS, and examine size and value effects in Malaysian market.

We begin with a literature review (section 2), and discuss our sentiment index in section 3. Section 4 specifies risk factors and methods of analysis with summary statistics. Empirical pricing model and summary of test portfolios formed are detailed in section 5. Results are demonstrated in section 6, and we offer conclusions in the section 7.

2. RELATED LITERATURE

Asset pricing has a task of examining how expected returns are related to risk and to investor misevaluations (Hirshleifer, 2001) while acknowledging that the pricing models are bound imperfect. Baker and Wurgler (2006) present evidence that IS has strong effects on cross-section of stock prices. Sentiment may play a significant role in identifying subsequent herding (Liao et al., 2011). Baker and Wurgler (2006; 2007) capture IS by 6 time series proxies of sentiment; Trading volume, premium for dividend paying stocks, closed-end fund discount, number of initial public offers, first-day IPO returns and equity issues for total issues. Huang et al. (2013) argue that the sentiment index of Baker and Wurgler (2007) underestimates predictive power due to the method of deriving the index. Researchers in other markets make use of different sentiment proxies, turnover ratio (TR) (Jun et al., 2003), change in margin borrowing and put-call ratio (Brown and Cliff, 2004), advance-decline ratio (ADR) (Finter et al., 2011), buy and sell imbalance ratio (Kumar and Lee, 2006), share turnover velocity (Mahakud and Dash, 2012), net cash flows to equity funds (Randall et al., 2003), institutional churn (Chae et al., 2008) and number of new stock accounts (Changsheng and Yongfeng, 2012) are examples. IS, whether rational or irrational, may influence stock prices according to the stock's sensitivity to risk characteristics, for instance size and liquidity. Overconfident traders can outperform informed traders in an imperfect market (Kyle and Wang, 1997). A growing body of research (e.g. Brown and Cliff, 2004; Baker and Wurgler, 2006; 2007; Kumar and Lee, 2006; Finter et al., 2011; Chung et al., 2012) provides evidence of pricing implications. These studies apply both direct and indirect methods in measuring market wide irrational sentiment.

Fama and French (1993) three factor (FF 3F) model has received a substantial support subsequently. Fama and French (2015) use SMB (size effect) and high minus low book-to-market (HML, value effect, Rosenberg et al., 1985). Chen and Zhang (2010) reason why FF 3F model fails, relationship of average returns with short-term prior returns, and with financial distress, net stock issues, and asset growth are some of them. Among many risk factors augmented FF 3F model, liquidity (Amihud and Mendelson, 1986; Pastor and Stambaugh, 2003; Lam and Tam, 2011), momentum (Jegadeesh and Titman, 1993; Carhart, 1997) are noteworthy. Theoretically, illiquid stocks carry higher returns because of the risk. Consequently ILQ is hypothesized to show a positive association with returns. But this has not been always the fact, Nguyen and Lo (2013) give evidence of an ILQ discount. Liu (2006) find a subsuming power of liquidity premium, and suggest augmenting the capital asset pricing model (CAPM) with liquidity. Lam and Tam (2011) extend FF 3F with liquidity factor. Their work also consults how well the available liquidity measures, including that of Amihud (2002), perform in pricing models.

3. SENTIMENT

Prior studies (among others, Baker and Wurgler, 2007; Finter et al., 2011) use a top down approach, a reduced form of aggregate IS, which uses implicit market wide sentiment proxies to trace its impact on aggregate market and individual stocks return. Following these studies, we use six aggregate market sentiment proxies in this study. ADR (Brown and Cliff, 2004; Finter et al., 2011), TR (June et al., 2003), dividend premium (DivP) (Baker and Wurgler, 2007), first day return on initial public offers (Baker and Wurgler, 2007), change in margin finance position (CMF) (Brown and Cliff, 2004; Mahakud and Dash, 2012) and the change in open interest (COI). ADR is the ratio of number of advancing (market price) to declining stocks during a particular month. TR is the ratio between the value of shares traded and market capitalization. DivP is the log difference of the average market-to-book ratios of dividend payer and nonpayer stocks, CMF is the monthly percent change in margin finance position, and COI is the monthly percent COI from equity derivatives market. Open interest is a proxy for market depth (Bessembinder and Seguin, 1993) and indicates perceived trends in futures and options markets. The information role of open interest and their rselationship with price changes has been attractive to scholars (Wang and Yu, 2014). Accordingly, we use open interest to confirm trends and reversals in the market. An increased (decreased) open interest means inflow (outflow) of funds to the market, which suggests market is positively (negatively) perceived in investor. Hence, COI position would indicate market's sentiment direction, and the IS at time t is given by the Equation 1.

$$IS_t=ADR_t+TR_t-DivP_t+RIPO_t+CMF_t+COI_t \quad (1)$$

Literature argues that market sentiment partially shows a rationally developed economic reflection, the general economic indicators should rationally drive the sentiment up or down. Since the focus of our study is to examine pricing implications of irrational component of sentiment, the idiosyncratic sentiment that is likely to be included in each proxy is eliminated in an orthogonalising procedure (Baker and Wurgler, 2007). In this process, each proxy is regressed using three economy-reflective macro variables. They are, Growth in industrial production, Term spread and the composite coincident index (CCI). Logically, this ordinary least squares regression's retained residual is the irrational component in the proxy. CCI reflects ongoing business cycle changes thus it has the ability to form sentiment rationally. The orthogonalising equation confines to the following specification.

