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Testing Conditional Asset Pricing Models: An Emerging Market Perspective

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ABSTRACT

The CAPM as the benchmark asset pricing model generally performs poorly in both developed and emerging markets. We investigate whether allowing the model parameters to vary improves the performance of the CAPM and the Fama-French model. Conditional asset pricing models scaled by conditional variables such as Trading Volume and Dividend Yield generally result in small pricing errors. However, a graphical analysis shows that the predictions of conditional models are generally upward biased. We demonstrate that the bias in prediction may be caused by not accommodating frequent large variation in asset pricing models. In emerging markets, volatile institutional, political and macroeconomic conditions results in thick tails in the return distribution. This is characterized by excess kurtosis. It is found that the unconditional Fama-French model augmented with a cubic market factor performs the best among the competing models. This model is also more parsimonious compared to the conditional Fama-French model in terms of number of parameters.

Key words: Stochastic discount factor; conditional information; kurtosis; emerging markets;
JEL Codes: C51; G12

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1. Introduction

Pricing risky assets is a daunting task. This is especially true for emerging markets where institutional, political and macroeconomic conditions are generally volatile. This high volatility can have two important implications for the tests of asset pricing models. First, the parameters of the asset pricing models and expected returns are unlikely to remain constant over time. Second, the distribution of asset returns departs from the normal distribution. In emerging markets the frequency of extreme observations is considerably higher which results in thicker tails as indicated by high kurtosis values. In this paper we address both of these issues.

To account for the first implication, we evaluate the performance of unconditional and conditional CAPM and Fama-French models for an emerging market in a discount factor framework for which GMM may be used for estimation and inference. It is well known that the GMM does not require strong distributional assumptions. Moreover, the discount factor methodology requires minimal assumptions regarding the individual investor's preferences. The expected return and parameters of the stochastic discount factor are allowed to vary with investors' information set through a scaled factor methodology advocated by Cochrane (1996). The information set consists of variables that could either predict future returns or summarize business cycle variation. To account for the fact that emerging markets returns may be driven by non-information trading based on speculative motives we also include trading volume as a conditioning variable. This variable has been shown in the literature as an indicator of the extent of speculative trading as well as an indicator of the extent of non-trading of relatively illiquid securities of emerging markets. To investigate whether scaled or unscaled factors earn any risk premia, the paper applied the Fama-

MacBeth and the sequential GMM approach recently investigated by Shanken and Zhou (2007).

To account for thick tails and excess kurtosis we investigate discount factor models augmented with a cubic market factor. The higher order co-moment literature provides evidence that for emerging markets kurtosis is more relevant than skewness. See for example Hwang and Satchell (1999). The cubic market return is consistent with co-kurtosis as a pricing factor.

Using 16 Size $\times$ Book-to-Market portfolios as test assets from Pakistan's stock market[1] it is found that unconditional CAPM is rejected in favour of the Fama-French model. The Fama-French model performs better in terms of Hansen-Jagannathan distance measure. The performance of the conditional models depends on the conditioning variable employed. Some conditioning variables such as Trading Volume and Dividend Yield results in small pricing errors but the best conditional model suffers from the parameter instability as signalled by the Sup LM test of Andrews (1993). It is found that an unconditional Fama-French model augmented with a cubic market factor performs the best among the competing models with stable parameters. This model is also more parsimonious compared to the conditional Fama-French model in terms of the number of parameters. In summary, we investigated two plausible improvements in the benchmark unconditional CAPM (i) accounting for the time variation in expected returns and parameters and (ii) allowing for thicker tails and excess kurtosis relative to the normal distribution which is an inherent assumption of the CAPM. It is found that for the emerging market under consideration, a discount factor model that takes account of the excess kurtosis in addition to the Fama-French

[1] The Karachi Stock Exchange is the largest of the three stock markets in Pakistan. On mid of 2006 the market capitalization was US$ 57 billions which is 46 percent of Pakistan' GDP for Fiscal Year 2005-06. (Ref: Pakistan Economic Survey 2005-06)

factors explain the expected returns of asset returns better than the conditional models scaled by term spread, short term interest rate, dividend yield, trading volume, cyclical component of manufacturing production and a January dummy.

