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EVALUATING THE ACCURACY OF FAMA-FRENCH MODEL *VERSUS* LIQUIDITY-BASED THREE-FACTOR MODELS IN FORECASTING PORTFOLIO RETURNS

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Abstract

This paper evaluates the forecasting accuracy of the Fama-French three-factor model versus two liquidity-based three-factor models, referred as SiLiq and DiLiq, that have been developed as potential improvements on the Fama-French model. The study uses the period of 1987:01 to 2000:12 for estimation and sets the period of 2001:01 to 2004:12 as the forecast sample. The test assets are 27 portfolios nine each formed from the intersections of the following firm characteristics: (i) size and book-to-market ratio (B/M), (ii) size and share turnover (TURN), and (iii) B/M and TURN. Once the models are estimated using multiple time-series regressions, the forecasting accuracy of the competing models are evaluated using three error metrics; mean absolute errors (MAE), mean absolute percentage errors (MAPE), and Theil's U statistics. Our results suggest that in predicting the Malaysian stock returns, the Fama-French model is dominated by its liquidity-based model counterparts, specifically, the DiLiq model.

JEL Classifications: G12
Keywords: Liquidity; Fama-French Model; Liquidity-Based Asset Pricing Model; Illiquidity Risk Factor; Multifactor Model

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1. Introduction

In the midst of Sharpe (1964), Lintner (1965), and Black's (1972) capital asset pricing model (henceforth, CAPM) empirical frustration, interest on asset pricing model is suddenly revived with the Fama and French's (1993) finding. They find that returns on stocks can be explained by a multifactor model that adds risk premiums related to two firm-specific factors, size and distress, to the CAPM's market risk premium. Ever since, the three factor model (henceforth, Fama-French model) continues to capture attention to the extent that it becomes the workhorse for risk adjustment in academic circles (Hodrick and Zhang, 2001). While the model performs exceptionally well compared to the standard CAPM, empirical evidence on the model is still inconclusive because like any other model, it is not without limitation (Fama and French, 1996). Thus, this study finds it of a great contribution to the asset pricing literature if alternative models can be developed as potential improvement on the Fama-French model.

Motivated by Fama and French's (1996) conclusion that three-factor model suffice to explain stock returns and the fact that the additional risk factor in the Fama-French model are firm-specific factors, this study plans to achieve its objective by developing variants of three-factor models that incorporate other firm-specific factor that is of greater concern to the investors in the studied market. For the purpose of this study, liquidity seems to match the description perfectly because "… liquidity is a natural choice as an asset-pricing factor since it is a state variable in the ICAPM sense" Chollete (2004) which explains the superior performance of liquidity-adjusted versions of the CAPM (Acharya and Pedersen, 2005; Lo and Wang, 2001; Liu, 2004) and Fama-French model (Bali and Cakici, 2004; Chollete, 2004; Liu, 2004; Chan and Faff, 2005; Miralles and Miralles, 2005). Furthermore, this study "… provides an ideal setting to examine the impact of liquidity on expected returns" (Bekaert *et al.*, 2005) because "… liquidity is one firm characteristic that is of particular concern to investors in emerging market" (Rowenhorst, 1999). Also as important is Hodrick and Zhang's (2001) proposition that liquidity should be incorporated in asset pricing model to improve its specification accuracy.

To examine whether the newly-developed liquidity-based models meet their purpose, this study follows Fama and French (1993; 1996) in adopting Black et al. (1972) approach in using time-series regressions to develop and then obtain the coefficient estimates of each tested model. The estimated models are then used to forecast portfolio returns during the post-estimation period (2000:01 to 2004:12) when their forecasting accuracy of the liquidity-based models are evaluated against the Fama-French model. While the re-examination of the Fama-French model naturally adds to existing literature particularly in this country where similar studies are still scant (Drew and Veeraraghavan, 2002, 2003), an effort to develop asset pricing models which incorporate the role of liquidity is a major contribution by itself merely because this factor has a significant impact on investment in emerging markets like Malaysia (Bekaert *et al.*, 2005; Dey 2005; Pástor and Stambaugh, 2003; Rowenhorst, 1999). The remaining of this paper is organized in the following manner: Section 2 reviews past related studies, Section 3 explains the data and methodology, Section 4 reports and elaborates on the findings while, Section 5 concludes.

2. Literature Review

The mounting evidence on the empirical failure of the CAPM and the theoretical appeal of multifactor model particularly the APT and ICAPM led to the development and widespread acceptance of a variant of asset pricing model referred as empirical multifactor models particularly after the success story of a three-factor model introduced by Fama and French (1993). Based on their earlier finding (Fama and French, 1992) that beta consistently fails while two firm-specific factors, namely market value of equity (ME) and book-to-market ratio (B/M), consistently, significantly explain the cross-section of stock returns, Fama and French (1993) argue and prove that the expected excess returns on stock ***i*** (R_i) can be explained by:

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

where $E(.)$ is the expected operator, $R_M - R_F$ is the market risk premium, *SMB* (*S*mall minus *B*ig ME portfolios) and *HML* (*H*igh minus *L*ow B/M portfolios) are the additional risk premium related to size and distress, respectively, while b_i, s_i, and d_i are the loadings of the respective risk factors.

Empirical supports for the Fama-French model can be adequately summarized with Hodrick and Zhang's (2001) assertion about the model being "...the workhorse for risk adjustment in academic circles". Nonetheless, given the number of studies that provide contradictory results on the Fama-French model (Hodrick and Zhang, 2001; Bali and Cakici, 2004; Chollete, 2004; Da and Gao, 2004; Bartholdy and Peare, 2005) and Fama and French's (1996) statement that like any other model, the Fama-French model also has important holes simply could not put an end to the search for a better asset pricing model. One such effort is initiated in this study which hypothesizes that alternative models that emphasize on the role of liquidity factor in asset pricing stand a chance as potential improvement on the standard Fama-French model.

In response to Fama and French's (1996) conclusion about the holes in their model and Hodrick and Zhang's (2001) argument about the importance of liquidity in asset pricing model, a surge of academic researches start to examine the role of liquidity in explaining asset returns. Evidently, as reported in Table 1, of 20 empirical studies that we manage to review in this study, almost all support the hypothesis that liquidity is a significant predictor of expected stock returns. This finding is expected because there is a consensus about the importance of liquidity in asset pricing. The delayed attention is most probably explained by the unavailability of data on direct measures of liquidity such as the bid-ask spread. This is because after new measures of liquidity based on trading-volume variables are found (Brennan *et al.*, 1998; Datar *et al.*, 1998), this factor immediately catches researchers' attention. As shown in Table 1, three trading volume variables that are mostly frequently used as basis for measuring liquidity are share turnover (TURN), dollar volume (DVOL), and absolute return-to-DVOL ratio (illiquidity or ILLIQ). While the relationship between volume-based liquidity factor and expected returns is well-established (Karpoff, 1987), the interest of recent studies shifts to its role in asset pricing model. In the spirit of Fama-French model, most of the studies (Bali and Cakici, 2004; Chollete, 2004; Liu, 2004; Chan and Faff, 2005; Miralles and Miralles, 2005) assign to liquidity a role of stock's common risk factor, similar to SMB and HML. The results of these studies are unanimously in favor of the asset pricing models that incorporate a liquidity factor.

3. Data and Methodology

The study spans 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). Two sets of data are used; (i) monthly data on stock closing prices of 230 to 480 companies listed in the Main Board of Bursa Malaysia, three-month Treasury Bills (T-Bills), and Exchange Main Board All Shares (EMAS) price index, and (ii) year-end data on number of shares outstanding (NOSH), trading volume (VOL), market capitalization of the equity (ME), and M/B ratio of the studied companies. The data is sourced from Thompson's DataStream and Investors' Digest.

The dependent variables or excess returns to be explained in this study are the monthly value-weighted average rate of returns on the test portfolio net of 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 percent smallest (S), 40 percent medium (M), and 30 percent biggest (B); (ii) three B/M categories i.e., 30 percent highest B/M (H), 40 percent medium (m), and 30 percent lowest B/M (L); and (iii) three TURN categories i.e., 30 percent lowest TURN ($\hat{L}$), 40 percent medium TURN, and 30 percent highest TURN ($\hat{H}$). Then, following the procedure illustrated in Figure 1, three sets of 9 test portfolios from each ME/BM, ME/TURN, and BM/TURN intersections are constructed.

