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A COMPARISON BETWEEN FAMA AND FRENCH MODEL AND LIQUIDITY-BASED THREE-FACTOR MODELS IN PREDICTING THE PORTFOLIO RETURNS

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ABSTRACT

The main objective of this paper is to evaluate the forecasting accuracy of two liquidity-based three-factor models, SiLiq and DiLiq, which have been developed as potential improvements on the Fama-French model. Using common stocks of 230 to 480 listed firms, this study constructs 27 test portfolios double-sorted on: (i) size and book-to-market ratio (B/M), (ii) size and share turnover (TURN) and (iii) B/M and TURN. The study sets the periods of January 1987 to December 2000 for estimation and January 2001 to December 2004 as forecast sample. The forecast errors are measured using mean absolute percentage errors and Theil's Inequality Coefficient. The preliminary results clearly document that three-factor models outperform CAPM. While the hypotheses of no significant differences cannot be rejected, the marginal difference in the errors of the competing three-factor models indicate that predicting returns on stocks traded on Bursa Malaysia can be slightly improved by incorporating illiquidity risk in a three-factor model in the form of DiLiq.

Keywords: illiquidity risks, Fama-French model, liquidity-based model, multifactor model

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INTRODUCTION

Since its introduction in 1993, Fama-French model has been extensively attended to the extent that it is currently considered the workhorse for risk adjustment in academic circles (Hodrick & Zhang, 2001). While the model performs exceptionally well compared to the capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972), its performance against other multifactor models in general is inconclusive. Consistent with Fama and French's (1996) assertion that like any other model, the Fama-French model is not without weakness (Fama & French, 1996), this study finds it of a great contribution to the asset pricing literature if alternative models can be developed as potential improvement on the model. Motivated by (i) Fama and French's (1996) conclusion that 3-factor model suffice to explain stock returns, (ii) the fact that the additional risk factor in the Fama-French model are firm-specific factors, and (iii) Dey's (2005) assertion that the sources and pricing of risk in emerging and developed markets are different, this study plans to achieve the objective by developing variants of 3-factor models that incorporate other firm-specific factor that is of greater concern to the investors in the studied market. Notwithstanding the fact that the concern on liquidity is a universal truth, as an emerging equity market Bursa Malaysia offers "… an ideal setting to examine the impact of liquidity on expected returns" (Bekaert, Harvey, & Lundblad, 2005) because "… liquidity is one firm characteristic that is of particular concern to investors in emerging market" (Rowenhorst, 1999: 1441). Furthermore, because the proposed models in this study are also an implication of Intertemporal CAPM (ICAPM), the choice of liquidity is judicious given that "… liquidity is a natural choice as an asset-pricing factor since it is a state variable in the ICAPM sense" (Chollete, 2004: 1). This hypothesis is supported with substantial evidence on the superior performance of liquidity-adjusted versions of the CAPM (Lo & Wang, 2001; Liu, 2004) and Fama-French model (Bali & Cakici, 2004; Chollete, 2004; Liu, 2004; Chan & Faff, 2005; Miralles & Miralles, 2005).

To test our hypotheses that the proposed liquidity-based models work as potential improvement on the Fama-French model, their forecasting accuracies are assessed against the benchmark model. While re-examination on the Fama-French model naturally adds to existing literature particularly in the sample market where similar studies are limited (Drew & Veeraraghavan, 2002; Drew, Naughton, & Veeraraghavan, 2003), the main contribution of this study is the development of liquidity-based 3-factor models which apparently is an effort that does not seem to have been attempted in any studies before. The remainder of the article is organized as follows. Section 2 reviews related studies, Section 3 describes the data and methodology, Section 4 presents the findings and discusses the results, while Section 5 concludes and discusses the implication.

LITERATURE REVIEW

The empirical frustrations over CAPM combined with the theoretical appeal of multifactor models particularly the APT and ICAPM led to the development of empirical multifactor models. While the simplicity in developing these models undoubtedly explains the attention, its widespread acceptance owes as much to the success story of a 3-factor model of Fama and French (1993). Following their earlier finding (Fama & French, 1992) that beta consistently fails while two firm-specific factors, market value of equity (ME) and book-to-market ratio (B/M), consistently and significantly explain the cross-section of stock returns, Fama and French (1993) asserted that the expected excess returns on stocks can be explained by a 3-factor model:

$$E(R_i) - R_F = b_i \left[E(R_M) - R_F \right] + s_i E(SMB) + d_i E(HML) , \qquad (1)$$

where $E(.)$ is the expected operator, $R_M - R_F$ is the market risk premium, *SMB* and *HML* are the additional risk premiums related to size and distress, respectively, while b_i, s_i, and d_i are the factor loadings.

Studies that provide supporting evidence for the Fama-French model are substantial, but those that provide contradictory results are not lacking either.[1] Despite the inconclusive performance, the model is currently considered as "…the workhorse for risk adjustment in academic circles" (Hodrick & Zhang, 2001: 329). It undeniably is a major breakthrough in the literature on asset pricing which for so long has been too intact with conventional asset pricing models such as CAPM and Arbitrage Pricing Theory (APT) of Ross (1976) and ICAPM of Merton (1973). While the CAPM is rigid in claiming that market risk alone is sufficient to explain asset prices, the APT and ICAPM leave an open question regarding what and how many factors should be priced in what kind of assets. In contrast, the Fama-French model specifically posits that there are three priced-factors in stocks and they are market risk and two additional risk factors, namely risks related to size and distress (Fama & French, 1993). Even though lacking in underlying theories, the Fama-French model has been successful in explaining most major anomalies of the conventional models (Fama & French, 1996). The additional risk factors in the model are firm-specific factors and yet it has been proven to be very effective. These paradoxes open up the feasibility for other effective empirical models to be developed and one such effort is initiated in this study. It hypothesizes that alternative models which emphasize on the role of liquidity factor in asset pricing qualify as potential improvement on the standard Fama-French model.