$$SP_{jt} = a_j + \sum_{k=1}^{l=3} b_j \, EF_{kt} + e_t \quad (2)$$

Where, SP_{jt} is the j^{th} sentiment proxy at time t, EF_{kt} is the k^{th} Economic Fundamental variable at time t. Term α_j is the constant of the j^{th} proxy with respect to l number of EF factors, limited to three. Estimated $\widehat{SP_{jt}}$ represents the rational component of the sentiment and the residual ($e = SP_{jt} - \widehat{SP_{jt}}$), which is orthogonal ($SP^{\perp}$) to original proxy, reflect the isolated irrational component included in the market proxy. Table 1 reports summary statistics of post-orthogonal sentiment proxies $SP^{\perp}$. We have used time series of monthly data pertaining to Malaysian capital market (Bursa Malaysia), for 168 months starting from January 2000 to January 2014. The number of stocks in this sample varies between 377 and 803 across the period. Each of the series shows zero mean as they are the normal residuals, and ADR has the highest standard deviation. TR is weakly-correlated with three other proxies, and COI weakly correlates with ADR. DivP shows negative correlations with other proxies, consistent with the fact that the market seeks (avoids) dividend payers in bearish (bullish) sentiment.

While many sentiment proxies are likely to capture some aspect of sentiment, they also contain an idiosyncratic component (Finter et al., 2011). Baker and Wurgler (2007) use principal components analysis of market proxies in order to identify the common component, which is the isolated sentiment component. This procedure allows to identify the contribution of each proxy to the index, the results are reported in Table 2, where we observe an inversion of expected relationships of three proxies in the 2nd principal component, ADR, DivP, and COI. Hence, we restrict ourselves in defining the factor loadings with first component. Then the index become as given by Equation 3.

$$IS_A = 0.459ADR + 0.531TR - 0.321DivP + 0.459RIPO + 0.215CMF + 0.382COI \quad (3)$$

In this index, IS_A is the macro adjusted IS. The index covers a proportion of 27.6% of the total variations, which corresponds to an Eigen value of 1.658. Note that the Table 2 report only four components (out of the six) as the Eigen value falls below 1.0 from fourth principal component.

Figure 1 displays the association of trend adjusted Kuala Lumpur composite ındex (KLCI) with market sentiment index. Vertical bars indicate positive sentiment periods, thus a "no-bar" means a period with a negative sentiment. The graph is in a two-scale format, where IS and KLCI correspond to the right Y-axis and to left Y-axis respectively. We observe that KLCI (dotted line)

Figure 1: This figure shows the association of Kuala Lumpur composite ındex (KLCI) and investor sentiment (IS). Periods of positive IS are indicated with vertical bars, consequently no bar means a negative IS period. Dotted line indicates de-trended KLCI. The graph is in a two-scale format, where IS and KLCI correspond to the right Y-axis and to left Y-axis respectively. The patterns suggest that that KLCI drops in negative sentiment periods and is sensitive to the behavior of IS. Improvements in KLCI during negative sentiment periods collapse in short cycles

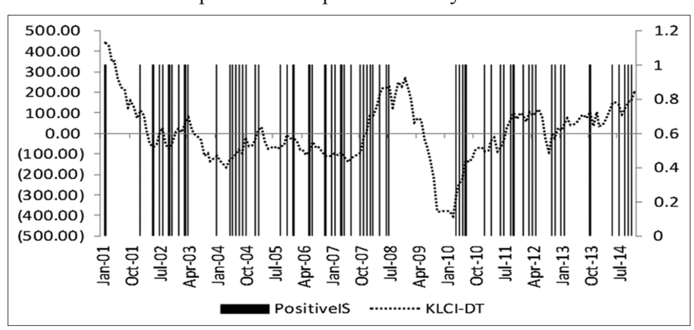

Table 1: Summary statistics

Statistics/variables	$ADR^{\perp}$	$TR^{\perp}$	$DivP^{\perp}$	$RIPO^{\perp}$	$CMF^{\perp}$	$COI^{\perp}$
(A) Summary statistics						
Mean	0.00	0.00	0.00	0.00	0.00	0.00
SD	1.72	0.01	0.49	0.23	0.06	0.20
Min	−1.82	−0.02	−1.32	−0.82	−0.4	−0.47
Max	10.27	0.04	1.34	0.97	0.62	1.02
(B) Correlation coefficients						
$ADR^{\perp}$	1					
$TR^{\perp}$	*0.21	1				
$DivP^{\perp}$	−0.09	−0.08	1			
$RIPO^{\perp}$	0.11	*0.31	−0.17	1		
$CMF^{\perp}$	0.00	*0.21	0.02	0.03	1	
$COI^{\perp}$	*0.27	0.09	−0.11	0.06	0.05	1

This table reports summary statistics (A) and correlation coefficients (B) of orthogonalized sentiment proxies. The market proxies have been regressed using Equation 2. *Indicates significance at 1% level. SD: Standard deviation, ADR: Advance-decline ratio, TR: Turnover ratio, DivP: Dividend premium, RIPO: Return on initial public offers, CMF: Change in margin finance, COI: Change in open interest declines in negative periods. Even though mounts are observable during negative sentiment periods, they do not exist to continue, and are temporary. KLCI rises during explicit-positive sentiment periods. This means that the index has the ability to capture market movements, and KLCI is sensitive to the behavior of IS.