Since this study adopts Black *et al.*'s (1972) time series regression approach, the explanatory variables or factors are the premiums for the Fama-French's SMB and HML and our measure of risk related to liquidity ($\hat{L}M\hat{H}$). From the portfolios that are constructed using the same procedure illustrated in Figure 1 (except for ME categories that are only divided into S and B categories), we form zero-investment portfolios to mimic risk related to size (SMB), distress (HML), and liquidity ($\hat{L}M\hat{H}$) in manner similar to Fama-French (1993).[1] We then develop two variations of the three-factor model that incorporate the role of liquidity as proxied by $\hat{L}M\hat{H}$. Prior to that, it is only appropriate to start by re-writing the basic three-factor model, i.e., the standard Fama-French model which in the time-series regression form is stated as follows:

$$R_{i,t} - R_{F,t} = \alpha_i + b_i(R_{M,t} - R_{F,t}) + s_i(SMB_t) + d_i(HML_t) + \varepsilon_{i,t}, \qquad (3)$$

where $R_{i,t}$ is the realized returns on portfolio i, i = 1, ..., 9 at month t, α_i is the intercept term, b_i, s_i, and d_i are the estimated factor loadings for portfolio i, $R_{M,t}$ is the realized rate of returns on the market portfolio as proxied by the EMAS index at month t, $R_{F,t}$ is the rate of return on the risk-free security as proxied by the T-Bill at month t, *SMB* and *HML* are respectively the relative size and distress factor formed from the intersection of ME/BM portfolios at month t, and ε_i is the error term. While KLSE Composite Index (KLCI) is undeniably the more widely used indicator of stock market performance in Malaysia, EMAS seems more appropriate for the purpose of this study because it is more consistent with the Markowitz's (1952) definition of market portfolio. Specifically, compared to KLCI which only comprises of 100 blue-chip stocks, EMAS is more representative of all stocks in the investment universe of concern in this study, namely the Main Board of Bursa Malaysia.

In the newly developed liquidity-based models which will be referred as "SiLiq" and "DiLiq", the market risk premium (R_M-R_F) remains as the main risk factor. This practice is common in the development of most

[1] Besides TURN, we also form $\hat{L}M\hat{H}$ using 5 other trading-volume variables i.e., DVOL, ILLIQ, and the coefficient of variations of each of these variables. Overall, the procedure in Figure 1 generates 12 $\hat{L}M\hat{H}$ alternatives. The results of univariate regressions (not reported) show that $\hat{L}M\hat{H}$ formed from the intersections of TURN and either ME or B/M consistently generate the highest *adj-*R^2 and thus, are considered most appropriate for developing the liquidity-based three-factor models.

extended variants of CAPM (Liu 2004), ICAPM (Lo and Wang 2004) or Fama-French model (Bali and Cakici 2004; Chan and Faff 2005; Miralles and Miralles 2005). By dropping HML, SiLiq is a three-factor model that combines of R_M-R_F, "SIze" (SMB), and LIQ ($\hat{L}M\hat{H}$):

$$R_{i,t} - R_{F,t} = \alpha_i + b_i (R_{M,t} - R_{F,t}) + s_i (SMB_t) + l_i (\dot{L}M\dot{H}_t) + \varepsilon_{i,t} . \qquad (4)$$

The second variation of the liquidity-based three-factor model, DiLiq, drops SMB to form a combination of R_M-R_F, "DIstress" (HML), and LIQ ($\hat{L}M\hat{H}$):

$$R_{i,t} - R_{F,t} = \alpha_i + b_i (R_{M,t} - R_{F,t}) + d_i (HML_t) + l_i \left(\dot{L}M\dot{H}_t\right) + \varepsilon_{i,t} , \qquad (5)$$

where α_i, b_i, s_i, d_i, R_i, R_M, R_F, and ε_i are as defined in Equation (3), l_i is the estimated loading of relative liquidity factor ($\hat{L}M\hat{H}$). Unlike the *SMB* and *HML* in Equation (3) which are formed from the intersection of ME/BM portfolios, *SMB* and *HML* in Equations (4) and (5) are formed from the intersections of ME/TURN and BM/TURN portfolios, respectively. Meanwhile, $\hat{L}M\hat{H}_t$ is the relative liquidity factor at month *t* which in Equation (4) is formed from the intersection of ME/TURN portfolios and while in Equation (5) is formed from the intersection of BM/TURN portfolios.

Like earlier studies (Fama and French, 1993, 1996a; Davis *et al.*, 2000; Drew and Veraraghavan, 2002, 2003; Bali and Cakici, 2004), this study also adopts Black et al. (1972) approach in using time-series multiple regressions to estimate the factor loadings for each of the 27 portfolios double-sorted on ME/BM, ME/TURN, and BM/TURN using the past 168 monthly observations from the estimation period of 1987:01 – 2000:12. We then use the estimated models to forecast stock returns over the remaining 48 months of the post-estimation period of 2001:01 – 2004:12 (Madalla, 2001; Chen, 2003; Cao *et al.*, 2004).

To determine whether the newly-developed models work as potential improvements on the Fama-French model, we test whether they are more accurate than the Fama-French model. For robustness, we measure and compare the forecasting accuracy of the competing models using the following three error metrics:

$$MAE = \sum_{t=N+1}^{N+\tilde{N}} \left| \hat{R}_t - R_t \right| \Big/ \left(\tilde{N}\right), \qquad (6)$$

$$MAPE = 100 \sum_{t=N+1}^{N+\tilde{N}} \left| \frac{\hat{R}_t - R_t}{R_t} \right| /(\tilde{N}) , \qquad (7)$$

$$U = \frac{\sqrt{\sum_{t=N+1}^{N+\tilde{N}} \left(\hat{R}_t - R_t\right)^2 / \left(\tilde{N}\right)}}{\sqrt{\sum_{t=N+1}^{N+\tilde{N}} \hat{R}_t^2 / \left(\tilde{N}\right)} + \sqrt{\sum_{t=N+1}^{N+\tilde{N}} R_t^2 / \left(\tilde{N}\right)}}, \tag{8}$$

where *MAE* is mean absolute error, *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, and *t* is the forecast sample period from N+1, ..., N+$\tilde{N}$. The MAE measures unbiasness in forecasting and is appropriate for comparing the accuracy across different models that explain the same time series. Unlike MAE, MAPE and Theil's U are invariant to scale. The U statistics is always between 0.0 and 1.0 with U = 0.0 indicates a perfect forecast while U = 1.0, the opposite. For the purpose of this study, a model is considered most accurate if it generates the smallest error relative to the competing models. In the form of a null hypotheses:

H_0: There is no difference in the forecasting accuracy across the three three-factor models. For statistical testing, the hypothesis is further divided based on the error metric. Specifically,

a. there is no difference across the three three-factor models in the forecasting accuracy as measured by MAE i.e., H_0: = {$MAE_{F\text{-}F}$ = MAE_{SiLiq} = MAE_{DiLiq}},
b. there is no difference across the three three-factor models in the forecasting accuracy as measured by MAPE i.e., H_0: {$MAPE_{F\text{-}F}$ = $MAPE_{SiLiq}$ = $MAPE_{DiLiq}$}, dan
c. there is no difference across the three three-factor models in the forecasting accuracy as measured by Theil's U i.e., H_0: = {$U_{F\text{-}F}$ = U_{SiLiq} = U_{DiLiq}}.

To formally test the hypotheses, we use the non-parametric Kruskal-Wallis test because of the small sample (27 test portfolios) and the comparisons involve more than two models. The Kruskal-Wallis test is stated in the form of H statistics, which is calculated as follows:

$$H = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{P_j^2}{n_j} \right) - 3(N+1) \tag{9}$$

where $P_j = \sum_{i=1}^{n_j} P_{i,j}$ is the total rank of error (MAE, MAPE, or U) for portfolio *i* = 1,..., *n* for model *j*, *j* = Fama-French, SiLiq, or DiLiq, and *N* = $\sum_{j=1}^{k} n_j$ is the number of test portfolio times the number of model *j*. Since the H statistics has an asymptotic distribution of χ^2 with d.f (k – 1), in general, the null hypothesis of no difference is rejected if H ≥ $\chi^2_{k-1,\alpha}$, or more specifically if $p \leq 0.05$ (Hollander and Wolfe, 1973).

4. Results and Discussion

4.1 Preliminary Statistical Analysis

Table 2 summarizes the statistical properties of the explanatory factors of each the competing models. Similar to Drew and Veeraraghavan (2002), the results suggest evidence of size premium (SMB) which is significant in both from the investment (1.2% per month or 14.4% per year) as well as statistical ($p \leq 0.01$) perspectives in this market. However, market risk premium (R_M-R_F) and value premium (HML) are negative and small, respectively. This finding is inconsistent with Fama and French (1993) who find positive and large premiums both for market risk and HML. Nonetheless, this finding is not unique to Malaysia because similar negative R_M-R_F results are also reported by Drew and Veeraraghavan (2003) in Korea and the Philippines and Chan and Faff (2005) in Australia. In the meantime, unlike the liquidity measure used by Chan and Faff (2005), both measures of $\hat{L}M\hat{H}$ in this study are also reported negative even though insignificantly different from zero. Like the R_M-R_F, these results contradict the risk-return trade-off theory (Amihud and Mendelson, 1986; Datar *et al.*, 1998; Amihud, 2002), but unfortunately is not an uncommon phenomenon in emerging markets. Rowenhorst (1999) finds HML (equivalent to the inverted $\hat{L}M\hat{H}$ in this study) is 0.11 percent in 60 percent of a sample of 20 emerging equity markets. Dey (2005) who investigates the liquidity issue in 48 countries (1995-2001) also finds that the return-TURN relationship is positive (which translate into negative $\hat{L}M\hat{H}$) and in emerging countries the relationship is significant. 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 also find that the through on the $\hat{L}M\hat{H}$ line take place in periods of crisis and deepest during the 1997 Asian Crisis.