Following this introduction the paper is organized as follows. Section 2 discusses the case for and against conditional asset pricing models. Sections 3 reviews the literature on conditional asset pricing models in the developed and emerging markets. Section 4 describes the modelling and estimation framework. The data is described in section 5. Results of the empirical analysis are discussed in section 6. Section 7 provides some robustness checks and section 8 concludes

2. The case for and against conditional models

The pioneers of asset pricing models [Sharpe (1964), Lintner (1965), Black (1972) and Ross (1978)] assume that expected asset returns, covariances of the asset with factor and factor risk premiums are time invariant. Several arguments are put forward against these assumptions. One argument is that expected returns and risk premium vary over the business cycle. In a recession investors are short of liquidity and require higher risk premiums for a given level of risk. In a boom they have extra cash for investment and therefore the expected risk premium is less than otherwise. The investment opportunities also vary over time. From the firm's point of view Jagannathan and Wang (1996) argue that systematic risk of the firm measured by CAPM beta vary over time. During a recession financial leverage of the troubled firms increases causing their beta to increase. Brooks *et al.* (1992) point out that the maturity and growth of firms also tends to change the riskiness of the firm over time. This is especially true for technological and communication firms which have shown tremendous growth over recent times in both developing and advanced countries. The relative share of different sectors may also change due to technological shocks.

Hence, betas and expected returns would depend on the nature of the information available and may vary over time. In response to these arguments many authors have concluded that the empirical failure of the unconditional CAPM might reflect the misspecification due to wrong assumptions about the constancy of expected return, beta and the risk premium. Consequently a strand of asset pricing literature has emerged which incorporates conditional information that available to investors in the asset pricing model.

The constancy of risk and expected return especially in emerging markets may be questionable as the unstable macroeconomic and political conditions can bring considerable variation in the risk and expected return. Further, in emerging markets there is evidence of stock return predictability which is believed to be caused by information inefficiency and thin-trading. Drobetz *et al*. (2002) argue that this does not necessarily imply that the markets are inefficient instead. Drobetz *et al*. (2002) advance Ferson and Korajczyk (1995) argument of the time variability in the information set of the investors as a possible reason for stock return predictability. Ferson and Korajczyk (1995) provide evidence supporting the notion that predictability is the result of time-variation in expected returns. Harvey (1995) documents that stock returns in emerging markets are predictable using local instead of global instrument variables.

Ghysels (1998) on the other hand points out that discount factor models that use conditional information may suffer from greater parameter instability than the corresponding unconditional models. Garcia and Ghysels (1998) provide such evidence in emerging markets and Schrimpf and Schroder (2007) observe similar results for a developed market. Our paper considers both conditional and unconditional models. We investigate the parameter instability problem by using the structural break test developed by Andrews (1993).

3. Literature Review of Conditional Asset Pricing Models

3.1 Developed Markets

Harvey (1989) is one of the early studies that employed conditioning variables to allow time variation in conditional covariances. Harvey (1989) set up the orthogonality restrictions and tested the empirical feasibility of the conditional asset pricing model as over identifying J-tests through the GMM approach. Using 10 size sorted CRSP portfolios from the New York Stock Exchange, Harvey (1989) reports that the Sharp-Lintner asset pricing model is rejected and that conditional covariance does change over time.

Jagannathan and Wang (1996) use the law of iterated expectations to derive the unconditional implications of the conditional asset pricing model that include the beta premium sensitivity in addition to the market beta. They were primarily interested in testing cross-section model implications on a large set of assets. Using 100 portfolios from the NYSE and AMEX sorted on the Fama-French factors they show that their model performed better compared to the static CAPM.