4. ILQ, SMB AND HML

Our monthly ILQ premium is the return on a zero-investment portfolio, is obtained by buying long the top 20% (ILQ) firms and selling short the bottom 20% (liquidity) firms. The return of each portfolio is equally weighted for stocks. Stocks are ranked according to ILQ, measured by Amihud (2002) indicator (Equation 4).

$$\text{Illiquidity}_{it} = \frac{1}{D_{it}} \sum_{d=1}^{idt} \frac{|R_{idt}|}{Vol_{idt}} \quad (4)$$

Where, ILQ is measured for firm i at month t. R is the return of firm i on day d in month t; Vol is the dollar volume of firm i on day d in month t. ILQ is equally weighted for days observed. ILQ is the price reaction to one unit of trading volume, thus a higher ratio corresponds an illiquid stock.

SMB and HML risk factors are determined following prior studies including Fama and French (1993), and Kim et al. (2012). Size (market capitalization) bisects (big/small) at 50% break point while BM trisects (high/medium/low) at 30th and 70th percentiles. SMB, is the return for the small stock portfolio in excess of big, is the simple average of value weighted returns of three small stock portfolios (small–high, small–middle, small–low) minus three big stock portfolios (big–high, big–middle, big–low). HML, is the return for the high BM portfolio over low, is the simple average of value weighted returns of two high BM portfolios (high–small, high–big) minus two low BM portfolios (low–small, low–big). Market risk premium (MRP) is the return of the market portfolio in excess of the risk free return. Monthly value-weighted market returns on KLCI and 1-month treasury yield serve proxy market return and risk free rate respectively. We use all stocks in Kuala Lumpur stock exchange, over 14 years up to December 2014. Table 3 reports summary statistics of risk factors.

Table 2: Principal component analysis

Variable	Components			
	1	2	3	4
ADR⊥	0.459	−0.361	0.324	0.336
TR⊥	0.531	0.393	−0.009	0.262
DivP⊥	−0.321	0.292	0.519	0.654
RIPO⊥	0.459	0.188	−0.514	0.255
CMF⊥	0.215	0.627	0.413	−0.519
COI⊥	0.382	−0.447	0.435	−0.233
Eigen	1.658	1.115	1.033	0.873
Proportion	0.276	0.185	0.172	0.145

Table reports variations explained by each principal component and respective Eigen values of correlation matrix. The variables are post-orthogonal. Eigen value falls below 1.0 starting from component 4. ADR: Advance-decline ratio, TR: Turnover ratio, DivP: Dividend premium, RIPO: Return on initial public offers, CMF: Change in margin finance, COI: Change in open interest

IS and MRP show a moderate positive correlation, suggesting a co-movement of the two. IS is zero centered, and has a higher standard deviation relative to other factors. Correlation coefficient between ILQ and SMB is noteworthy, the two return premiums are dependent and the source of the risk is not different in each factor. This is consistent with the evidence of importance of ILQ over size and value factors in Malaysian market (Jais and Gunathilaka, 2016). Thus, inclusion of both size and ILQ factors in a regression would produce marginal consequences.

Table 4 reports monthly average raw returns for SBM sorted six portfolios, where returns are decreasing from high to low BM portfolios for both small and big stocks. High BM group adds a premium of 1.88% relative to the low BM portfolio of small firms, and 1.75% in case of big group. The small return is less than the big counterpart, and paired sample t-tests confirm that the mean difference is significant. Hence, it is a reversal of small firm effect, the big stock portfolios outperform in all BM groups with significant mean differences. However, this does not mean that the size effect is dead in this market, tests of pricing models confirm the continuation of the size effect (section 6).

5. PRICING MODEL AND APPLICATION

Fama and French (1993) model includes SMB and HML factors and extends CAPM (Sharpe, 1964) in a time series regression, on the argument that size and value effects left unexplained in

Table 3: Risk factors

Statistics/variables	MRP	IS	SMB	HML	ILQ
(A) Summary statistics (monthly %)					
Mean	0.36	0.00	−1.21	−1.81	−2.37
SD	4.58	8.67	2.71	2.34	3.51
Min	−15.51	−13.1	−8.52	−12.71	−10.94
Max	13.39	48.17	9.09	4.55	9.75
(B) Correlation coefficients					
MRP	1				
IS	0.53*	1			
SMB	−0.11	0.18**	1		
HML	0.21*	0.08	−0.46*	1	
ILQ	−0.25*	0.04	0.66*	−0.21*	1

This table reports summary statistics (A) and correlation coefficients (B) of market risk premium, investor sentiment, small minus big, high minus low, and illiquidity. * and ** indicate significance 1% and 5% levels respectively. SD: Standard deviation, MRP: Market risk premium, HML: High minus low book-to-market, SMB: Small minus big, IS: Investor sentiment, ILQ: Illiquidity

CAPM. Studies confirm these effects in Malaysian market (Joher and Ahmed, 2009). The model given by Equation 5.

$$R_{it}-R_{ft}=\alpha_i+\beta_i\,(R_{mt}-R_{ft})+s_iSMB_t+h_iHML_t+e_{it} \quad (5)$$

In this equation, R_{it} is the expected return on asset i at time t; R_{ft} is the risk-free return at time t; R_{mt} is the return of the market portfolio at time t; SMB_t is the return for small stocks in excess of big stocks portfolio, HML_t is the return of high BM stocks over low BM stocks portfolio, α is the zero-expected intercept, β_i s_i h_i are the factor loadings, and e_{it} is the unexplained excess return for asset i at time t.