Table 2 also reports the results of normal distribution and unit root tests on the return series. The Jarque-Bera (J-B) statistics clearly suggest that none of the series are normally distributed, a finding which is rather a stylized fact when involving financial series data. Fortunately, of more concern in time series regression is the stationarity of the series which in this study is tested using the Augmented Dickey-Fuller (ADF) tests. The resulting ADF statistics suggest that all return series are stationary at level and accordingly support the adequacy of time series regression approach in this study.

4.2 Model Estimation Results

To determine the forecasting accuracy of the alternative models, we first estimate a regression of the portfolios' excess returns on the explanatory factors according to the respective model's specification using data for the estimation period of 1987:01 – 2000:12. To strengthen our argument for the need of multifactor model in explaining stock returns in Malaysia, we also run regression tests on the 1-factor model (CAPM). The results of CAPM, as reported in Table 3, show that while market risk premium (R_M-R_F) captures most of the variations in portfolio returns, there is still some fraction which is still left unexplained. As depicted in Tables 4 to 6, while market risk premium remain significant in the multifactor models, the additional risk factors of SMB, HML and $\hat{L}M\hat{H}$ are also significant in majority of the cases. These results suggest that most of the unexplained variations in CAPM are captured by the additional risk factors suggested in Fama-French model as well as the newly introduced liquidity-based models. Evidently, the adjusted R^2 of the multifactor models are significantly higher compared to those of the CAPM.[2] Of more importance to this study are the results in Table 5 and 6 which support our prediction that illiquidity risk is priced especially when this factor is incorporated in the form of DiLiq model. Evidently, even though the coefficients on $\hat{L}M\hat{H}$ in DiLiq model (Table 6) are less often significant than those of SMB or HML in Fama-French model (Table 4), the resulting adjusted R^2 in general suggest that at least there is a compatible accuracy in both models.

4.3 Diagnostic Testing

To check the specification accuracy of the competing models, we conduct diagnostic tests on the residuals. In general, except for the stability tests, the results of the diagnostic tests fail to differentiate the advantage of one model over the other and therefore only briefly reported here to conserve space. The results of the Jarque-Bera tests indicate that consistent with the return series, the model residuals are also not normally distributed. Fortunately, the LM Breusch-Godfrey and LM Engle or ARCH results confirm that the residuals of all the three competing models are neither auto-correlated nor their variance are heteroskedastic. However, the cumulative sum (CUSUM) of the recursive residual which tests the model parameter stability does

[2] The Kruskal-Wallis test comparing the adjusted R^2 values of CAPM *vs* three factor models are not reported to conserve space but will be made available upon request from the corresponding author.

indicate some encouraging results in favor of the liquidity-based model, specifically DiLiq.

Figure 2 depicts a good example of such cases when DiLiq model is superior to the other three-factor models. Specifically, Figure 2 shows the stability of the models when they are used to explain two of the portfolios (SH and BL) which CAPM (Panel A) initially exhibits some parameter instability problem. Obviously, Figure 2 shows that CAPM's problem in these two portfolios is solved by using DiLiq model (Panel D), as opposed to Fama-French model (Panel B) or even SiLiq model (Panel C). Notice that the CUSUM line of Fama-French model goes outside the 5 percent critical line in both portfolios while the CUSUM line of the DiLiq remains within the boundary throughout the estimation period. This finding represents good preliminary evidence on the potential of DiLiq model as an improvement on Fama-French model.

4.4 Forecasting Accuracy of the Competing Three-Factor Models

With the diagnostic check supports the specification accuracy of the estimated models, they are then used to forecast the excess returns on the portfolios over the post-estimation period of 2001:01 – 2004:12. Table 7 reports the forecast error metrics for all three forecasting models. Panel A of Table 7 reports the forecasting error as measured by MAE. Overall, the Fama-French model generates the smallest MAE in tests involving the ME/BM portfolios whereas SiLiq and DiLiq models generate the smallest MAE in tests involving the ME/TURN and BM/TURN portfolios, respectively. Specifically, for the ME/BM portfolios, the Fama-French model generates an average MAE of 2.2 percent which is 2.2 percent smaller than those generated by SiLiq ($\bar{\varepsilon}$ = 2.4%) and DiLiq ($\bar{\varepsilon}$ = 2.6%). Comparisons at the individual portfolio levels also indicate a similar conclusion. The MAE of the Fama-French model are smallest in 6 (66.7%) of the 9 test portfolios. By the same token, SiLiq model dominates the other models when the test portfolios are formed on ME/TURN when on average, SiLiq model reports an MAE of 1.9 percent, i.e., 9.5 percent smaller than that of the Fama-French ($\bar{\varepsilon}$ = 2.1%) and 17.4 percent smaller than that of the DiLiq ($\bar{\varepsilon}$ = 2.3%) models. At the individual portfolio levels, the SiLiq model reports the smallest MAE in 4 (44.4%) of the test portfolios. Compared to the other two competing models, the DiLiq model seems to show a more convincing advantage. Even though similar to Fama-French model in terms of smallest MAE (66.7% of test portfolios), the average MAE of DiLiq model ($\bar{\varepsilon}$ = 1.8%) is 14.3 percent smaller than that of the Fama-French ($\bar{\varepsilon}$ = 2.1%) and 18.2 percent smaller than that of the SiLiq ($\bar{\varepsilon}$ = 2.2%) models. The results so far suggest that to a certain extent the portfolios that are used to form a model influence the resulting MAE of the respective model.

Panel B of Table 7 reports the forecasting error as measured by MAPE. Unlike the conclusion that we made based on the results of MAE, the MAPE appears to be more in favor of the DiLiq model. This is because not only the average MAPE of the DiLiq model is smallest when forecasting excess returns on the BM/TURN portfolios ($\bar{\varepsilon}$ = 144.24), but it is also smallest when predicting those of the ME/BM portfolios ($\bar{\varepsilon}$ = 162.75) (notwithstanding the fact that the Fama-French model still reports more lowest MAPE i.e., in 5 portfolios). In the BM/TURN portfolio category, DiLiq model reports a dominating number of lowest MAPE (7 portfolios). SiLiq model remains as the dominant model when forecasting excess returns on the ME/TURN portfolios. It generates the smallest average MAPE ($\bar{\varepsilon}$= 117.50) and lowest MAPE in 5 test portfolios.

The third forecasting error metric as measured with Theil's U is reported in Panel C of Table 7. Similar to the results of the MAE, the Theil's U also suggests that the relative performance of the competing models is somewhat influenced by their base portfolios. When predicting excess returns on ME/BM portfolios both the average U and the times U is smallest suggest that the Fama-French model is the best model ($\bar{\varepsilon}$= 0.192 and $\Sigma\varepsilon_{min}$ = 6 portfolios). By the same token, SiLiq model is relatively most accurate in predicting excess returns on ME/TURN portfolios ($\bar{\varepsilon}$= 0.172 and $\Sigma\varepsilon_{min}$ = 4 portfolios). However, the performance of SiLiq model is less pronounce compared to DiLiq model. In predicting the excess returns on BM/TURN portfolios, DiLiq model generates an average error of 0.189 and lowest U in 8 portfolios.

To visualize the forecasting ability of these models, Figure 3 shows the scatter plots for the fitted returns obtained from the estimated models against the actual returns of three selected portfolios during the post-estimation period of 2001:01 to 2004:12. To conserve space, we select portfolios which are predicted to be of highest risk from each portfolio categories (i.e. SH from ME/BM, SĹ from ME/TURN and HĹ from BM/TURN categories). While the empirical fits of the standard CAPM (top left panel) in each portfolio categories significantly improve with the three-factor models. In general there is clear improvement in the quality of regression fit for the three factor model when forecasting portfolio HL as compared to portfolio SL) . However, to strengthen the above argument we following Cao et al. (2004) and decide to formally examine the statistical differences for better inferences.

4.5 Hypothesis Testing

To formally determine whether the differences reported in Table 7 (and illustrated in Figure 3) are statistically significant, we run the Kruskal-Wallis tests. Prior to that, we run Mann-Whitney U tests and the results are apparently more in line with the growing contention on the superiority of multifactor models over the standard CAPM. As depicted in Figure 3, the results in Table 8 suggest that each of the three-factor models highlighted in this study produces forecasting errors that are consistently, significantly ($p \leq 0.05$) smaller than those of the CAPM except for comparisons based on MAPE related to the Fama-French and SiLiq models.

With the predictive power of the three-factor models against the CAPM is no longer an issue, we focus on the relative performance of the competing three-factor models. As shown in Panel A to C of Table 9, none of the differences is significant (i.e., $p > 0.05$). Specifically, the null hypothesis H_0(a): $\{MAE_{FF} = MAE_{SiLiq} = MAE_{DiLiq}\}$ consistently cannot be rejected in each of the test portfolio category. The largest average rank gap is associated with the DiLiq model (H = 3.932) but even then the *p*-value (0.140) is still inadequate to reject H_0(a). Similar results are obtained from comparisons based on the other two forecasting error metrics. Both H_0(b): $\{MAPE_{FF} = MAPE_{SiLiq} = MAPE_{DiLiq}\}$ and H_0(c): $\{U_{FF} = U_{SiLiq} = U_{DiLiq}\}$ cannot be rejected for the same reasons that the *p*-value is greater than 0.05. However, as observed in the MAE comparison, the greatest difference is consistently associated with the BM/TURN portfolio category in which case the DiLiq model is always the best model.