[1] For details see Ruzita Abdul Rahim (2006).

The approach of this study is also consistent with the recent surge in consensus among academic researches regarding the role of liquidity in explaining asset returns. While Fama and French's (1996) conclusion about the holes in their model opens the opportunity to seek improvement on the model, Hodrick and Zhang's (2001) suggestion about the importance of liquidity in asset pricing models is a strong indication regarding which factor should be given priority in developing the new model. Evidently, as reported in Table 1, almost all of 20 empirical studies that we manage to review support the hypothesis that liquidity is an important driver of expected stock returns. Despite the importance, the role of liquidity in asset pricing only gains its momentum recently mainly because the difficulty to define and therefore, to find the right measurement of liquidity.

Generally defined as the ability to trade quickly at low cost with little price impact, liquidity is an elusive concept which involves four dimensions: trading quantity, trading speed, trading costs and price impact (Liu, 2004). So far, none of suggested proxies has been successful to capture all of these dimensions. Despite being recognized as a direct measure of liquidity, bid-ask spread of Amihud and Mendelson (1986) only concentrates on the trading costs. The difficulties to find sufficient data on bid-ask and other direct measures of liquidity further delay the incorporation of liquidity in asset pricing studies. Brennan, Chordia, and Subrahmanyam (1998), Datar, Naik, and Radcliffe (1998) and Amihud (2002) among others managed to solve the problem by resorting to alternative liquidity measures based on trading-volume variables. Table 1 shows good variations of these measures, three of which are:

$$DVOL_{j,t} = P_{j,t} x VOL_{j,t} \tag{2}$$

$$TURN_{j,t} = \frac{VOL_{j,t}}{NOSH_{j,t}} \tag{3}$$

$$ILLIQ_{j,t} = \frac{\left|R_{j,t}\right|}{DVOL_{j,t}} \tag{4}$$

where *DVOL* is dollar volume, *P* is price per share, *VOL* is trading volume, *TURN* is share turnover, *NOSH* is number of shares outstanding, *ILLIQ* is illiquidity and $|R|$ is absolute returns on stocks *j, j* = 1, …, *N* at the end of month *t*. Proponents of volume-based liquidity measures argue that trading activity, particularly in the form of *ILLIQ*, is a good proxy of liquidity because liquidity is the impact of order flows on price resulting from adverse selection and inventory costs. Others empirically prove that volume-based liquidity

Table 1
Empirical Studies on the Role of Liquidity

Panel A. Empirical studies in the United States

No.	Studies	Sample	Study period	Liquidity measures	Sig.?	Sign
1	Brennan et al. (1998)	ALL	1966–1995	DVOL	Yes	–
2	Datar et al. (1998)	NYSE	1962–1991	TURN	Yes	–
3	Chordia, Subrahmanyan, & Anshuman (2001)	ALL	1996–1995	DVOL; TURN; CVs	Yes	–
4	Lo & Wang (2001)	MOST	1962–1996	β^{HR}; β^{HQ}[a]	Yes	–
5	Amihud (2002)	NYSE	1963–1997	MILLIQ[M]	Yes	+
6	Ali, Hwang, & Trombley (2003)	MOST	1976–1997	VOL	Yes	–
7	Pástor & Stambaugh (2003)	ALL	1965–2000	LIQ_{Value}; LIQ_{Equal}[*,b,M]	Yes	+
8	Bali & Cakici (2004)	ALL	1963–2001	HILLIQ[*]	Yes	±
9	Chollete (2004)	MOST	1962–2001	LIQ; Vol.(LIQ)[*,c]	No;Yes	–
10	Liu (2004)	ALL	1960–2003	LIQ[*,d]	Yes	+
11	Acharya & Pedersen (2005)	MOST	1962–1999	$Cov(c^i,c^M)$; (c^i, r^M); (r^i,c^M)[e,M]	Yes	–
12	Spiegel & Wang (2005)	ALL	1962–2003	Gibbs; Gamma[f]; ILLIQ DVOL	All No Yes	+; ±

Panel B. Empirical studies in the other countries

No.	Studies	Sample	Study period	Liquidity measures	Sig.?	Sign
1	Chan & Faff (2003)	Australia	1989–1999	TURN	Yes	–
2	Chan & Faff (2005)	Australia	1989–1998	IMV[*,j]	Yes	–
3	Miralles & Miralles (2005)	Spain	1994–2002	β_{IMV}[*,k]	Yes	+
4	Sheu, Wu, & Ku (1998)	Taiwan	1976–1996	VOL	Yes	–
5	Ku & Lin (2002)	Taiwan	1985–1999	VOL; TRO = TURN[*]	No	–; +
6	Rowenhorst (1999)	20 countries[g]	1982–1997	$HML = -\dot{L}M\dot{H}$[*,l]	No	+
7	Bekaert et al. (2005)	19 countries[h]	1987–2003	$\gamma_{L,S}$; $\gamma_{L,W}$[m,M]	Yes	+
8	Dey (2005)	48 countries[i]	1995–2001	$TURN_{Dev}$; $TURN_{Emerg}$	No; Yes	+