Ahead of Malaysian evidence on ILQ exposure of size (Jais and Gunathilaka, 2016), liquidity effect (Joher and Ahmed, 2009), herd effect (Jarita and Salina, 2009), and IS effect (Ibrahim, 2013) among others, we suggest an alternative three factor model including ILQ and sentiment factors.

$$R_{it}-R_{ft}=\alpha_i+\beta_i\,(R_{mt}-R_{ft})+l_iILQ_t+is_iIS_{At}+e_{it} \quad (6)$$

Where, ILQ_t is the return for illiquid stocks in excess of liquid stocks portfolio, IS_A is the macro adjusted IS, and l_i is_i are the factor loadings. In order for us to assess how well the model performs, we make use of GRS statistic (Gibbons et al., 1989) in addition to adjusted R^2 of the model. Hence we hypothesize zero intercept (α_i) for all assets (i), under the assumption that the model explains the expected returns fully. Thus the deviation from the assumption would increase GRS F-statistic, and obviously α_i.

We form ten-decile equally-weighted size and liquidity portfolios examining disproportionate reactions of sentiment. Additionally, six SBM (2 × 3) double-sorted portfolios are formed examining diversified effect. For SBM portfolios, size (big/small) bisects at 50% break point while BM (high/medium/low) trisects at 30th and 70th percentiles. All are end of the year formations, resulting in stock portfolios for which monthly value weighted average returns are obtained for the succeeding year. The Table 5a reports summary statistics of liquidity portfolios formed. Illiquid portfolio has 75 stocks on average over sampling period. It reveals that liquid stocks carry a premium while ILQ exhibits a discount, with analogous return variations. The liquidity premium is (Liquid minus Illiquid) is substantial, at 2.53% per month on average. The returns of neutral portfolios (4, 5, 6, 7) are <0.1% p.m. Table 5b reports statistics of size portfolios, where "big" categories account for more stocks relatively, and surprisingly, instead of being left behind, large firms outperform. Small premium is negative (SMB) 4.42% per month on average. Return variation decreases as the size increases.

As the model efficiency directly relates to the risk characteristics of the test portfolios, we also form SBM sorted six assets, the Table 6 reports statistics for them. It emphasizes the same, large stocks outperform the small. Many small firms fall in high BM category (i.e. value stocks) while many of the big falls in low BM. Furthermore, many of the small (big) firms carry high (low) returns. On the other hand, high (low) BM stocks show higher (low) average returns confirming the value premium.

Table 4: Small versus big returns

Portfolio	BM		
	High	Medium	Low
Small	−0.10	−0.88	−1.98
SD	7.68	6.21	6.58
Big	1.16	0.10	−0.59
SD	5.75	5.71	6.98
Small-big	−1.26	−0.98	−1.39
t-stat (small/big)	3.69		6.63

This table reports monthly average raw returns per cent, SD and paired sample t-stats for size-BM sorted portfolios. t-statistic for mean differences is obtained by pairing small and big samples. SD: Standard deviation

6. RESULTS

Liquid stocks shows higher R^2 (Table 7a: 0.69 highest R^2) than illiquid stocks in CAPM regression. In the Table 7b, the results for three factors model are reported. When MRP, IS and ILQ factors are combined, the coefficient of MRP decreases. IS coefficient is significant in all assets. ILQ risk factor is negatively related in liquid stocks while positively related in ILQ, suggesting an ILQ (liquidity) premium (discount). GRS statistic for CAPM (Table 7a) indicates that the intercepts are away from zero in majority, especially for illiquid stocks. Moreover, it reports a significant nonzero constant term. Testing how well the factors explain returns of assets formed, we observe that CAPM's efficiency improves with liquidity. Illiquid portfolio has a R^2 of 0.42 compared with 0.69 in the liquid. As in the Table 7b, the significant IS and ILQ factors improves R^2 to 0.76 (ılliquid) and 0.78 (liquid) showing a better stability of the model across all liquidity levels. On the other hand, constant term has become insignificant mostly. With these results, we turn in to size-ranked 10 decile portfolios as reported in Table 8.

Table 5: Ten decile portfolios

Panel A: Liquidity deciles										
	Liquid	2	3	4	5	6	7	8	9	Illiquid
Return	1.07	0.53	−0.01	0.16	−0.53	−0.61	−0.56	−1.13	−1.56	−1.46
SD	6.01	7.07	6.9	6.47	6.34	6.26	6.35	6.26	6.15	6.93
No. of stocks	69	60	59	60	60	60	61	61	62	75
Panel B: Size deciles										
	Small	2	3	4	5	6	7	8	9	Big
Return	−3.66	−1.39	−0.76	−0.51	−0.17	−0.14	0.19	0.49	0.52	0.76
SD	8.33	6.97	6.8	6.47	6.21	6.13	6.51	6.91	6.54	5.01
No. of stocks	56	60	61	61	63	63	64	65	65	65

Table reports summary statistics of liquidity and size 10 decile portfolios across the sample period of 180 months. Returns and standard deviations are percentages. Table also gives average number of stocks included in each portfolio. Portfolios are arranged from liquid to illiquid (A), and small to big (B). SD: Standard deviation