Albeit the insignificant differences, the Kruskal-Wallis tests provide average ranks that allow us to identify relatively the best model of the three alternatives. As indicated with the figures in parentheses in each of the three test portfolio categories, the most accurate model is; (i) Fama-French for forecasting the excess returns on the ME/BM portfolios, (ii) SiLiq for forecasting the excess returns on the ME/TURN portfolios, and (iii) DiLiq for forecasting excess returns on BM/TURN portfolios. Since such results do not allow us to identify one particular model that will best predict the stock returns, we proceed by running the Kruskal-Wallis test on all 27 test portfolios simultaneously. The result indicates that while the Fama-French model is the best model based on MAE, the DiLiq model is the best model based on MAPE and Theil's U. Notwithstanding the fact that the differences are insignificant, overall the results of this study suggest that returns on stocks traded on the Malaysian equity market should be slightly more accurately forecasted by employing the DiLiq model. As noted earlier, the differences between models are always greatest (*p*-value is smallest) when it involves forecasting the BM/TURN portfolios' excess returns in which case DiLiq model is always the best model. In addition, the results from comparing all the 27 forecasted portfolios simultaneously also suggest that DiLiq model is the best forecasting model in two of the three forecasting error metrics. Furthermore, when the Fama-French model appears as the best model based on MAE comparison, the DiLiq model follows very closely (differ by 0.11).

5. Conclusions

This paper evaluates the forecasting accuracy of the Fama-French three-factor model versus two liquidity-based three-factor models, referred as SiLiq and DiLiq, that have been developed as potential improvements on the Fama-French model. These models, which are estimated using time series regressions using monthly returns on stocks of 230 to 480 companies for the estimation period of 1987:01 to 2000:12, are then tested for its forecasting accuracy during the post-estimation period of 2001:01 to 2004:12. The results suggest that the three-factor models are more capable than the CAPM in predicting returns on portfolio of stocks traded on Bursa Malaysia. This implies that instead of simply relying on the market factor (R_M-R_F), investors in this equity market must also be concerned with firm-specific factors particularly the firm's distres and liquidity levels. Such suggestions owe to the fact that even though the forecasting accuracy of the competing three-factor models is consistently not statistically different, the DiLiq model apparently is more prevalent relative to the its counterparts. Not only does this finding correctly reflect the concern of investors in emerging equity markets on liquidity (Rowenhorst, 1999; Bekaert *et al.*, 2005), it is also consistent with findings of most recent studies (Acharya and Pedersen, 2005; Bali and Cakici, 2004; Chollete, 2004; Liu, 2004; Lo and Wang, 2004; Chan and Faff, 2005; Miralles and Miralles, 2005) on the role of liquidity in asset pricing models. In the meantime, without testing the predictive power of any extended model such as those suggested in other recent studies (Bali and Cakici, 2004; Chollete, 2004; Chan and Faff, 2005; Miralles and Miralles, 2005), the results of this study does not by itself validate Fama and French's (1996) proposition that three-factor model suffice to explain stock returns. Assuming that the proposition were to hold, the finding of this study suggests that the predictive power of the three-factor model is optimized by combining market risk factor (R_M-R_F) with distres (HML) and liquidity ($\hat{L}M\hat{H}$) risk factors. However, until further evidence regarding the DiLiq model is found, investors in this market are strongly recommended to consider firm size in setting stock prices particularly given the significant premium on size found in this study.

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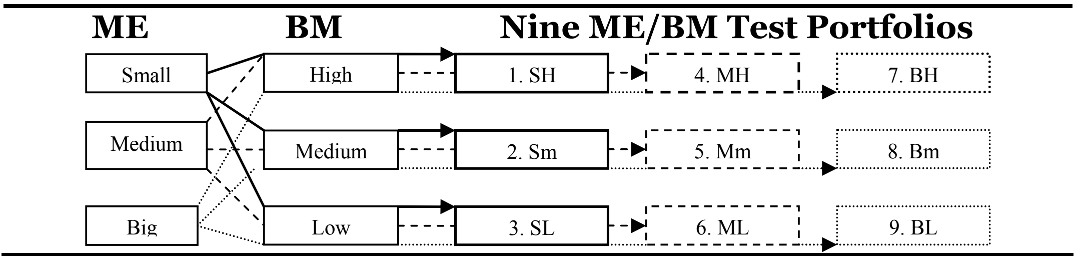
Figure 1
Procedure for Constructing the Test Portfolios on ME and BM Criteria

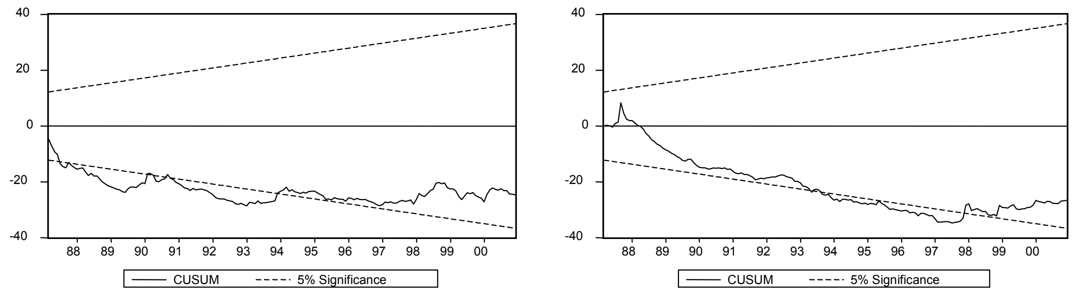


Notes: Abbreviations S = small, M = medium ME, B = big, H = high, m = medium BM, and L = low. The resulting portfolio SH for instance represent portfolio which comprises of small ME and high BM stocks. This procedure produces 9 ME/BM portfolios. When repeated using two other firm characteristics at a time, it produces 9 ME/TURN portfolios and 9 BM/TURN portfolios.

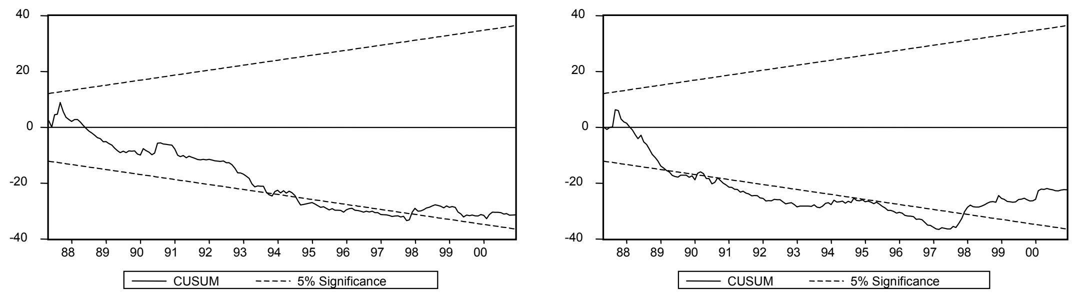
Figure 2
Results of CUSUM tests of CAPM and Alternative Three-Factor Models on 2 Portfolios Selected from the ME/BM Portfolios