Notes: ALL = NYSE, AMEX, & NASDAQ, MOST = NYSE & AMEX, [a]R (returns) & Q ($returns) on a Hedged portfolio formed on TURN, [b]LIQ formed on β^{λ} where $\lambda = (sign(R_i - R_M)$, [c]formed on LIQ of Pástor & Stambaugh (2003), [d]formed on *No*0Vol*y* = number of days without trading at year $t \times \{(1/TURN) \times 10^6\}$, [e]covariance where c = illiquidity (ILLIQ), i = individual stock, M = market, & r = returns, [f]Gibbs = Bayesian's version of transaction costs (Spiegel & Wang, 2005: 7), & Gamma = inverted LIQ of Pástor & Stambaugh (2003), [g]including Indonesia, Malaysia, & Thailand, [h]emerging countries including Indonesia, Malaysia, & Thailand, [i]member countries of the World Federation of Exchanges including Malaysia, Indonesia, & Thailand, [j]IMV (*I*lliquid *M*inus *V*ery Liquid) formed on TURN, [k]IMV formed on ILLIQ, [l]formed on TURN, [m]L = *P*rice *I*mpact formed on ILLIQ (Bekaert et al., 2005: 5) where w = world & s = domestic, [M]market liquidity factor, & [*] liquidity factor is calculated similar to $\dot{L}M\dot{H}$.

measures are highly correlated with bid-ask spread (Liu, 2004; Bekaert et al., 2005; Lesmond, 2005). While convenient in terms of available data, these volume-trading measures do not solve the multidimensionality of liquidity. Turnover of Datar et al. (1998) captures only the trading quantity dimension whereas the illiquidity of Amihud (2002) and Pástor and Stambaugh (2003) focus only on the price impact.

The search for a better liquidity measure is undoubtedly critical in realizing its impact on pricing, but of more interest to this study is its role in explaining variation in portfolio returns. Adhering to the established evidence regarding the relationship between volume-based liquidity factor and expected returns, this study reflects the interest of recent studies on the explicit role of liquidity in asset pricing models (Bali & Cakici, 2004; Chollete, 2004; Liu, 2004; Chan & Faff, 2005; Miralles & Miralles, 2006). Most of them assigned to liquidity a role of stock's common risk factor, similar to SMB and HML in the framework of Fama-French model. The results are unanimously in favor of the asset pricing models that incorporate a liquidity factor. The present study deviates slightly from previous studies in that instead of incorporating liquidity as an additional risk factor, it incorporates liquidity as an alternative to Fama-French factors to develop two variants of 3-factor models.

DATA AND METHODOLOGY

This study covers an 18-year period from January 1987 to December 2004, which is further divided into the estimation period (1987:01–2000:12) and the post-estimation period (2001:01–2004:12). The sample comprises 230 to 480 companies listed on the Main Board of Bursa Malaysia. Two sets of data are used: (i) monthly data on stock closing prices, 3-month Treasury Bills rates and Exchange Main Board All Shares (EMAS) price index, and (ii) year-end data on number of shares outstanding (NOSH), trading volume (VOL), market value of equity (ME) and M/B ratio (inverted to yield B/M). The data is sourced from Thompson's *DataStream* and *Investors' Digest*. This study chooses EMAS Index over the Kuala Lumpur Stock Exchange Composite Index (KLCI) to proxy for market portfolio because the former is more representative of the sample population, i.e. Main Board companies. Unlike KLCI, which is based on 100 component stocks, EMAS is composed of all Main Board stocks and as such, is more consistent with the market portfolio formed by Fama and French (1993, 1996) which includes all stocks listed on NYSE, NASDAQ and AMEX. Following Fama and French (1993), this study uses ME and B/M to proxy for size and distress, respectively. Share turnover (TURN) described in Equation (3) is used to proxy for liquidity.[2] The proxy for the risk-free rate of return (R_F) is the monthly-adjusted-rate of return on the T-Bills.

[2] Besides TURN we also consider five other measures of illiquidity by forming $\widehat{LMH}$ using DVOL, ILLIQ, and the coefficient of variations of each of these variables. Overall, the procedure in Figure 1 generates 12 $\widehat{LMH}$ alternatives. The results of univariate regressions (not reported to

Dependent and Explanatory Variables

The dependent variables in this study are the monthly value-weighted average rate of returns on the test portfolio minus the risk-free rate of returns ($R_i - R_F$). To construct the test portfolio, at the end of December of year $t - 1$, the sample stocks will be sorted into: (i) three ME categories i.e., 30% smallest (S), 40% medium (M), and 30% biggest (B); (ii) three B/M categories i.e., 30% highest (H), 40% medium (M), and 30% lowest (L); and (iii) three TURN categories i.e., 30% lowest (Ĺ), 40% medium (M), and 30% highest (Ĥ). Then, following the procedure illustrated in Figure 1, three sets of nine test portfolios double-sorted on ME and BM, ME and TURN, and BM and TURN are constructed. The monthly return (R_i) on each of the 27 portfolios is then calculated for January to December of year t. This procedure will be repeated every year throughout the 18-year study period.