CAPM explains big stocks substantially with R^2 (adjusted) of 0.79 (big) but poor in small (R^2 of 0.33) portfolio. A significant intercept term is observed in small stock portfolios. GRS statistic indicates similarly, non-zero intercept exists among the 10 size-ranked portfolios. Note that we use KLCI, a market portfolio which consist of big stocks, thus it could explain the big, and thus use of more diversified proxy would make it more inefficient than efficient in explaining big stocks. As reported in the 8B, the IS and ILQ factors improve the model efficiency up to a R^2 (adjusted) of 0.84 in big portfolio and 0.65 in small. It reports zero intercepts for all portfolios, except in the small portfolio. However, GRS statistic indicates that the intercepts are jointly distinguishable from zero (at 1% level of significance). Magnitude of IS coefficient increases from big to small suggesting that small stocks hold a higher influence of IS. ILQ shows a negative association in big stocks suggesting liquidity discount as they are mostly liquid portfolios. Since the IS show a disproportionate reaction, we check non-linearity in a quantile regression, and results are reported in Table 9.

Table 6: Size-BM six portfolios

Portfolio	Return	SD	No. of stocks
SL	−0.97	5.56	94
SM	−0.25	5.12	107
SH	0.32	5.61	143
BL	−0.52	5.45	136
BM	0.14	5.15	122
BH	0.46	6.31	86

Table reports summary statistics of size-BM sorted portfolios across the sample period of 180 months. Returns and SD are percentages. SD: Standard deviation

Table 7: Liquidity-ranked portfolios

Liquidity	Liquid	2	3	4	5	6	7	8	9	Illiquid	GRS (p)
Panel A											
CAPM											
MRP	1.11	1.20	1.18	1.09	1.09	1.07	1.04	1.01	0.95	1.01	
t stat	19.13	15.21	15.20	14.73	15.40	15.26	13.96	13.35	12.28	11.12	
Cons	0.01	0.00	−0.01	0.00	−0.01	−0.01	−0.01	−0.02	−0.02	−0.02	10.81
t stat	1.97	−0.16	−1.69	−1.19	−3.41	−3.68	−3.26	−4.89	−6.00	−4.87	(0.00)
R^2	0.69	0.58	0.58	0.57	0.59	0.58	0.54	0.52	0.47	0.42	
Panel B											
With IS and ILQ											
MRP	0.79	0.71	0.76	0.72	0.75	0.75	0.72	0.73	0.72	0.79	
t stat	12.92	9.16	9.70	9.76	10.58	11.04	10.16	10.67	10.47	11.08	
IS	0.22	0.37	0.35	0.32	0.31	0.30	0.30	0.30	0.27	0.32	
t stat	7.19	9.57	9.14	8.87	8.79	8.95	8.49	8.84	7.92	9.06	
ILQ	−0.40	−0.41	−0.12	0.00	0.04	0.15	0.14	0.34	0.45	0.74	
t stat	−6.08	−4.91	−1.48	−0.01	0.57	2.00	1.84	4.63	6.10	9.69	
Cons	0.00	−0.01	−0.01	0.00	−0.01	−0.01	−0.01	−0.01	−0.01	0.00	3.33
t stat	−1.46	−1.92	−2.54	−1.23	−1.17	−2.72	−2.64	−3.03	−1.60	−0.98	(0.00)
R^2	0.78	0.74	0.72	0.71	0.73	0.74	0.71	0.73	0.71	0.76	

The table reports time series regression results. Dependant variable is returns of 10 decile portfolios, independent variables are MRP, IS and ILQ. Test assets are ranked in order of liquidity, from liquid (1) to illiquid (10). Each coefficient is reported with corresponding t-statistic. Panel A reports CAPM with adjusted R^2, and Panel B reports similar results of model with three factors, MRP, IS and ILQ. For both models, we also report the GRS F statistic with P value (in parenthesis) testing whether intercepts are jointly away from zero. MRP: Market risk premium, ILQ: Illiquidity, IS: Investor sentiment, CAPM: Capital asset pricing model

Table 8: Size-ranked portfolios

Size	Small	2	3	4	5	6	7	8	9	Big	GRS (p)
Panel A											
CAPM											
MRP	1.08	1.06	1.07	1.03	0.99	1.02	1.11	1.18	1.17	0.99	
t stat	9.24	12.06	12.91	13.25	13.31	14.60	15.30	15.42	17.48	25.04	
Cons	−0.04	−0.01	−0.01	−0.01	0.00	0.00	0.00	0.00	0.00	0.00	12.51
t stat	−7.99	−4.88	−3.50	−2.96	−2.06	−2.13	−1.11	−0.25	−0.17	1.33	(0.00)
R^2	0.33	0.46	0.50	0.51	0.51	0.56	0.58	0.58	0.64	0.79	
Panel B											
With IS and ILQ											
MRP	0.75	0.80	0.75	0.71	0.61	0.67	0.75	0.77	0.79	0.79	
t stat	7.32	10.19	9.57	9.16	8.91	9.97	10.30	9.80	11.26	18.43	
IS	0.41	0.30	0.33	0.30	0.35	0.32	0.31	0.34	0.28	0.13	
t stat	8.20	7.54	8.41	7.94	10.21	9.51	8.55	8.90	8.16	6.21	
ILQ	0.76	0.50	0.30	0.14	0.07	0.05	−0.03	−0.14	−0.35	−0.27	
t stat	6.96	5.86	3.63	1.75	1.00	0.77	−0.38	−1.65	−4.61	−5.99	
Cons	−0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.03
t stat	−5.53	−2.35	−1.78	−2.17	−1.80	−1.83	−1.40	−1.13	−2.70	−2.02	(0.00)
R^2	0.65	0.69	0.69	0.67	0.72	0.72	0.72	0.72	0.75	0.84	