Portfolio SH	Portfolio BL

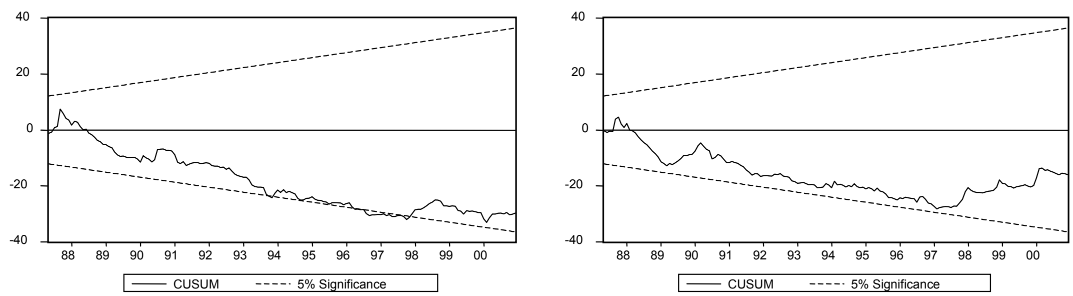
Panel A. CAPM



Panel B. Fama-French Model



Panel C. SiLiq Model



Panel D. DiLiq Model

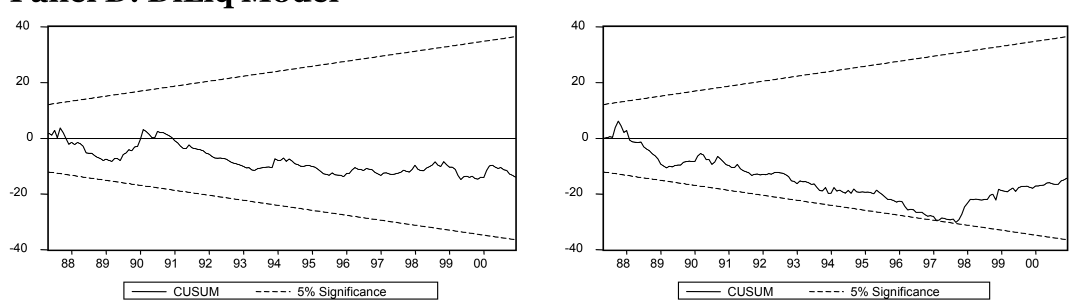
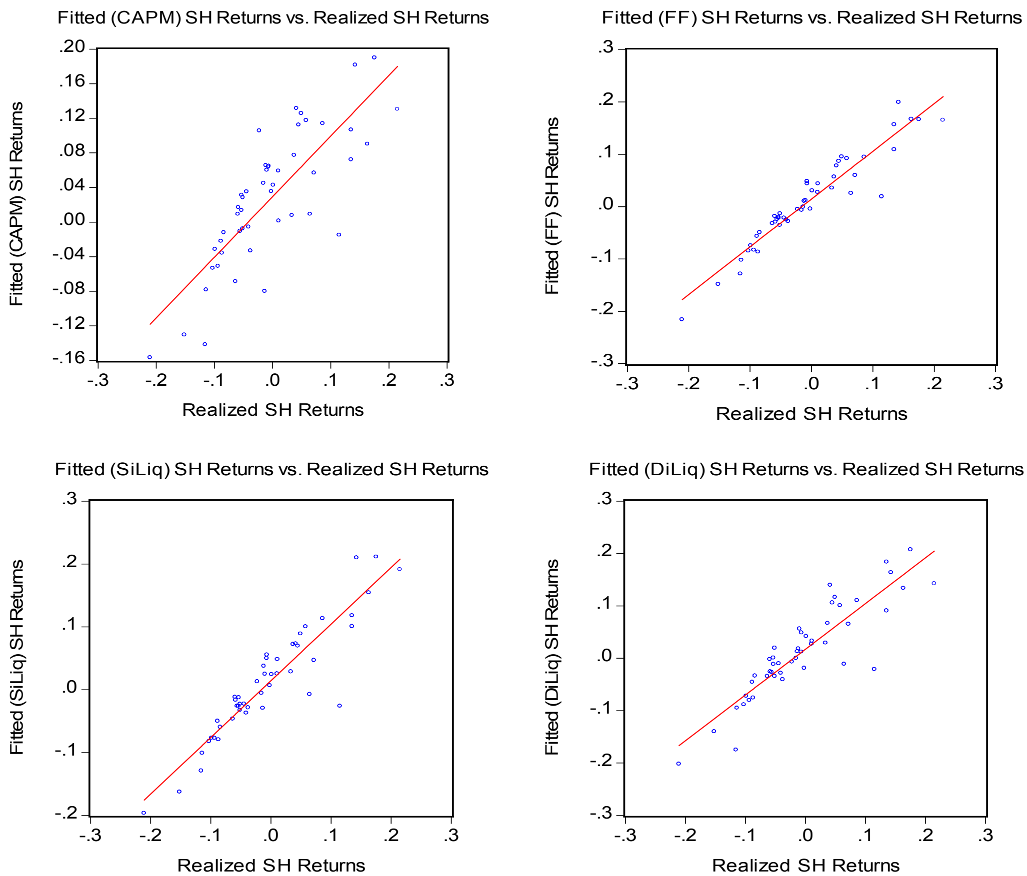
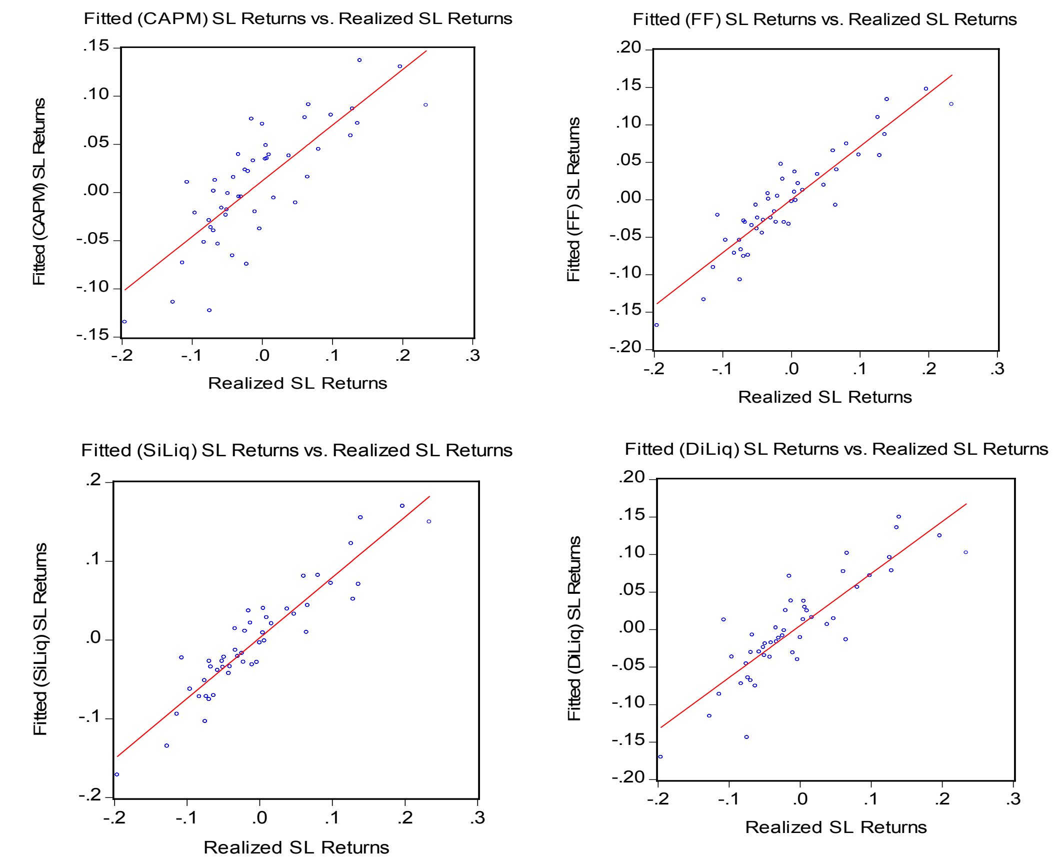


Figure 3
Empirical Fits of the CAPM and Alternative Three-Factor Models on Portfolio SH selected from the 9 Portfolios Double-Sorted on ME/BM



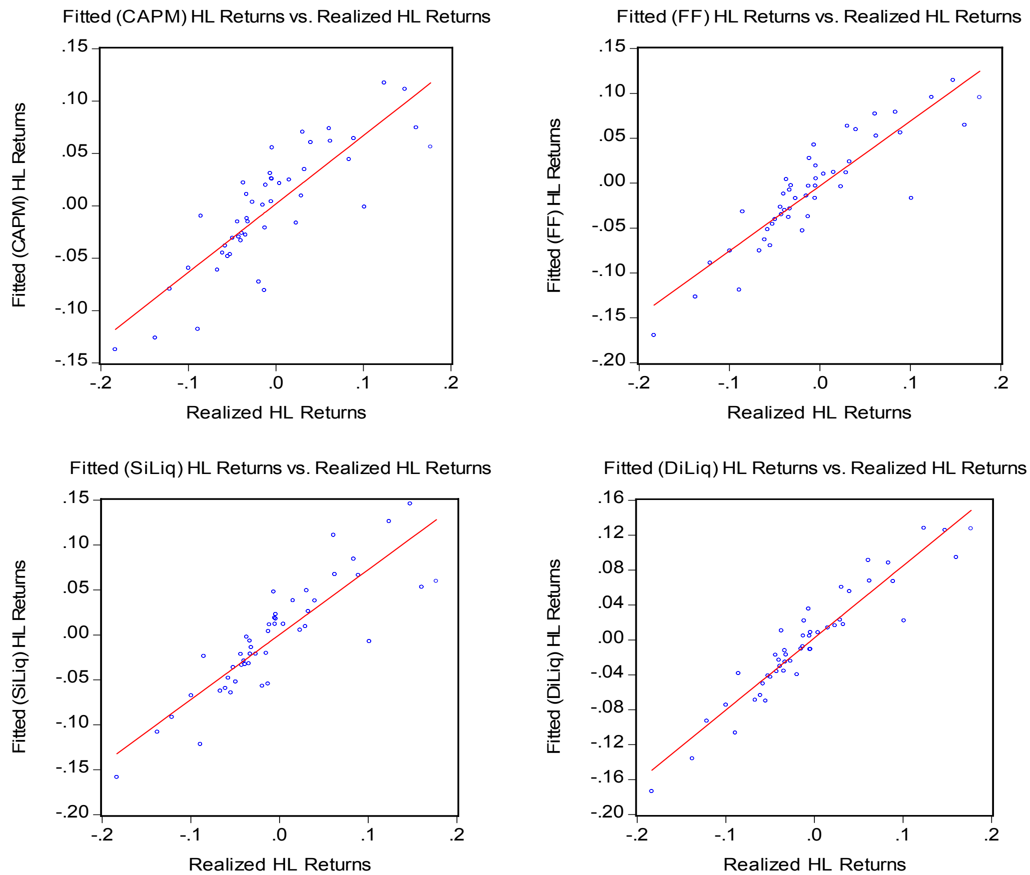
Notes: Fitted monthly excess returns on Portfolio SH are generated from the regression equation obtained from the estimation period of 1987:01 to 2000:12 of the respective asset pricing models whereas realized returns are the actual monthly excess returns on Portfolio SH. Abbreviations FF = Fama-French model, SH = portfolio comprises of small ME and high B/M stocks, ME = market capitalization of equity and BM = book-to-market ration.