Cochrane (1996) proposed to incorporate time variability in the stochastic discount factor by expressing it as a linear combination of risk factors where the coefficients of the factors vary with the available information set. Cochrane used the term 'scaled factors' to represent the risk factor multiplied by the information variables. This approach thus results in a general conditional factor model with conditional information based on instruments. Cochrane (1996) estimated and tested the implication of investment based asset pricing model through GMM on 10 size portfolios from the NYSE. His model performs better than a simple consumption based model

Lettau and Ludvigson (2001) developed a conditional asset pricing model by following Cochrane's (1996) scaled factor approach. Using the consumption-aggregate wealth ratio as the conditioning variable they show that their approach performs better than the unconditional CAPM and consumption CAPM and performs at least as good as the Fama-French three factor model. Employing 25 Fama-French portfolios as test assets they estimated the risk premia for the scaled factor model with a single Fama-MacBeth cross section regression.

Schrimpf and Schroder (2007) tested conditional asset pricing model using the scaled factor approach of Cochrane (1996) on the German stock market. Using 16 portfolios sorted on size and book-to-market they provide evidence in favour of conditional CAPM with Term Spread as conditioning variable. This model performs the best in terms of the HJ-Distance and is as good as the Fama-French model. The conditional asset pricing model with scaled factors is however shown to fail the parameter stability test in most cases they considered.

Using the industry portfolios from the UK, Fletcher and Kihanda (2005) tested several formulations of the conditional asset pricing model including the higher co-moment model. They found that the stochastic discount factor of the four-moment CAPM has the best performance among all the models they considered in terms of the lowest HJ-Distance and its ability to predict industry portfolios return. However their conditional models results in poor out-of-sample predictive power.

For the case of Japan using three portfolios based on the size, Hamori (1997) tested the conditional asset pricing model employing the conditional covariances similar to the GMM approach of Harvey (1989). The model specification was rejected and the time varying CAPM did not provide a satisfactory approximation to the movements of time varying risk premia in Japan.

3.2 Emerging Markets

Using local and global instruments to allow time variability in the expected returns and risk premia, Harvey (1995) reveals that (i) predicability in the emerging markets can be traced by the time variation in the risk premia through local information (ii) the asset pricing model could not price the time varying risk and (iii) both conditional and unconditional asset pricing models are rejected.

Few studies provide empirical evidence on conditional asset pricing in emerging markets. For example, following the autoregressive approach of Bodurtha and Mark (1991), Garcia and Bonomo (2001) tested a conditional CAPM on the Brazilian stock market. They also include a variable to proxy inflation in an APT setting. Using three size portfolios their model could not be rejected as seen by an over-identifying J-statistic. This statistic is based on a large number of over identifying conditions and therefore they advice caution in drawing any strong conclusion.

Exploiting the fact that emerging market returns are predictable to some extent on the basis of proper information variables, Drobetz, *et al.* (2001) used the scaled factor methodology of Cochrane (1996) to test a conditional asset pricing model on a group of emerging markets. Treating the country International Finance Corporation (IFC) index for eight large emerging markets as a homogenous group of assets and using the MCSI Word Index as the benchmark portfolio they estimated a linear discount factor model through GMM. They do not consider estimating risk premia. Using the J-test of over identifying restrictions as evidence they conclude that the predictability in the emerging market returns can be explained by time varying risk premia and therefore conclude that asset pricing in these markets is rational. They analyse from the point of view of a Swiss investor.

Garcia and Ghysels (1998) expressed concern that the J-tests for the over identifying restrictions for the overall validity of conditional asset pricing model may have low power and may lead to erroneously accepting that risk premia as time varying. They tested the structural stability of the coefficient of the instrumental variables. These instrumental variables capture time variation in the risk premia. They emphasized that the structural stability test may provide a more powerful test of the conditional model. Using a set of ten emerging markets they tested the structural stability of the parameter through the Sup LM test using both views of the markets i.e. integrated and segmented. They conclude that models which assume integration using a global instrument results in instable parameters while local models provide the time variation asset pricing with stable coefficients.