The table reports time series regression results. Dependant variable is returns of 10 decile portfolios, independent variables are MRP, IS and ILQ. Test assets are ranked in order of size, from small (1) to big (10). Each coefficient is reported with corresponding t-statistic. Panel A reports CAPM with adjusted R^2, and panel B reports similar results of model with three factors, MRP, IS and ILQ. For both models, we also report the GRS F statistic with P value (in parenthesis) testing whether intercepts are jointly away from zero. MRP: Market risk premium, ILQ: Illiquidity, IS: Investor sentiment, CAPM: Capital asset pricing model

We observe a replicating pattern of higher IS coefficients in small and illiquid stocks (Table 9). Results reveal an insignificant difference between OLS and quantile regressions, and t statistic reads significance of all coefficients. However, the coefficients become larger as the quantile increases in case of small, and illiquid portfolios. It suggests that IS impact is higher for small and illiquid stocks, especially for those stocks with higher returns. Thus it leaves a high chance of overvaluing them. Liquid stocks show a lower influence relative to illiquid, yet the magnitude of the coefficient become larger for increased quantiles within liquid category. It means IS influences more on liquid stocks with higher returns than stocks with lower returns. Therefore, we think IS has the ability of influencing the value, in particular stocks with opaque risk characteristics and higher returns. Accumulating these results, it is our observation that the three factor model perform better, yet it leaves a substantial variation unexplained in small stocks, and thus we include size premium as analyzed in Table 10.

Table 10 reports results of FF 3F model applied for liquidity 10-decile portfolios. Evidently, FF 3F model performs better than CAPM and shows stability in explanation of all liquidity ranked assets. According to GRS statistic, FF 3F model shows non-zero

Table 9: Quantile regression results

OLS/	Size 10 decile portfolios			Liquidity 10 decile portfolios		
quantile	1 (small)	5 (middle)	10 (big)	1 (liquid)	5 (middle)	10 (Illiquid)
OLS						
Coef.	0.64	0.52	0.35			
t stat	11.51	13.64	9.73			
0.1						
Coef.	0.63	0.51	0.34	0.40	0.53	0.52
t stat	3.55	4.80	3.39	3.02	4.10	4.18
0.3						
Coef.	0.66	0.52	0.37	0.44	0.57	0.59
t stat	9.74	11.22	8.81	9.02	10.63	8.85
0.7						
Coef.	0.69	0.51	0.29	0.48	0.48	0.58
t stat	12.36	15.55	8.53	12.26	11.47	14.04
0.9						
Coef.	0.75	0.45	0.45	0.52	0.62	0.65
t stat	10.08	5.77	6.94	6.01	11.33	6.99

This table reports coefficients for IS in time series quantile regressions: $R_{it}-R_{ft}=\alpha_{it}+is_{it}\,IS_t+e_{it}$. R_{it} is the return on i[th] portfolio, and is_{it} is the coefficient for IS. Three portfolios have been selected from size and liquidity 10 deciles portfolios: 1[st], 5[th], and 10[th]. IS: Investor sentiment, OLS: Ordinary least squares

Table 10: Liquidity-ranked portfolios

Model	Liquid	2	3	4	5	6	7	8	9	Illiquid	GRS (p)
Panel A											
FF 3 F											
MRP	1.12	1.20	1.19	1.10	1.09	1.09	1.07	1.04	0.98	1.06	
t stat	18.64	15.03	15.77	15.95	16.84	17.44	16.42	17.55	15.87	15.57	
SMB	0.01	0.37	0.60	0.74	0.75	0.81	0.94	1.14	1.16	1.45	
t stat	0.08	2.52	4.40	5.93	6.32	7.14	7.97	10.59	10.34	11.61	
HML	−0.01	0.27	0.28	0.37	0.39	0.29	0.36	0.39	0.47	0.41	
t stat	−0.11	1.59	1.76	2.49	2.81	2.16	2.62	3.10	3.54	2.81	
Cons	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	1.67
t stat	1.21	1.61	1.27	2.47	1.19	0.81	1.57	1.07	0.39	1.05	(0.09)
R^2	0.68	0.59	0.62	0.64	0.66	0.68	0.67	0.71	0.68	0.69	
Panel B											
With IS and ILQ											
MRP	0.80	0.69	0.74	0.70	0.73	0.75	0.71	0.72	0.70	0.79	
t stat	13.09	9.32	9.79	9.99	10.83	11.40	10.72	11.66	10.66	11.24	
SMB	0.46	0.79	0.69	0.77	0.73	0.70	0.87	0.95	0.69	0.58	
t stat	3.15	4.47	3.83	4.60	4.58	4.44	5.59	6.44	4.40	3.46	
HML	0.14	0.48	0.38	0.45	0.45	0.30	0.45	0.41	0.42	0.22	
t stat	1.32	3.55	2.76	3.52	3.67	2.52	3.82	3.65	3.51	1.75	
IS	0.19	0.32	0.31	0.28	0.27	0.26	0.25	0.24	0.23	0.29	
t stat	6.20	8.56	8.11	7.82	7.76	7.85	7.38	7.71	6.89	8.01	
ILQ	−0.63	−0.79	−0.46	−0.37	−0.31	−0.20	−0.29	−0.13	0.12	0.45	
T stat	−6.49	−6.66	−3.80	−3.31	−2.88	−1.88	−2.74	−1.32	1.13	4.05	
Cons	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.55
T stat	−0.29	−0.08	−0.25	1.27	−0.22	−0.56	0.26	−0.23	−0.66	0.36	(0.12)
R^2	0.79	0.77	0.74	0.75	0.76	0.76	0.76	0.78	0.74	0.77	