Figure 3 (Continued)



Notes: Fitted monthly excess returns on Portfolio SH are generated from the regression equation obtained from the estimation period of 1987:01 to 2000:12 of the respective asset pricing models whereas realized returns are the actual monthly excess returns on Portfolio SH. Abbreviations FF = Fama-French model, SL = portfolio comprises of small ME and low TURN stocks, ME = market capitalization of equity and TURN = shares turnover ratio.

Figure 3 (Continued)



Notes: Fitted monthly excess returns on Portfolio HL are generated from the regression equation obtained from the estimation period of 1987:01 to 2000:12 of the respective asset pricing models whereas realized returns are the actual monthly excess returns on Portfolio HL. Abbreviations FF = Fama-French model, HL = portfolio comprises of high BM and low TURN stocks, BM = book-to-market ratio and TURN = shares turnover ratio.

Table 1
Evidence on the Role of Liquidity Factor from Previous Empirical Studies

No	Studies	Sample Markets	Study Period	Measures of Liquidity	Significant?	Sign
Panel A. Empirical Evidence From the United States						
1	Brennan *et al.* (1998)	NYSE, AMEX, NASDAQ	1966-1995	DVOL	Yes	–
2	Datar *et al.* (1998)	NYSE	1962-1991	TURN	Yes	–
3	Chordia *et al.* (2001)	NYSE, AMEX, NASDAQ	1996-1995	DVOL; TURN; CVs	Yes	–
4	Lo and Wang (2001)	NYSE & AMEX	1962-1996	β^{HR}; $\beta^{HQ\ a}$	Yes	–
5	Amihud (2002)	NYSE	1963-1997	$MILLIQ^{M}$	Yes	+
6	Ali *et al.* (2003)	NYSE & AMEX	1976-1997	VOL	Yes	–
7	Pástor and Stambaugh (2003)	NYSE, AMEX, NASDAQ	1965-2000	LIQ_{Value}; $LIQ_{Equal}^{*,b,M}$	Yes	+
8	Bali and Cakici (2004)	NYSE, AMEX, NASDAQ	1963-2001	$HILLIQ^{*}$	Yes	±
9	Chollete (2004)	NYSE & AMEX	1962-2001	LIQ; Vol.$(LIQ)^{*,c}$	No Yes	– –
10	Liu (2004)	NYSE, AMEX, & NASDAQ	1960-2003	$LIQ^{*,d}$	Yes	+
11	Acharya and Pedersen (2005)	NYSE & AMEX	1962-1999	$Cov(c^i,c^M)$; $(c^{i,}\ r^M)$; $(r^i,c^M)^{e,M}$	Yes	–
12	Spiegel and Wang (2005)	NYSE, AMEX, NASDAQ	1962-2003	Gibbs; $Gamma^f$; ILLIQ;DVOL	No No;Yes	+ +; ±

Table 1 (Continued)

No	Studies	Sample Markets	Study Period	Measures of Liquidity	Significant?	Sign
Panel B. Empirical Evidence From the Other Countries						
1	Chan and Faff (2003)	Australia	1989-1999	TURN	Yes	–
2	Chan and Faff (2005)	Australia	1989-1998	$IMV^{*,j}$	Yes	–
3	Miralles and Miralles (2005)	Spain	1994-2002	$\beta_{IMV}{}^{*,k}$	Yes	+
4	Sheu *et al.* (1998)	Taiwan	1976-1996	VOL	Yes	–
5	Ku and Lin (2002)	Taiwan	1985-1999	VOL &	No	–
				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	$TURN_{Developed}$; $TURN_{Emerging}$	No	+
					Yes	+

Notes: Abbreviations VOL = volume turnover, LIQ = liquidity, TURN = share turnover = VOL/NOSH, NOSH = number of shares outstanding, ILLIQ = illiquidity = |R|/DVOL, and CV = coefficient of variations. Superscripts [a] R (returns) & Q ($returns) on a *H*edged portfolio formed on TURN, [b] LIQ formed on β^{λ} where $\lambda = (sign(R_i\text{-}R_M)$, [c] formed on LIQ of Pástor & Stambaugh(2003), [d] formed on *No*0Vol*y* = number of days without trading at year *t* x {(1/TURN) x 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 $\dot{L}M\dot{H}$.

Table 2
Summary Statistics and Correlation Coefficients of Explanatory Factors, 1987:01 – 2004:12

Panel A. Explanatory Factors for Fama-French Model									
Factors	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**	**J-B**	**ADF**	**R_M-R_F**	**SMB**	**HML**
R_M-R_F	-0.003 (-0.480)	0.088	0.148	5.507	57.33	-3.744	1.000		
SMB	0.012 (2.896)**	0.061	1.795	9.892	543.48	-4.295	0.345	1.000	
HML	0.004 (0.993)	0.060	1.803	17.755	2076.5	-4.026	0.356	0.244	1.000
Panel B. Explanatory Factors for SiLiq Model									
Factors	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**	**J-B**	**ADF**	**R_M-R_F**	**HML**	$\hat{L}M\hat{H}$
R_M-R_F	-0.003 (-0.480)	0.088	0.148	5.507	57.33	-3.744	1.000		
SMB	0.012 (2.681)**	0.068	1.655	10.44	596.72	-4.051	0.382	1.000	
$\hat{L}M\hat{H}$	-0.005 (-1.424)	0.051	-0.303	5.645	66.28	-4.112	-0.575	-0.425	1.000
Panel C. Explanatory Factors for DiLiq Model									
Factors	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**	**J-B**	**ADF**	**R_M-R_F**	**HML**	$\hat{L}M\hat{H}$
R_M-R_F	-0.003 (-0.480)	0.088	0.148	5.507	57.33	-3.744	1.000		
HML	0.009 (1.637)	0.078	3.166	27.801	5896.5	-3.839	0.489	1.000	
$\hat{L}M\hat{H}$	-0.006 (-1.553)	0.057	-0.385	5.393	56.86	-4.361	-0.606	-0.496	1.000

Note: ** and * denote significance at 1 and 5 percent levels, respectively. Figures in parentheses are the *t*-statistcis. Augmented Dickey-Fuller (ADF) is tested using 12 lags. In each case, N = 216 monthly observations. All correlations are significant at 5 percent level while all Jarque-Bera (J-B) and ADF statistics are significant at 1 percent level.

Table 3
Estimates of the CAPM for the Estimation Period of January 1987 to December 2000

Portfolios	α	b	t(α)	t(b)	adj-R^2	s(e)	D.W
Panel A. Regression of the 9 ME/BM Portfolios							
SH	0.035	1.508	4.730**	19.359**	0.6912	0.097	1.537
SM	0.030	1.326	4.082**	17.241**	0.6395	0.096	1.748
SL	0.035	1.354	4.116**	15.175**	0.5786	0.111	1.895
MH	0.023	1.328	4.765**	26.666**	0.8096	0.062	1.953
MM	0.015	1.229	3.925**	30.135**	0.8445	0.051	1.933
ML	0.015	1.255	3.358**	27.198**	0.8156	0.057	2.072
BH	0.017	1.428	2.701**	22.440**	0.7506	0.079	1.812
BM	0.013	1.080	5.351**	41.377**	0.9111	0.032	1.773
BL	0.007	0.874	2.655**	30.757**	0.8498	0.035	1.951
Panel B. Regression of the 9 ME/TURN Portfolios							
SĹ	0.025	1.184	4.357**	19.962**	0.7042	0.074	1.935
SM	0.037	1.448	5.084**	19.401**	0.6921	0.093	1.666
SĤ	0.035	1.443	4.772**	19.066**	0.6846	0.094	1.703
MĹ	0.011	1.039	3.138**	28.753**	0.8318	0.045	2.174
MM	0.019	1.292	4.950**	32.450**	0.8630	0.041	1.775
MĤ	0.024	1.478	4.660**	27.957**	0.8238	0.066	1.913
BĹ	0.009	0.821	2.328*	21.309**	0.7307	0.048	1.991
BM	0.009	0.970	4.386**	47.089**	0.9299	0.026	1.848
BĤ	0.015	1.170	4.840**	36.016**	0.8859	0.040	1.977
Panel C. Regression of the 9 BM/TURN Portfolios							
HĹ	0.016	1.106	3.728**	27.278**	0.8165	0.050	1.990
HM	0.021	1.381	3.991**	25.689**	0.7978	0.067	1.784
HĤ	0.027	1.578	4.387**	24.800**	0.7862	0.079	1.916
MĹ	0.010	0.978	3.035**	27.514**	0.8191	0.044	2.027
MM	0.016	1.163	6.101**	42.874**	0.9167	0.034	1.752
MĤ	0.020	1.297	4.388**	26.923**	0.8125	0.060	1.842
LĹ	0.007	0.744	1.421	15.058**	0.5748	0.062	2.001
LM	0.007	0.896	2.633**	33.827**	0.8725	0.033	2.050
LĤ	0.016	1.141	4.073**	28.198**	0.8262	0.050	1.857

Notes: Abbreviations BM = Book-to-market ratio, ME = market capitalization of equity, and TURN = shares turnover ratio. Symbols ** and * indicate 1 percent and 5 percent significant, respectively. In each case, N = 168 monthly observations. Durbin-Watson statistics, D-W ~ 2.00 suggests no auto-correlations in regression residuals.