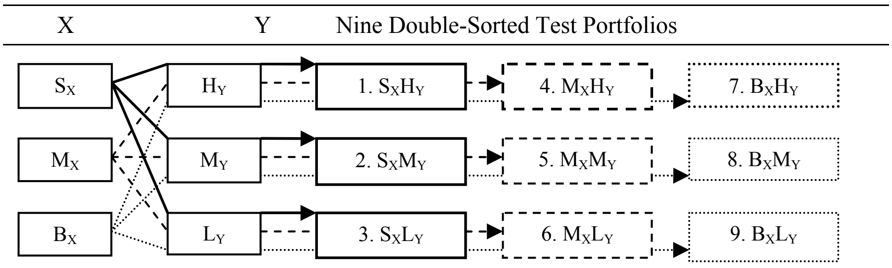

Figure 1. Procedure for constructing the double-sorted test portfolios

Notes: The portfolios are double-sorted on X and Y which represent two of the firm-specific factors, i.e., ME, B/M, and TURN. For instance, when X = ME and Y = B/M, portfolio SH consists of stocks that are Small in ME category and also High in B/M category. Whereas, portfolio SL is composed of stocks that are also Small in ME category but Low in B/M category.

The explanatory factors in this study are those of Fama-French model and the illiquidity risk premium proposed in this study. The development of Fama-French model follows the time series regressions proposed by Black et al. (1972) which use excess returns or returns on zero-investment portfolios as explanatory factors. Accordingly, Fama and French (1993) measured market risk premium ($R_M - R_F$) as return on market portfolio (R_M) net of risk-free security (R_F) whereas premiums on size and distress risks as returns on zero-investment portfolios. Specifically, using the same procedure illustrated in Figure 1 (except for ME categories which are only divided into S and B categories), they formed zero-investment portfolios to mimic risk related to size (SMB) and distress

conserve space) show that $\hat{L}M\hat{H}$ formed from the intersections of TURN and either ME or B/M consistently generate the highest $adj\text{-}R^2$ and thus, are considered most appropriate for developing the liquidity-based 3-factor models.

(HML). SMB is the difference between the simple average of returns on Small and Big ME portfolios (i.e., [*SH* + *SM* + *SL*]/3 – [*BH* + *BM* + *BL*]/3). This procedure ensures that the premium on size risk is relatively free from the influence of distress risk because the Small and Big portfolios have about the same weighted-average B/M. Similarly, HML is the simple average of the returns on High and Low B/M portfolios (i.e. [*HS* + *HB*]/2 – [*LS* + *LB*]/2).

As an implication of Fama-French model, the proposed models estimate illiquidity risk premium in a similar manner. Identified as $\hat{\mathrm{L}}\mathrm{M}\hat{\mathrm{H}}$, it is the difference between the simple average of the returns on High and Low TURN portfolios (i.e. $[\acute{L}H + \acute{L}M + \acute{L}L]/3 - [\hat{H}H + \hat{H}M + \hat{H}L]/3$). This approach is indeed consistent with the liquidity theory which posits that stocks with low levels of trading volume are less liquid and therefore command higher returns. The liquidity risk premium ($\hat{\mathrm{L}}\mathrm{M}\hat{\mathrm{H}}$) essentially reflects the inverse relationship, the premium that investors would require for holding less liquid stocks because they anticipate the payment of higher trading costs when reselling the stocks in the future (Datar et al., 1998; Dey, 2005).

Development of the Liquidity-Based Models

To differentiate the proposed 3-factor models from the standard Fama-French model, we re-write Fama-French model in time-series regression form:

$$R_{i,t} - R_{F,t} = \alpha_i + b_i(R_{M,t} - R_{F,t}) + s_i(SMB_{FF,t}) + d_i(HML_{FF,t}) + \varepsilon_{i,t} \tag{5}$$

where R_i is the realized returns on portfolio *i*, $i = 1, \ldots, 27$, α_i is the intercept, b_i, s_i, and d_i are the estimated factor loadings, R_M is the realized returns on the market portfolio, R_F is the return on risk-free security, SMB_{FF} and HML_{FF} are respectively the size and distress risk premium formed from the intersection of ME/BM portfolios and ε_i is the error term at the end of month *t*.

Like most extended variants of CAPM (Liu, 2004), ICAPM (Lo & Wang, 2001) and Fama-French model (Bali & Cakici, 2004; Chan & Faff, 2005; Miralles & Miralles, 2006), the proposed liquidity-based models maintain market risk as the main risk factor. By dropping HML, the first variant of the model referred as "SiLiq" combines market risk premium ($R_M - R_F$) with "SIze" (SMB) and LIQuidity ($\hat{\mathrm{L}}\mathrm{M}\hat{\mathrm{H}}$) premiums:

$$R_{i,t} - R_{F,t} = \alpha_i + b_i(R_{M,t} - R_{F,t}) + s_i(SMB_{\dot{L}IQ,t}) + l_i(\dot{L}M\dot{H}_{j,t}) + \varepsilon_{i,t}\,. \tag{6}$$