There have been very few studies that compare the performance of unconditional and conditional asset pricing models especially those that embody the Fama-French factors and the excess kurtosis frequently reported in the emerging market returns. No study on emerging markets has compared the unconditional and conditional Fama-French models. Studies such as Garcia and Ghysels (1998) and Garcia and Bonomo (2001) use only three size portfolios therefore cross sectional implications of the model are difficult to ascertain. On the other hand studies such as Drobetz, *et al.* (2001) consider a sample of country indices as a homogenous group of assets. However the internal institutional, industrial and economic structure of the markets may be different therefore and it is worthwhile to focus on a particular market in order to gain a detailed view of the risk-return relationship in the conditional asset pricing framework. The stock market of Pakistan is of special interest from two aspects.

Firstly, as point out by Khawaja and Mian (2005) this market shares the typical characteristics and features of an emerging market such as high return accompanied with excessive volatility, thickset tails and excess kurtosis in the returns distribution, low market capitalization but higher trading volume. Secondly, from an asset allocation perspective this market may be important given that in recent years its performance in terms of the local index gain has been impressive. In 2002 for example, this market was declared the best performing capital market in the world in terms of percent increase in the local market index.

In earlier studies on the Pakistan's stock market Iqbal and Brooks (2007) found evidence of non-linearity in the risk return relationship. Iqbal *et al.* (2008) also found that the restrictions of the Black CAPM in a multivariate simultaneous equation framework could not be rejected for Pakistan but the power of the Wald and GMM tests remain a concern as in the case of the GMM test in Garcia and Ghysels (1998).

4. Conditional asset pricing models

4.1 Modelling and Estimation framework

According to Cochrane (2001) a necessary and sufficient condition for the absence of arbitrage is the existence of a positive stochastic discount factor M that prices all the payoffs

$$E_t(M_{t+1} R_{i,t+1}) = E(M_{t+1} R_{i,t+1} \mid I_t) = 1 \qquad (1)$$

Where $R_{i,t+1}$ denotes gross (raw) returns on the assets *i*. I_t contains the investor's information set at time t. This Euler equation holds for all the assets in the economy. The discount factor (pricing kernel) has different specification and interpretation for every asset pricing model. For example for the consumption based asset pricing model M_{t+1} represents the marginal rate of substitution of utility of consumption between the next period and current period. In the current study we are interested in the linear general factor pricing model for which the discount factor is linear in factors i.e.

$$M_{t+1} = a_t + b_t' F_{t+1} \quad (2)$$

In our case (2) nests two specifications of the factor models corresponding to the CAPM and the Fama French three factor models.

(i) $F_{1,t+1} = [\, RM_{t+1} \,]$

(ii) $F_{2,t+1} = [\, RM_{t+1} \;\; SMB_{t+1} \;\; HML_{t+1} \,]$

It can be seen that in the conditional case the time variation in the expected returns and risk premia are introduced by allowing the parameters of the linear discount factor to vary over time. To ascertain whether this discount factor prices all the assets under study or in other words to investigate whether time variation in the expected return really matters one can estimate the Euler equation (1) by GMM and subsequently testing for the validity of the model by some measures such as the J-test for over identifying restrictions. However this is complicated from two perspectives. Firstly the information set I_t is not observable by the econometrician and secondly in (2) two parameters have to be estimated for each time point making the estimation infeasible. In deriving unconditional implications for the conditional model similar to Jagannathan and Wang (1996) we could take unconditional expectation of (1) but note that $E(M_{t+1} R_{i,t+1} \mid I_t) = 1$ does not implies $E(M_{t+1} R_{i,t+1}) = 1$. That is conditional mean variance efficiency does not imply unconditional mean variance efficiency. This observation led Hansen and Richard (1987) to assert that in general no conditional asset pricing model is testable. Cochrane (1996, 2001) offers a partial solution to this problem by setting the parameters of the SDF to depend on the time t information set linearly i.e.

$$a_t = a' z_t \, , b_t = b' z_t \qquad (3)$$

Cochrane calls this approach of representing the discount factor as the scaled factor model. Using a single factor his model leads to

$$M_{t+1} = a_0 + a_1 z_t + b_0 RM_{t+1} + b_1 (z_t RM_{t+1}) \qquad (4)$$

While in the three factor case

$$M_{t+1} = a_0 + a_1 z_t + b_1 RM_{t+1} + b_2 SMB_{t+1} + b_3 HML_{t+1} + b_4 (z_t RM_{t+1}) + b_5 (z_t SMB_{t+1}) + b_6 (z_t HML_{t+1}) \qquad (5)$$