Table 4
Estimates of the Fama-French Model for the Estimation Period of January 1987 to December 2000

Portfolios	α	b	s	h	t(α)	t(b)	t(s)	t(h)	*adj*-R^2	s(e)	D-W
Panel A. Regression of the 9 ME/BM Portfolios											
SH	0.020	1.126	0.811	0.769	3.887**	19.844**	10.272**	9.404**	0.8689	0.063	1.376
SM	0.011	0.955	1.176	0.358	2.505*	20.098**	17.787**	5.234**	0.9554	0.053	1.948
SL	0.018	1.141	1.229	-0.346	2.814**	15.782**	12.220**	-3.324**	0.7785	0.080	2.075
MH	0.013	1.060	0.488	0.619	4.606**	34.457**	11.403**	13.963**	0.9419	0.034	1.969
MM	0.007	1.047	0.446	0.307	2.492*	32.236**	9.884**	6.572**	0.9212	0.036	2.021
ML	0.006	1.113	0.562	0.026	1.709	27.302**	9.905**	0.436	0.8848	0.045	1.994
BH	0.010	1.191	0.192	0.783	2.064*	21.660**	2.505*	9.886**	0.8508	0.061	1.664
BM	0.015	1.077	-0.184	0.195	6.697**	41.571**	-5.111**	5.234**	0.9299	0.029	1.907
BL	0.012	0.995	-0.207	0.294	5.565**	41.757**	-6.248**	-8.572**	0.9155	0.027	1.782
Panel B. Regression of the 9 ME/TURN Portfolios											
SĹ	0.013	0.926	0.683	0.382	2.998**	19.440**	10.307**	5.570**	0.8472	0.053	1.956
SM	0.018	1.097	1.149	0.303	4.212**	23.384**	17.606**	4.486**	0.9026	0.052	1.991
SĤ	0.016	1.063	1.084	0.487	3.774**	22.346**	16.391**	7.116**	0.9003	0.053	1.548
MĹ	0.004	0.860	0.351	0.391	1.638	33.158**	9.739**	10.464**	0.9308	0.029	2.113
MM	0.010	1.093	0.488	0.334	4.097**	39.826**	12.792**	8.461**	0.9479	0.031	1.688
MĤ	0.013	1.237	0.588	0.411	3.515**	30.029**	10.272**	6.927**	0.9145	0.046	1.944
BĹ	0.012	0.895	-0.204	-0.106	3.355**	21.784**	-3.563**	-1.792	0.7546	0.046	1.993
BM	0.011	1.021	-0.167	-0.041	6.175**	48.836**	-5.743**	-1.347	0.9424	0.023	1.789
BĤ	0.015	1.190	0.019	-0.100	4.770**	32.913**	0.376	-1.913	0.8870	0.040	1.967
Panel C. Regression of the 9 BM/TURN Portfolios											
HĹ	0.009	0.938	0.232	0.460	2.934**	27.379**	4.861**	9.317**	0.8951	0.038	1.860
HM	0.013	1.128	0.247	0.796	4.305**	30.420**	4.800**	14.922**	0.9231	0.041	1.764
HĤ	0.016	1.268	0.447	0.833	4.048**	27.995**	7.093**	12.790**	0.9134	0.050	1.992
MĹ	0.009	0.895	0.028	0.314	2.678**	24.900**	0.560	6.070**	0.8520	0.040	2.066
MM	0.015	1.116	-0.001	0.195	6.000**	39.026**	-0.014	4.726**	0.9260	0.032	1.900
MĤ	0.014	1.143	0.345	0.293	3.300**	24.342**	5.282**	4.338**	0.8576	0.052	1.910
LĹ	0.011	0.872	-0.161	-0.363	2.423*	17.224**	-2.293*	-4.984**	0.6438	0.056	2.065
LM	0.009	0.966	-0.063	-0.227	3.690**	36.349**	-1.693	-5.945**	0.8973	0.029	1.928
LĤ	0.014	1.167	0.194	-0.297	3.849**	27.979**	3.342**	-4.952**	0.8525	0.046	1.979

Notes: See Notes to Table 3.

Table 5
Estimates of the SiLiq Model for the Estimation Period of January 1987 to December 2000

Portfolio	α	b	s	l_{MT}	t(α)	t(b)	t(s)	t(l_{MT})	*adj*-R²	s(e)	D-W
Panel A. Regression of the 9 BM/ME Portfolios											
SH	0.020	1.211	0.912	-0.099	3.483**	16.293**	10.415**	-0.740	0.8219	0.074	1.374
SM	0.011	0.961	1.208	-0.043	2.913**	19.850**	21.179**	-0.491	0.9093	0.048	2.056
SL	0.021	1.053	0.784	-0.218	2.782**	10.891**	6.882**	-1.249	0.6860	0.096	2.021
MH	0.013	1.136	0.650	-0.010	3.660**	25.906**	12.572**	-0.124	0.9063	0.043	1.996
MM	0.008	1.090	0.500	0.015	2.573*	28.405**	11.067**	0.217	0.9128	0.038	1.954
ML	0.007	1.100	0.537	0.004	1.868	24.500**	10.156**	0.051	0.8892	0.045	2.049
BH	0.009	1.328	0.628	0.245	1.651	19.323**	7.756**	1.980*	0.8153	0.068	1.904
BM	0.015	1.148	-0.027	0.179	6.124**	36.133**	-0.720	3.127**	0.9164	0.031	1.720
BL	0.012	0.979	-0.271	0.080	5.145**	32.912**	-7.726**	1.487	0.8956	0.029	1.695
Panel B. Regression of the 9 ME/TURN Portfolios											
SĹ	0.016	1.110	0.911	0.564	4.546**	25.392**	17.702**	7.158**	0.8981	0.043	2.022
SM	0.020	1.168	1.155	0.162	4.813**	22.157**	18.608**	1.707	0.9026	0.052	1.874
SĤ	0.014	0.946	1.030	-0.589	3.639**	19.944**	18.437**	-6.882**	0.9214	0.047	1.451
MĹ	0.005	0.975	0.536	0.271	2.213*	34.050**	15.883**	5.255**	0.9330	0.028	2.228
MM	0.011	1.138	0.538	0.004	3.985**	33.602**	13.500**	0.063	0.9372	0.034	1.591
MĤ	0.012	1.217	0.631	-0.234	3.223**	26.069**	11.470**	-2.777**	0.9129	0.046	2.037
BĹ	0.015	1.049	-0.074	0.615	4.968**	27.243**	-1.640	8.856**	0.8291	0.038	1.765
BM	0.011	0.990	-0.197	-0.110	6.040**	44.022**	-7.436**	-2.711**	0.9470	0.022	1.690
BĤ	0.013	1.042	-0.214	-0.562	5.288**	32.394**	-5.640**	-9.695**	0.9290	0.032	1.880
Panel C. Regression of the 9 BM/TURN Portfolios											
HĹ	0.010	1.085	0.481	0.352	3.255**	27.426**	10.326**	4.942**	0.8892	0.039	1.936
HM	0.013	1.244	0.568	0.083	2.839**	22.222**	8.619**	0.823	0.8609	0.055	1.748
HĤ	0.015	1.330	0.676	-0.152	2.996**	20.945**	9.037**	-1.325	0.8648	0.063	1.947
MĹ	0.010	1.043	0.267	0.423	3.234**	26.827**	5.838**	6.038**	0.8627	0.039	1.933
MM	0.015	1.159	0.088	0.063	5.708**	34.334**	2.224*	1.043	0.9182	0.033	1.758
MĤ	0.012	1.062	0.330	-0.413	2.883**	20.881**	5.505**	-4.505**	0.8675	0.050	1.811
LĹ	0.014	0.985	-0.152	0.585	3.316**	18.201**	-2.379*	5.991**	0.6766	0.054	1.881
LM	0.008	0.891	-0.207	-0.193	3.433**	29.527**	-5.826**	-3.550**	0.8951	0.030	1.937
LĤ	0.013	0.973	-0.172	-0.647	3.799**	22.828**	-3.428**	-8.425**	0.8778	0.042	1.856

Notes: See Notes to Table 3.