The second variant referred as "DiLiq" drops size premium (SMB) to form a combination of market risk premium ($R_M - R_F$), "DIstress" (HML) and LIQuidity ($\hat{\mathrm{L}}\mathrm{M}\hat{\mathrm{H}}$) premiums:

$$R_{i,t} - R_{F,t} = \alpha_i + b_i(R_{M,t} - R_{F,t}) + d_i(HML_{LIQ,t}) + l_i\left(\dot{L}M\dot{H}_{j,t}\right) + \varepsilon_{i,t}, \qquad (7)$$

where α_i, b_i, s_i, d_i, R_i, R_M, R_F, and ε_i are as defined in Equation (5), l_i is the estimated loading of liquidity factor ($\hat{\mathrm{L}}\mathrm{M}\hat{\mathrm{H}}$), SMB_{LIQ} is the size premium formed from the ME/TURN portfolios, HML_{LIQ} is the distress premium formed from the BM/TURN portfolios, and $\hat{L}M\hat{H}_{j,t}$ in Equations (6) and (7) are the illiquidity premium formed from the ME/TURN and BM/TURN portfolios at the end of month t, respectively.

Statistical Methods and Hypotheses

This study employs time-series multiple regressions (cf., Fama & French, 1993, 1996; Davis et al., 2000; Drew & Veeraraghavan, 2002; Drew et al., 2003; Bali & Cakici, 2004) to estimate the factor loadings for each of the three sets of nine tests portfolios double-sorted on ME/BM, ME/TURN, and BM/TURN using the data from the 1987:01–2000:12 estimation period. The estimated models are then used to forecast returns over the 2001:01–2004:12 post-estimation period (Maddala, 2001; Chen, 2003; Cao et al., 2005). Since the objective of this study is to determine whether the liquidity-based 3-factor models are more accurate than the Fama-French model, we compare the forecasting accuracy of the competing models. Note that because forecasting errors in this study are derived from models that are estimated from period of different economic and stock market conditions, the resulting errors could vary slightly from one metric to another. Therefore for robustness, we measure the forecasting accuracy using two error metrics:

$$MAPE = 100 \sum_{t=N+1}^{N+\tilde{N}} \left| \frac{\hat{R}_t - R_t}{R_t} \right| / (\tilde{N}), \qquad (8)$$

$$U = \frac{\sqrt{\sum_{t=N+1}^{N+\tilde{N}} \left(\hat{R}_t - R_t\right)^2 / \left(\tilde{N}\right)}}{\sqrt{\sum_{t=N+1}^{N+\tilde{N}} \hat{R}_t^2 / \left(\tilde{N}\right)} + \sqrt{\sum_{t=N+1}^{N+\tilde{N}} R_t^2 / \left(\tilde{N}\right)}}, \qquad (9)$$

where *MAPE* is mean absolute percentage error, *U* is the Theil's inequality coefficient, *R* and $\hat{R}$ are the realized ($R_i - R_F$) and forecasted ($\hat{R}_i - \hat{R}_F$) excess returns on the test portfolios, respectively and *t* is the forecast sample period from $N + 1, \ldots, N + \tilde{N}$. Compared to other error metrics such as mean absolute error (MAE) and mean squared error (MSE), MAPE and Theil's U are considered to be more robust against extreme values (Maddala, 2001).

A model is considered most accurate if it generates the smallest error relative to the competing models. In the form of a null hypothesis, H_0: There is no difference in the forecasting accuracy across the three three-factor models. For statistical testing, the hypothesis is stated according to the error metrics:

(a) There is no difference across the three 3-factor models in the forecasting accuracy as measured by MAPE, i.e., H_0: $\{MAPE_{F\text{-}F} = MAPE_{SiLiq} = MAPE_{DiLiq}\}$, and

(b) There is no difference across the three 3-factor models in the forecasting accuracy as measured by Theil's U, i.e., H_0: $\{U_{F\text{-}F} = U_{SiLiq} = U_{DiLiq}\}$.

Due to small sample (nine test portfolios per run) and three models comparisons, we test the hypotheses using the non-parametric Kruskal-Wallis test:

$$H = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{P_j^2}{n_j} \right) - 3(N+1) \tag{11}$$

where $P_j = \sum_{i=1}^{n_j} P_{i,j}$ is the total rank of the errors (MAPE or Theil's U) for portfolio $i = 1, \ldots, n$ for model *j*, *j* = Fama-French, SiLiq or DiLiq and $N = \sum_{j=1}^{k} n_j$ is the number of test portfolios times the number of model *j*. The H-statistic has an asymptotic distribution of χ^2 with d.f. (k – 1). Thus, the null hypothesis of no difference is rejected if $H \geq \chi^2_{k-1,\alpha}$ (Hollander & Wolfe, 1973).

RESULTS AND DISCUSSION

Table 2 presents the descriptive statistics of the explanatory factors of each competing models. The results obviously indicate that only SMB is large both from investment (1.2%/month or 14.4%/year) and statistical (*p*-value ≤ 0.01) perspectives. Unlike Fama and French (1993) who found positive and large premiums on both market risk and HML, we find $R_M - R_F$ and HML to be negative and small, respectively. However, negative $R_M - R_F$ was also reported in Korea and Philippines (Drew & Veeraraghavan, 2002) and in Australia (Chan & Faff, 2005). The negative $R_M - R_F$ in Malaysian market could be attributed to the period of study which is characterized as one with great economic and stock market uncertainties, particularly surrounding the dreadful period of the 1997 Asian crisis. Throughout the 216-month study period, the $R_M - R_F$ is negative 51% of the time. During the worst period of the 1997/98 crisis, the $R_M - R_F$ is negative 67% of the time. In contrast to the straight-forward interpretation of the risk-return trade-off theory (Amihud & Mendelson, 1986; Datar et al., 1998) that higher risk assets must be compensated by higher returns, the negative $R_M - R_F$ rather reasonably suggests that returns on risky assets (market portfolio) are more sensitive (greater fluctuations) to macroeconomic factors. A negative shock like the financial crisis inflicts effects on the risky assets more damaging (larger drops) than that on the riskless (stable returns) assets, and thus the negative $R_M - R_F$.