In the actual application we will drop the terms not involving the risk factor following Cochrane (1996). We will investigate the consequence of this approach in section 8. It is interesting to note that the scaled multi factor models (4) and (5) are now effectively expressed in unconditional form with constant coefficients. This enables us to estimate the model through GMM by plugging (4) and (5) in the usual SDF equation

$$E(M_{t+1} R_{i,t+1}) = 1 \qquad (6)$$

The GMM will yield estimates of b_i and the associated standard errors and the t-test on the coefficients will enable us to ask whether the associated unscaled or scaled factor helps explaining the variation in the pricing kernel. But we are also interested in assessing whether any unscaled or scaled factor commands a risk premium. There are various ways of estimating and testing the significance of risk premia associated with the factors. Using the beta representation of the SDF model Lettau and Ludvigson (2001) employ the two-step procedure of Fama and MacBeth (1973) to estimate risk factor premia. In the first step they estimate the discount risk factors through OLS via a time series regression and in the second step multiple regression they estimate the cross sectional risk premia. According to Lettau and Ludvigson (2001) in a short time series samples the optimal GMM (in contrast to the non-iterated

OLS) may yield imprecise estimates of the weighting matrix which may give unrealistic parameter estimates. The link between the discount factor approach and expected return-beta representation approach is pointed out by many authors such as Wang (2005).

Equation (6) using the definition of covariance can be written as

$$E(M_{t+1})E(R_{i,t+1}) + Cov(M_{t+1}, R_{i,t+1}) = 1$$

Which gives

$$E(R_{i,t+1}) = \frac{1}{E(M_{t+1})} - \frac{Cov(M_{t+1}, R_{i,t+1})}{E(M_{t+1})}$$

$$E(R_{i,t+1}) = \frac{1}{E(M_{t+1})} - \frac{b' Cov(f_{t+1}, R_{i,t+1})}{E(M_{t+1})}$$

Here b is the vector of the coefficients of the linear factor model. Let

$$\lambda_0 = \frac{1}{E(M_{t+1})} = \frac{1}{E(a_t + b_t' f_{t+1})}$$

$$\lambda = -\lambda_0 Var(F_{t+1})' b$$

$$\beta_i = \frac{Cov(f_{t+1}, R_{i,t+1})}{Var(f_{t+1})}$$

Here f_{t+1} is the vector of unscaled and scaled factors. For example in the single factor case

$$f_{t+1} = [RM_{t+1} \;\; z_t RM_{t+1}]'$$

Then the beta representation of the SDF can be expressed as

$$E(R_{i,t+1}) = \lambda_0 + \lambda' \beta_i \tag{7}$$

Our second method of estimating risk premia is the sequential GMM approach of Ogaki (1993) which has been recently investigated by Shanken and Zhou (2007). We express (7) in following way:

$$E(R_{i,t+1}) = \lambda_0 1_N + \lambda_1 \frac{Cov(R_{i,t+1}, f_{1,t+1})}{Var(f_{1,t+1})} + \lambda_2 \frac{Cov(R_{i,t+1}, f_{2,t+1})}{Var(f_{2,t+1})} + \ldots + \lambda_k \frac{Cov(R_{i,t+1}, f_{k,t+1})}{Var(f_{k,t+1})} \quad (8)$$

The sample moment conditions are set up as follows:

$$E[h_{t+1}(\theta)] = E\begin{bmatrix} R_{t+1} - \mu \\ F_{t+1} - \mu_f \\ (f_{1,t+1} - \mu_1)^2 - \sigma_1^2 \\ \vdots \\ (f_{k,t+1} - \mu_k)^2 - \sigma_k^2 \\ R_{i,t+1} - \lambda_0 1_N - \Sigma_{j=1}^{k} \lambda_j \dfrac{(R_{t+1} - \mu)(f_{j,t+1} - \mu_j)}{\sigma_j^2} \end{bmatrix} = 0 \quad (9)$$