The table reports time series regression results. Dependant variable is returns of 10 decile portfolios, independent variables are MRP, SMB, HML, IS and ILQ. Test assets are ranked in order of liquidity, from liquid (1) to illiquid (10). Each coefficient is reported with corresponding t statistic. Panel A reports FF 3F model with GRS statistic, and adjusted R^2. Panel B reports similar results of FF model with two factors, IS and ILQ. MRP: Market risk premium, SMB: Small munus big, HML: High minus low, IS: Investor sentiment, ILQ: Illiquidit intercepts. Coefficients for SMB and HML decrease significantly in liquid assets, suggesting size and value premiums play a less role in liquidity. The magnitude of negative ILQ coefficient decreases towards, and turns positive at ILQ. However, R^2 results reported in Table 7b (MRP/IS/ILQ model) and Table 10b (FF+IS+ILQ) show no significant improvement for same test assets. Hence IS and ILQ jointly display an ability of capturing variation explained by size and value premiums. Furthermore, adjusted R^2s of FF 3F model (Table 10a) are less than the three factor model results reported in Table 7b. Table 10b shows an increased coefficient for SMB in liquid portfolio than Table 10a, indicating a release of the liquidity discount that was absorbed by SMB. Table 10b also displays a low GRS value and an insignificant P value, indicating intercepts are almost negligible. With this result, we jump to test portfolios formed on size, and the results are reported in Table 11.

Similar to results discussed so far, a three factor model with MRP, IS and ILQ (Table 8b, size ranked portfolios) performs better than FF 3F model reported in Table 11a for identical stock portfolios. We observe an increasing SMB factor loading from big to small, with a negative and insignificant loading for big portfolio. It implies that small stocks are risky and thus are connected with a size premium, which is consistent with related studies including Fama and French (1993). In the model with IS and ILQ (Table 11b), the size factor becomes insignificant while ILQ stays significant among big stocks. IS shows its significance across all small-big categories, and the inclusion of IS significantly improves model efficiency. GRS statistic explains that the intercept is non-zero for the model presented in Table 11a. However, it shows a reduced value in the model with five factors in Panel B.

Table 12 reports application of Fama and French (1993) three factor (FF 3F) model with SBM sorted six portfolios. FF model accounts for a substantial return variation of all portfolios, however, HML is insignificant in low BM stocks. SMB has a low factor loading in big stocks and is insignificant in Low to medium BM stocks (Table 12b). IS and ILQ are significant for all portfolios, and ILQ shows a negative association in all cases. Moreover, irrespective of the significance of SMB and HML, the model with IS and ILQ achieves a higher efficiency (R^2 from 0.72 to 0.79) than FF 3F model (R^2 from 0.57 to 0.69) as reported in Table 12a and b. However, FF model's intercept term is higher in high BM portfolios.

7. CONCLUSIONS

Our six-variable sentiment index has significant factor loadings at all the models regardless of risk blending the test asset has. Behavioral biasness causes irrational demand shifts and generates sentiment risk, and especially the small and illiquid stocks bear high sentiment risk in this market. Analysis suggests that stock market, proxied by KLCI, drops in negative sentiment periods and is sensitive to the behavior of sentiment. Short rising cycles of KLCI are observed during the periods of continuous negative sentiment. We also observe sentiment's asymmetric implications on stocks, and it has a large impact on stocks with higher returns.

Evidence reveals a reversal of small firm effect during the post 2000 period, on average basis. However, we have not extended procedures to examine the timing and cyclical patterns of small