Table 6
Estimates of the DiLiq Model for the Estimation Period of January 1987 to December 2000

Portfolios	α	b	h	l_{BT}	t(α)	t(b)	t(h)	t(l_{BT})	*adj*-R^2	s(e)	D-W
Panel A. Regression of the 9 BM/ME Portfolios											
SH	0.026	1.126	0.712	-0.198	4.054**	13.428**	8.085**	-1.527**	0.7915	0.080	1.450
SM	0.021	0.966	0.579	-0.284	3.178**	11.065**	6.310**	-2.102*	0.7290	0.083	1.670
SL	0.025	0.958	0.279	-0.699	3.087**	8.927**	2.476*	-4.212**	0.6444	0.102	2.021
MH	0.014	0.968	0.649	-0.207	4.961**	26.659**	17.004**	-3.691**	0.9409	0.035	2.031
MM	0.009	0.975	0.413	-0.197	2.974**	24.705**	9.954**	-3.218**	0.9151	0.037	2.122
ML	0.011	1.101	0.304	-0.059	2.622**	19.841**	5.213**	-0.683	0.8442	0.053	2.012
BH	0.008	1.103	0.847	0.095	2.057*	20.615**	15.052**	1.151	0.8970	0.051	1.624
BM	0.014	1.099	0.176	0.240	6.084**	35.961**	5.484**	5.074**	0.9288	0.029	1.774
BL	0.012	1.051	-0.300	0.124	5.811**	38.965**	-10.57**	2.969**	0.9210	0.026	1.759
Panel B. Regression of the 9 ME/TURN Portfolios											
SĹ	0.019	0.939	0.560	-0.013	3.813**	14.506**	8.226**	-0.131	0.7942	0.062	1.819
SM	0.028	1.121	0.611	-0.167	4.426**	13.310**	6.907**	-1.280	0.7714	0.080	1.602
SĤ	0.023	0.994	0.600	-0.487	3.829**	12.414**	7.135**	-3.932**	0.7942	0.076	1.620
MĹ	0.006	0.853	0.505	0.075	2.900**	30.134**	16.986**	1.715	0.9398	0.027	2.115
MM	0.013	1.052	0.427	-0.146	4.461**	27.676**	10.680**	-2.485*	0.9272	0.036	1.998
MĤ	0.013	1.075	0.536	-0.441	3.916**	23.934**	11.345**	-6.340**	0.9258	0.043	1.812
BĹ	0.015	1.071	0.007	0.640	5.319**	28.182**	0.186	10.888**	0.8470	0.036	1.733
BM	0.010	1.019	-0.129	-0.017	5.201**	40.250**	-4.848**	-0.427	0.9383	0.024	1.635
BĤ	0.011	1.024	-0.209	-0.595	5.000**	34.527**	-6.703**	-12.97**	0.9445	0.028	2.000
Panel C. Regression of the 9 BM/TURN Portfolios											
HĹ	0.011	0.976	0.564	0.282	4.555**	29.581**	16.273**	5.517**	0.9291	0.031	1.931
HM	0.011	1.008	0.770	-0.109	4.250**	29.106**	21.153**	-2.037*	0.9510	0.033	1.813
HĤ	0.013	1.051	0.829	-0.434	4.562**	27.240**	20.443**	-7.265**	0.9541	0.037	1.739
MĹ	0.010	0.974	0.405	0.427	4.153**	29.244**	11.573**	8.280**	0.9074	0.032	1.986
MM	0.015	1.124	0.168	0.084	5.992**	33.595**	4.791**	1.616	0.9260	0.032	1.838
MĤ	0.012	0.984	0.241	-0.532	3.170**	19.351**	4.507**	-6.766**	0.8783	0.048	1.995
LĹ	0.016	1.079	-0.230	0.597	4.037**	21.172**	-4.295**	7.576**	0.736	0.048	1.830
LM	0.008	0.962	-0.276	-0.130	3.929**	34.109**	-9.305**	-2.972**	0.9156	0.027	1.729
LĤ	0.012	0.994	-0.331	-0.729	4.393**	27.811**	-8.806**	-13.18**	0.9209	0.034	2.030

Notes: See Notes to Table 3.

Table 7
Summary of the Forecasting Errors of the Competing Three-Factor Models

	ME/BM Portfolios			ME/TURN Portfolios			BM/TURN Portfolios		
Models	**Range**	$\bar{\varepsilon}$	$\Sigma\varepsilon_{min}$	**Range**	$\bar{\varepsilon}$	$\Sigma\varepsilon_{min}$	**Range**	$\bar{\varepsilon}$	$\Sigma\varepsilon_{min}$
Panel A. Mean Absolute Error (MAE)									
FF	0.010-0.044	0.022	6	0.012-0.037	0.021	2	0.015-0.028	0.021	2
SiLiq	0.013-0.046	0.024	2	0.012-0.035	0.019	5	0.016-0.031	0.022	0
DiLiq	0.011-0.057	0.026	1	0.011-0.043	0.023	2	0.014-0.021	0.018	7
Panel B. Mean Absolute Percentage Error (MAPE)									
FF	48.11-410.0	180.7	5	55.92-563.7	156.9	1	55.45-344.6	160.3	1
SiLiq	55.65-497.1	220.0	1	55.92-269.7	117.5	5	63.49-258.5	151.1	1
DiLiq	52.55-347.4	162.7	3	48.44-364.1	142.2	3	56.71-432.8	144.2	7
Table 3 - continue									
Panel B. Theil's Inequality Coefficient U (Theil's U)									
FF	0.120-0.302	0.192	6	0.143-0.267	0.195	2	0.156-0.335	0.222	1
SiLiq	0.145-0.341	0.214	2	0.130-0.261	0.172	4	0.175-0.276	0.223	0
DiLiq	0.125-0.404	0.218	1	0.125-0.294	0.202	3	0.116-0.286	0.189	8

Notes: ε = error metric, $\bar{\varepsilon}$ = average error, and Σe_{min} = number error metric is lowest in a particular portfolio category.

Table 8
Results of Mann-Whitney Tests: CAPM *versus* the Alternative Three-Factor Models

Pair wise Comparisons	MAE		MAPE		Theil's U	
	Ave. ε	Ave. Rank	Ave. ε	Ave. Rank	Ave. ε	Ave. Rank
Panel A. CAPM *vs*. Fama-French Model						
CAPM	0.030	32.39	251.2	31.37	0.262	34.57
Fama-French	0.021	22.61	166.0	23.63	0.203	20.43
Z-Statistics		-2.289		-1.808		-3.305
		(0.022)*		(0.071)		(0.001)**
Panel B. CAPM *vs*. SiLiq Model						
CAPM	0.030	31.98	251.2	31.59	0.262	34.70
SiLiq Model	0.022	23.02	162.9	23.41	0.203	20.28
Z-Statistics		-2.096		-1.912		-3.374
		(0.036)*		(0.056)		(0.001)**
Panel C. CAPM *vs*. DiLiq Model						
CAPM	0.030	32.00	251.2	32.11	0.262	34.39
DiLiq Model	0.022	23.00	149.7	22.89	0.203	20.61
Z-Statistics		-2.105		-2.154		-3.218
		(0.035)*		(0.031)*		(0.001)**

Notes: Symbol ε is the respective error metrics while ** and * indicate significant at 1 and 5 percent levels, respectively. In each comparison, N = 18 (9 error measures per model). Figures in parentheses are the *p*-values.

Table 9
Results of Kruskal-Wallis Tests: Forecasting Errors of the Competing Three-Factor Models

Statistics	**Competing Models**	**Test Portfolios**			
		ME/BM	**ME/TURN**	**BM/TURN**	**Full Sample**
Panel A. Mean Absolute Error (MAE)					
Mean Rank	Fama-French	12.11 (*1*)	14.06 (*2*)	15.56 (*3*)	40.33 (*1*)
	SiLiq	14.89 (*2*)	12.83 (*1*)	16.67 (*2*)	42.22 (*3*)
	DiLiq	15.00 (*3*)	15.11 (*3*)	9.78 (*1*)	40.44 (*2*)
H-Statistics		0.767 [0.681]	0.372 [0.830]	3.932 [0.140]	0.110 [0.946]
Panel B. Mean Absolute Percentage Error (MAPE)					
Mean Rank	Fama-French	13.11 (*1*)	14.11 (*2*)	15.11 (*3*)	42.15 (*3*)
	SiLiq	15.56 (*3*)	13.00 (*1*)	14.89 (*2*)	42.04 (*2*)
	DiLiq	13.33 (*2*)	14.89 (*3*)	12.00 (*1*)	38.81 (*1*)
H-Statistics		0.522 [0.770]	0.257 [0.879]	0.861 [0.650]	0.350 [0.840]
Panel C. Inequality Coefficient of U Theil					
Mean Rank	Fama-French	12.00 (*1*)	15.22 (*2*)	14.72 (*2*)	41.46 (*2*)
	SiLiq	15.33 (*3*)	11.11 (*1*)	17.00 (*3*)	41.98 (*3*)
	DiLiq	14.67 (*2*)	15.67 (*3*)	10.28 (*1*)	39.56 (*1*)
H-Statistics		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. At sub-sample level N = 27 (9 error measures per model) while at full sample level N = 81 (27 error measures per model). Figures in bracket are the p-values and figures in parentheses are the relative ranking of the models.