Here R_{t+1} is a $N \times 1$ vector of asset returns with mean vector μ, F_{t+1} is a $k \times 1$ vector of scaled and unscaled factor with mean vector μ_f and $\sigma_j^2 = Var(f_{j,t+1})$. In the moment conditions given in (9) there are two sets of parameters. The first set $\theta_1 = [\mu' \ \mu_f' \ \sigma_f'^2]'$ consists of means and variances of the returns and factors. The second set $\theta_2 = [\lambda_0 \ \lambda_1 \ \lambda_2 \ \ldots \lambda_k]'$ contains the expected zero-beta rate $'\lambda_0'$ and the factor risk premia. In all there are $2(N+k)$ moment conditions. These conditions can be partitioned into two sets $h_{1,t+1}(\theta_1)$ and $h_{2,t+1}(\theta_1, \theta_2)$. In the first set there are $N + 2k$ moment conditions and same number of parameters. This subsystem is therefore exactly identified giving the GMM estimator of θ_1 as $\hat{\theta}_1 = [\bar{R}' \ \bar{f}' \ \hat{\sigma}_f^2]'$ independent of the weighting matrix. Substituting these estimates into the last N moment conditions yield the GMM estimates of risk premia by setting $E[h_{2,t+1}(\hat{\theta}_1, \theta_2)] = 0$. This sub system will be generally over-identified with N moment conditions and $k + 1 < N$ parameters. This GMM estimator is not subject to the errors-in-variables problem as the generated regressors are not employed in the estimation of risk premia. Only the parameter estimates i.e. the means and variances of assets returns and factors from the first stage are employed to estimate risk premia in the second step. Another usual GMM advantage is robustness to heteroskedasticity and serial correlation in the assets returns.

4.2 Model Specification Tests

Using the Euler equation (6) for the model with the SDF factor given by either (4) or (5) the pricing error for the model can be expressed as

$$g(b) = E(b' F_{t+1} R_{t+1} - 1) \tag{10}$$

Here b is the vector of all the coefficients of the SDF model. The sample analogue of the pricing errors is:

$$g_T(b) = \frac{1}{T} \sum_{t+1=1}^{T} (b' F_{t+1} R_{t+1} - 1) \tag{11}$$

For the true model, $g(b) = 0$. GMM selects b such that the following weighted combination of the sample pricing errors is minimized.

$$J_T = g_T(b)' W_T g_T(b) \tag{12}$$

Here W_T is the weighting matrix. In the literature W_T is specified as either the optimal weighting matrix $W_T^* = S_T^{-1}$ proposed by Hansen (1982) or the weighing matrix $W_T = E[RR']^{-1}$ which is suggested by Hansen and Jagannathan (1997). Here $S = T\,Var(g_T)$. The weighting matrix W_T^* is optimal in the sense that it yields the smallest possible variances of the estimated parameters. Using this matrix the tests for the null hypothesis that all pricing errors $g_T(b)$ are zero are carried out by the J-statistic of the over-identifying restrictions which also serves as a model specification test:

$$TJ_T(\hat{b}) \sim \chi^2(\text{number of moments} - \text{number of paramters}) \tag{13}$$

Hansen and Jagannathan (1997) argue that this test may not distinguish between models that result really in small pricing errors or a model which gives a small J-statistic value because the estimation errors captured by matrix S are large. The J-statistic places more weights on the moment conditions which are measured with smaller estimation error. This statistical criterion may not be economically interesting. When the Hansen-Jagannathan weighting matrix is used $\sqrt{J_T}$ measures the minimum distance from the pricing kernel of the model under consideration to the true pricing kernels. This distance measure is named as HJ-Distance. As Wang (2005) describes this distance measure also represents the maximum Sharpe-ratio for the model under consideration and any portfolio based on the test assets. For a correctly specified model the HJ-Distance is zero. While the optimal weighting matrix changes with different models, the weighting matrix $W_T = E[RR']^{-1}$ remains invariant across the models that employ the same set of test assets. This is advantageous when comparing different models. One difficulty with using the non-optimal weighting matrix is that Chi Square asymptotic p-values are not applicable. Jagannathan and Wang (1996) show that $TJ_T(\hat{b})$ is distributed as a weighted sum of $\chi^2(1)$ random variables. In practice the p-value is obtained by simulation using the sample analogue of $E[RR']^{-1}$ as weighting matrix to estimate b and constructing the test statistic $TJ_T(\hat{b})$.