Table 2
Descriptive statistics and correlation coefficients

Panel A. Explanatory factors in Fama-French Model						
	Mean	*t*-statistics	Std. Dev.	$R_M - R_F$	SMB_{FF}	HML_{FF}
$R_M - R_F$	–0.003	–0.480	0.088	1.000		
SMB_{FF}	0.012	2.896*	0.061	0.345	1.000	
HML_{FF}	0.004	0.993	0.060	0.356	0.244	1.000
Panel B. Explanatory factors in SiLiq						
	Mean	*t*-statistics	Std. Dev.	$R_M - R_F$	SMB_T	LMH_{MT}
$R_M - R_F$	–0.003	–0.480	0.088	1.000		
SMB_T	0.012	2.681*	0.068	0.382	1.000	
LMH_{MT}	–0.005	–1.424	0.051	–0.575	–0.425	1.000
Panel C. Explanatory factors in DiLiq						
	Mean	*t*-statistics	Std. Dev.	$R_M - R_F$	HML_T	LMH_{BT}
$R_M - R_F$	–0.003	–0.480	0.088	1.000		
HML_T	0.009	1.637	0.078	0.489	1.000	
LMH_{BT}	–0.006	–1.553	0.057	–0.606	–0.496	1.000

Notes: * and ** denote significance at 1% and 5% levels, respectively.
All correlations are significant at 5% level.

In the meantime, unlike the liquidity measure used by Chan and Faff (2005), both $\hat{L}M\hat{H}$ measures in this study produce negative premiums ($\hat{L}M\hat{H}_{BT}$ = –0.6% and $\hat{L}M\hat{H}_{MT}$ = –0.5%). Even though insignificantly different from zero, these results like the $R_M - R_F$ contradict the risk-return trade-off theory. Unfortunately similar finding is reported by many for emerging markets.

For instance, Rowenhorst (1999) found HML (equivalent to invert-$\hat{L}M\hat{H}$) is 0.11% in 60% of 20 emerging equity markets. Dey (2005) who investigated the liquidity issue in 48 countries found the return-TURN relationship is positive (translates into negative $\hat{L}M\hat{H}$) and such relationship is only significant in emerging countries. According to Pástor and Stambaugh (2003), the negative $\hat{L}M\hat{H}$ can be explained by a phenomenon where due to macroeconomic shocks that threatens market liquidity, the value of portfolio that is more sensitive to liquidity drops dramatically, forcing the affected investors to liquidate. Similar to Pástor and Stambaugh (2003), we find that the trough on the $\hat{L}M\hat{H}$ line occur in periods of crisis and deepest during the 1997 crisis.

Another concern in asset pricing model is the independence between explanatory factors. The application of ICAPM (or APT) requires that in a market where K state-variables exist, return on a multifactor-minimum-variance (MMV) portfolio is spanned (explained) by returns on risk-free security plus any $K + 1$ MMV portfolios that are linearly independent from one another (Fama & French, 1996). Accordingly, even though other variants of 3-factor models produced better explanatory power, Fama-French model remains the preferred choice because it exhibits independent explanatory factors which consequently allow direct interpretation of the model's intercept (Fama & French, 1996). Such a strong argument is difficult to neglect because as reported in the right columns of Table 2, the correlations between Fama-French factors (0.244–0.356) are the lowest compared to those of SiLiq (0.382–0.575) and DiLiq (0.489–0.606).

Forecasting Accuracy of the Competing Three-Factor Models

Prior to determining the forecasting accuracy of the alternative models, we estimate the models by regressing the portfolios' excess returns on the explanatory factors according to the respective model specification using data for the estimation period of 1987:01–2000:12. Since the regressions involve time series, we test using augmented Dickey-Fuller and find all variables are stationary up to lag 12. We run diagnostic tests (to check for heteroscedasticity, serial correlation and parameter stability) on the models and the results suggest that they fulfill the model specification tests. The results of the stationary tests, regressions and diagnostic tests are not reported to conserve space. The estimated models are then used to forecast the excess returns on the portfolios over the post-estimation period of 2001:01–2004:12. Before we concentrate on the 3-factor models, our preliminary results from the Wilcoxon matched-pair test in Table 3 tend to strongly support our emphasis on the three-factor models. Each of the three-factor models has forecast errors that are consistently significantly smaller than those of the CAPM (p-value ≤ 0.05). Two exceptions are differences based on MAPE in Panel A concerning Fama-French and SiLiq models which are still significant at conventional level (p-value ≤ 0.10). With the superiority of three-factor models against the CAPM is no longer an issue, we shift our focus on the relative performance of the competing three-factor models.