Table 11: Size-ranked portfolios

Model	Small	2	3	4	5	6	7	8	9	Big	GRS (p)
Panel A											
FF 3 F											
MRP	1.15	1.12	1.12	1.06	1.02	1.04	1.12	1.19	1.14	0.99	
t stat	13.32	17.95	17.16	16.11	15.30	15.96	15.76	15.49	16.83	24.46	
SMB	1.92	1.49	1.25	1.06	0.89	0.72	0.55	0.45	0.06	−0.13	
t stat	12.26	13.16	10.45	8.77	7.31	6.10	4.23	3.23	0.50	−1.72	
HML	0.62	0.43	0.34	0.40	0.34	0.33	0.29	0.27	0.33	−0.03	
t stat	3.34	3.24	2.40	2.84	2.41	2.35	1.91	1.66	2.29	−0.35	
Cons	−0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	2.47
t stat	−1.31	1.50	1.77	2.11	2.17	1.77	1.69	1.81	1.36	0.11	(0.00)
R^2	0.66	0.74	0.70	0.67	0.63	0.64	0.62	0.61	0.65	0.79	
Panel B											
With IS and ILQ											
MRP	0.75	0.82	0.77	0.70	0.60	0.66	0.73	0.75	0.75	0.79	
t stat	8.01	12.05	11.14	10.30	9.38	10.01	9.97	9.51	10.81	17.95	
SMB	1.40	1.38	1.26	1.19	0.83	0.59	0.32	0.36	0.10	0.02	
t stat	6.27	8.56	7.72	7.37	5.46	3.74	1.82	1.90	0.58	0.15	
HML	0.54	0.48	0.40	0.53	0.41	0.36	0.32	0.31	0.40	0.03	
t stat	3.20	3.90	3.23	4.29	3.59	3.00	2.42	2.18	3.20	0.41	
IS	0.34	0.22	0.26	0.24	0.30	0.29	0.29	0.33	0.28	0.13	
t stat	7.01	6.33	7.27	6.78	9.25	8.52	7.86	8.15	7.97	5.91	
ILQ	0.07	−0.19	−0.33	−0.44	−0.33	−0.23	−0.17	−0.30	−0.37	−0.28	
t stat	0.47	−1.73	−2.99	−4.08	−3.26	−2.14	−2.48	−2.42	−3.33	−4.04	
Cons	−0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.04
t stat	−2.62	0.38	0.50	0.85	0.82	0.47	0.47	0.53	−0.08	−1.30	(0.03)
R^2	0.72	0.79	0.77	0.75	0.76	0.75	0.73	0.73	0.77	0.84	

The table reports time series regression results. Dependant variable is returns of 10 decile portfolios, independent variables are MRP, IS and ILQ. Test assets are ranked in order of size, from small (1) to big (10). Each coefficient is reported with corresponding t statistic. Panel A reports CAPM with adjusted R^2, and Panel B reports similar results of model with three factors, MRP, IS and ILQ. For both models, we also report the GRS F statistic with P value (in parenthesis) testing whether intercepts are jointly away from zero. MRP: Market risk premium, SMB: Small munus big, HML: High minus low, IS: Investor sentiment, ILQ: Illiquidit

Table 12: Size-BM sorted portfolios

Model	SL	SM	SH	BL	BM	BH	GRS (p)
Panel A							
FF 3 F							
MRP	0.90	0.88	0.93	1.05	0.93	1.07	
t stat	12.96	15.08	15.15	18.08	16.49	14.50	
SMB	0.96	0.94	1.03	0.29	0.17	0.37	
t stat	7.68	8.99	9.35	2.78	1.75	2.82	
HML	0.06	0.29	0.67	0.14	0.35	0.67	
t-stat	0.42	2.39	5.24	1.20	3.04	4.39	
Cons	0.00	0.00	0.02	0.00	0.00	0.01	28.94
t stat	−0.80	1.93	5.12	−1.74	0.76	2.74	(0.00)
AR^2	0.57	0.65	0.67	0.69	0.67	0.62	
Panel A							
With IS and ILQ							
MRP	0.52	0.58	0.59	0.74	0.63	0.63	
t stat	7.41	9.53	9.57	12.46	10.87	8.90	
SMB	0.94	0.93	0.99	0.20	0.18	0.36	
t stat	5.94	7.24	7.20	1.50	1.39	2.25	
HML	0.04	0.29	0.64	0.10	0.34	0.65	
t stat	0.32	2.75	6.02	1.02	3.42	5.24	
IS	0.28	0.21	0.26	0.24	0.22	0.32	
t stat	8.30	7.19	8.83	8.36	8.04	9.44	
ILQ	−0.29	−0.29	−0.25	−0.18	−0.25	−0.34	
t stat	−2.81	−3.15	−2.74	−2.03	−2.89	−3.24	
Cons	−0.01	0.00	0.01	−0.01	0.00	0.00	26.85
t stat	−2.76	0.60	4.40	−3.79	−0.84	1.41	(0.00)
AR^2	0.72	0.75	0.79	0.79	0.77	0.78	

The table reports time series regression results. Dependant variable is returns of size-BM portfolios, small/low, small/medium, small/high, big/low, big/medium, and Bg/high. Size bisects at 50% and BM trisects at 30th and 70th percentiles, resulting in 2×3=6 portfolios. Independent variables are MRP, SMB, HML, IS and ILQ. Each coefficient is reported with corresponding t statistic. Panel A reports FF 3F model with adjusted R^2, and Panel B reports similar results for the model with IS and ILQ. For both models, we also report the GRS F statistic with P value (in parenthesis) testing whether intercepts are jointly away from zero. MRP: Market risk premium, SMB: Small munus big, HML: High minus low, IS: Investor sentiment, ILQ: Illiquidit

premium. Both SMB and BM effects remains significant in explaining equity returns. Fama-French three-factor model, while efficient than CAPM, leaves a substantial unexplained component, consistent with the observation of Fama and French (2015).

ILQ has a primary role and subsumes size factor. ILQ and sentiment factors jointly explain the return variation explained by SMB and HML factors. Our test results reveal that application of an alternative three factor model, extending CAPM with IS and ILQ risk factors in an APT setting, is persuasive. Given the asset pricing models are bound imperfect, we are interested in the improved efficiency of the model regardless of the fact that model's intercept is distinguishable from zero in few cases.

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