Garcia and Ghysels (1998) express the concern that the J-tests for the over identifying restriction for the overall validity of a conditional asset pricing model may have low power especially for emerging markets for which the structural stability of the economic relationships may be questionable. They alternatively advocate using a Sup LM of Andrews (1993) to test the structural stability of the SDF parameters which may be a more powerful test of model specification. The null hypothesis is that the SDF parameter b is constant and the alternative hypothesis assumes that there is a single break at some unknown point π in the sample.

5. The data and Diagnostics Tests

5.1 The price data

The data consisting of monthly closing prices of 101 stocks and the Karachi Stock Exchange 100 index (KSE-100) are collected from the DataStream database. Stocks selection was based on the availability of time series data on active stocks for which the prices have been adjusted for dividend, stock split, merger and other corporate actions. The KSE-100 is a market capitalization weighted index. The sample period spans 13 ½ years from October 1992 to March 2006 and includes 162 monthly observations. The 101 stocks in the sample account for approximately eighty per cent of the market in terms of capitalization. Complete market capitalization data is not routinely available for all firms in the database. However the financial daily, the Business Recorder[2] reports some information over the recent past. We selected the market capitalization of all selected stocks at the beginning of July 1999 which corresponds roughly to the middle of the sample period considered in the study. We use monthly data and compute raw returns assuming continuous compounding.

5.2 The portfolio returns and the Fama-French factors

We employ 16 size $\times$ book-to-market portfolios from the emerging market of Pakistan as our test assets. Construction of the portfolios and the Fama-French factors requires firm level data on shareholder equity, number of outstanding stocks and market capitalization. The State Bank of Pakistan's document "Balance sheet analysis of joint

[2] www.businessrecorder.com.pk

stock companies" publishes annual data on balance sheet items for non-financial firms. For financial firms the data is obtained from other unpublished sources in the State Bank[3]. The data related to the market capitalization and the number of outstanding stocks is collected through the financial daily 'Business Recorder'. As the accounting and capitalization data are not available for the full sample period the data employed corresponds to roughly the middle of the sample period. The book value is obtained as the net assets of the firms excluding any preferred stocks. The stocks are classified into quartiles according to their market capitalization. A separate sorting classifies the stock accordingly their book-value. From the intersection of these two sets of quartiles 16 equally weighted size and book-to market portfolios are constructed. The mimicking portfolios of the size and book-to-market are constructed according to the Fama and French (1993) methodology. The stocks are divided into two parts (small and large) depending on whether their market equity is above or below the median. Another sort of the stocks classifies them into three parts using the break points of the lowest 30 %, middle 40 % and the highest 30 % based on their book-to market value. We construct six portfolios from the intersection of two size and three book-to-market portfolios (S/L, S/M, S/H, B/L, B/M, B/H). Equally weighted portfolios are constructed for the full sample range. The SMB factor is the return difference between the average returns on the three small-firms portfolios; (S/L+S/M+S/H)/3 and the average of the returns on three big-firms portfolios; (B/L+B/M+B/H)/3. In a similar way the HML factor is the difference between the return of the two high book-to-market portfolios; (S/H+B/H)/2 and the average of the returns on two low book-to-market portfolios; (S/L+B/L)/2. The construction in this

[3] We thank Mazhar Khan and Kamran Najam for their helpful cooperation in the balance sheet data access.

way ensures that the two constructed factors represent independent dimensions in relation to the stock returns.

Table 1 presents some descriptive statistics for the tests assets portfolios and the Fama-French factors. The last two columns report the Jarque-Bera normality test statistic and the associated p-value. The skewness of the market return is negative. The returns are quite volatile as observed by their standard deviations. The source of non-normality appears to be the excess kurtosis.