Table 3
CAPM versus Three-Factor Models

Panel A: Mean Absolute Percentage Error						
	CAPM	Fama-French	CAPM	SiLiq	CAPM	DiLiq
Average errors	251.2	166.0	251.2	162.9	251.2	149.7
Total ranks	31.37	23.63	31.59	23.41	32.11	22.89
Z-statistics (p-value)	–1.808 (0.071)		–1.912 (0.056)		–2.154 (0.031)	
Panel B: Theil's Inequality Coefficient U						
	CAPM	Fama-French	CAPM	SiLiq	CAPM	DiLiq
Average errors	0.262	0.203	0.262	0.203	0.262	0.203
Total ranks	34.57	20.43	34.70	20.28	34.39	20.61
Z-statistics (p-value)	–3.305 (0.001)		–3.374 (0.001)		–3.218 (0.001)	

Notes: The differences are tested using nonparametric Wilcoxon matched-pair tests.

Table 4 reports the error metrics for all three forecasting models. At this stage, the relative performance of the three-factor models is evaluated on two criteria, first based on the relative size of the average errors and second based on the number of portfolios with smallest errors. Panel A of Table 4 reports the forecast errors as measured by MAPE which appear to be somewhat lenient toward supporting DiLiq. Not only the average MAPE of DiLiq ($\bar{\varepsilon}$ = 144.24) is smallest when forecasting excess returns on the BM/TURN portfolios, it is also smallest ($\bar{\varepsilon}$ = 162.75) when predicting those on the ME/BM portfolios. This is notwithstanding the fact that Fama-French model still reports more portfolios (55.6%) with the smallest MAPE when predicting ME/BM portfolios. In the BM/TURN portfolio category, DiLiq reports a dominating number of smallest MAPE in 7 (77.8%) test portfolios. When forecasting excess returns on the ME/TURN portfolios, SiLiq appears to be more prevailing than the other models by generating the smallest average MAPE ($\bar{\varepsilon}$ = 117.50) and smallest MAPE in 5 (55.5%) test portfolios.

Panel B of Table 4 reports forecast errors as measured by Theil's U. Unlike the results based on the MAPE, Theil's U suggests that the relative performance of the competing models is somewhat influenced by their base portfolios. Both the average U and the times U is smallest when predicting excess returns on ME/BM portfolios suggest that the Fama-French model is the preferred model ($\bar{\varepsilon}$ = 0.192 and $\Sigma\varepsilon_{min}$ = 6 portfolios). On the same ground, SiLiq is most accurate in predicting excess returns on ME/TURN portfolios ($\bar{\varepsilon}$ = 0.172 and $\Sigma\varepsilon_{min}$ = 4 portfolios). However, such influence does not totally hinder the advantage of DiLiq previously detected from the MAPE results. The differences shown by both Fama-French model and SiLiq are less pronounced compared to the difference created by DiLiq. Specifically, in predicting excess returns on the BM/TURN portfolios, DiLiq reports an average U ($\bar{\varepsilon}$ = 0.189) which is 14.9% and 15.3% smaller than those of Fama-French model and SiLiq, respectively. Furthermore, DiLiq also reports a dominating number of smallest U in 8 (88.9%) of test portfolios. Overall, the evidence that we gather based on the two criteria so far indicates that liquidity-based models, specifically DiLiq has the potential to improve Fama-French model for predicting stock returns.

Table 4
Forecast Errors of the Competing Three-Factor Models

Models	9 ME/BM Portfolios			9 ME/TURN Portfolios			9 BM/TURN Portfolios		
	Range	$\bar{\varepsilon}$	$\Sigma\varepsilon_{min}$	Range	$\bar{\varepsilon}$	$\Sigma\varepsilon_{min}$	Range	$\bar{\varepsilon}$	$\Sigma\varepsilon_{min}$
Panel A. Mean Absolute Percentage Error (MAPE)									
Fama-French	48.11–410.0	180.7	5/9	55.92–563.7	156.9	1/9	55.45–344.6	160.3	1/9
SiLiq	55.65–497.1	220.0	1/9	55.92–269.7	117.5	5/9	63.49–258.5	151.1	1/9
DiLiq	52.55–347.4	162.7	3/9	48.44–364.1	142.2	3/9	56.71–432.8	144.2	7/9
Panel B. Theil's U									
Fama-French	0.120–0.302	0.192	6/9	0.143–0.267	0.195	2/9	0.156–0.335	0.222	1/9
SiLiq	0.145–0.341	0.214	2/9	0.130–0.261	0.172	4/9	0.175–0.276	0.223	0/9
DiLiq	0.125–0.404	0.218	1/9	0.125–0.294	0.202	3/9	0.116–0.286	0.189	8/9

Notes: ε = error metric, $\bar{\varepsilon}$ = average error and $\Sigma\varepsilon_{min}$ = number error metric is smallest within a particular portfolio category.

Hypothesis Testing

To statistically examine if the differences reported in Table 4 are significant, we run Kruskal-Wallis tests. As shown in Panels A and B of Table 5, none of the differences is significant (p-value > 0.05). Specifically both H_0(a): {$MAPE_{FF}$ = $MAPE_{SiLiq}$ = $MAPE_{DiLiq}$} and H_0(b): {$U_{FF} = U_{SiLiq} = U_{DiLiq}$} cannot be rejected at 10% significant level. Albeit the insignificant differences, we could identify the preferred of the three alternative models based on the relative ranks in the Kruskal-Wallis results. As indicated with the figures in parentheses for each of the three test portfolio categories, the preferred model is: (i) Fama-French for predicting the excess returns on ME/BM portfolios, (ii) SiLiq for predicting excess returns on the ME/TURN portfolios, and (iii) DiLiq for predicting excess returns on BM/TURN portfolios.

Table 5
Kruskal-Wallis Tests for Comparisons Among 3-Factor Models

Competing 3-factor models		Nine test portfolios per category			Full sample (27 Portfolios)
		ME/BM	ME/TURN	BM/TURN	
Panel A. Mean Absolute Percentage Error (MAPE)					
Fama-French model	Mean rank	13.11 (1)	14.11 (2)	15.11 (3)	42.15 (3)
SiLiq model		15.56 (3)	13.00 (1)	14.89 (2)	42.04 (2)
DiLiq model		13.33 (2)	14.89 (3)	12.00 (1)	38.81 (1)
H-statistics [*p*-value]		0.522 [0.770]	0.257 [0.879]	0.861 [0.650]	0.350 [0.840]
Panel B. Inequality coefficient of U Theil					
Fama-French model	Mean rank	12.00 (1)	15.22 (2)	14.72 (2)	41.46 (2)
SiLiq model		15.33 (3)	11.11 (1)	17.00 (3)	41.98 (3)
DiLiq model		14.67 (2)	15.67 (3)	10.28 (1)	39.56 (1)
H-statistics [*p*-value]		0.889 [0.641]	1.802 [0.406]	3.345 [0.188]	0.159 [0.923]

Notes: In all cases d.f. = $k - 1 = 2$ where k = number of models being compared and $\chi^2_{2,0.05} = 5.9915$.
Figure in the parenthesis indicates relative position of the competing models.

However, the slight advantage of DiLiq detected earlier in Table 4 is reflected here when the largest gap of total rank is always associated with the model. When errors are measured with MAPE in Panel A, the smallest *p*-value (0.650) is associated with DiLiq. The gap is larger when errors are measured with Theil's U. As reported in Panel B, DiLiq dominates the other models with a marginal significant difference (*p*-value = 0.188). To see from a broader perspective, we proceed by running the Kruskal-Wallis test on all 27 test portfolios simultaneously. Despite the fact that the difference remain insignificant, the relative ranks again suggest that DiLiq is the preferred model as it consistently prevails as the best forecasting model based on MAPE and Theil's U. In other words, regardless of the error metrics, the greatest difference is consistently associated with the BM/TURN portfolio category in which case DiLiq is always the preferred model. It is also worth noting that Kruskal-Wallis tests may fail to detect the difference in this study due to relatively small sample size and the less powerful non-parametric test employed (Hollander & Wolfe, 1973). Taking that into account, the evidence that we obtain so far may be considered sufficient to surmise that forecasting returns on portfolio of stocks traded on the Malaysian equity market can be slightly improved by incorporating illiquidity risk in a 3-factor model in the form of DiLiq.

CONCLUSION AND IMPLICATION

The preliminary results of this study reinforce current perception that empirically multifactor models are more capable than the CAPM in predicting stock returns. The results clearly document that market factor ($R_M - R_F$) alone cannot capture other risks in stocks. The implication on investment is that instead of merely relying on the market factor, investors particularly in this equity market must also be concerned with firm-specific factors like the distress and liquidity levels. Such recommendation owes to the fact that even though the forecasting accuracy of the competing three-factor models is consistently insignificantly different from one another, DiLiq tends to slightly outperform the others. Given that DiLiq introduces distress (as proxied by HML) and illiquidity (as proxied by $\hat{\text{L}}\text{M}\hat{\text{H}}$) as the additional risk factors, this finding to a certain extent correctly reflects the concern of investors in emerging equity markets on liquidity (Rowenhorst, 1999; Dey, 2005; Bekaert et al., 2005). This finding also allows us to more convincingly argue that investors require additional premiums to compensate risks due to distress and illiquidity, rather than just to compensate risks due to being small. Rationally, being small by itself does not make a company riskier. Rather, it is the company's risk of being in distress and risk of losing liquidity that trigger investors to demand higher than market risk premiums.

Overall, our empirical findings lend strong support to current view regarding the role of liquidity in asset pricing models (Bali & Cakici, 2004; Chollete, 2004; Liu, 2004; Lo & Wang, 2004; Chan & Faff, 2005; Miralles & Miralles, 2006). The insignificant differences in forecasting accuracy at the very least prove that the liquidity-based models are compatible with Fama-French model. Nonetheless, without testing the predictive power of extended models such as those suggested in recent studies (Bali & Cakici, 2004; Chollete, 2004; Chan & Faff, 2005; Miralles & Miralles, 2006), the results of this study cannot be used to validate Fama and French's (1996) proposition that three-factor model is adequate to explain stock returns. Had their proposition hold, the results of this study may be interpreted as an indication that the predictive power of the three-factor model can be slightly improved by combining market risk factor ($R_M - R_F$) with distress (HML) and illiquidity ($\hat{\text{L}}\text{M}\hat{\text{H}}$) risk factors. However until further evidence regarding DiLiq is found, investors are suggested to continue to consider firm size in setting the stock prices.

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