5.3 The Conditioning Variables

Although the investor's information set is unobservable several studies have employed a selected set of conditioning variables. The criteria for inclusion in the model are that the information variables must be a predictor of returns or be a leading indicator of business cycle. Following the previous literature we include the following variables. (i) 'Term Spread' defined as the difference in long maturity bond and a short maturity bill. We employ the yield rate on 10 years maturity Pakistan Government bond and 30 days repurchase option rate for measuring the rates of return on the long and short maturity bonds. The selection is dictated by the availability of these variables in the DataStream database. This variable is found to be a good predictor of the business cycle in developed markets. (ii) The short term interest rate is proxied by the 30 day repo rate. (iii) The aggregated 'Dividend Yield' on the market as this yield is part of the return to assets. (iv) Cyclical component of manufacturing production. This is the only measure of real activity usually available for developing economies at higher than annual frequency. For Pakistan's economy the manufacturing activity accounts for approximately 25 % of the GDP. In the absence of a better proxy we employ the manufacturing production and estimated the cyclical component by using the Hodrick and Prescott (1980) filter. Several studies in developed countries have employed dummy variables to capture seasonality in returns. To investigate whether such variables can be justified for the emerging market under consideration Table 2 presents the results of t-test on equality of two population means allowing for the possibility of unequal variances. We test whether returns for a particular month is on average equal to the rest of the months. In particular we compare the average return for January, June and July with the rest of the months. This choice is made as fiscal year in Pakistan's is from July-June. The January seasonality is usually observed in developed markets particularly in the US market. The test reveals that January returns are on average higher than the rest of the months in 9 out of 16 portfolios and the market portfolio. Although tax-loss selling explanation is not relevant here higher January returns may be an indication of the presence of operations of multinational corporations in the market. We therefore include a (v) January dummy variable. In addition we include (vi) aggregate 'Trading Volume' on the market. This variable is found to have special relevance for emerging markets due to two reasons. Firstly trading volume is an indicative of liquidity of stocks. Illiquidity and non-trading is an issue for emerging markets. Lesmond (2005) has employed trading volume as an indicator of liquidity in emerging markets. Jones (2002) and Amihud (2002) show that measures of liquidity such as high turnover predicts stock returns. High trading volumes may also be indicative of speculative bubbles. In Pakistan and India until recently some forms of over-the-counter market was prevailing known as 'Badla'. The trading in this market is considered to be highly speculative. Ali (1997) employs this trading volume variable on the Pakistan market to capture non-information trading.

Figure 1 presents the time series pattern of the fundamental risk factors and the mean-centred conditioning variables employed in the study. The conditioning variables have different time series patterns. Panel (e) of Figure 1 reveals that 'Dividend Yield' appears to have a long duration cycle. On the other hand as evident from Panel (f) 'Trading Volume' represent a tranquil time path before 1999 but in later years the trading activity is quite volatile. This seems to be caused by the additional liquidity injected in the market by banks after 9/11 following a global ban on transferring overseas workers remittances informally.

Table 3 reports the test of predictive power of the set of information variables employed in the study. The Wald test is the test of joint restriction *(H_0: $b = 0$)* in the following regression.

$$R_{i,t+1} = a + b'z_t + \varepsilon_{t+1} \tag{14}$$

Here z_t is the vector of conditioning variables. The test statistic is asymptotically distributed as Chi-Square with number of degrees of freedom as the number of restrictions in each equation which is 6 in this case corresponding to the number of conditioning variables. The conditioning variables exhibit significant predictability in a majority of portfolios. The p-values show that in these cases the test is significance at the 10 % level. The conditioning variables in the small size portfolio and in high book-to-market portfolios do not indicate any sign of predictability. Table 4 reports the test of relative importance of the conditioning variables. The Wald test reported here is the test of the cross-equation zero restriction on the coefficients of conditioning variables of the system of portfolio equations. In this system the dependent variable for each equation is the portfolio return and the independent variables are the six conditioning variables. The test is asymptotically distributed as Chi-Square with number of degrees of freedom as the number of restrictions which is 16 in the present case corresponding to the number of test portfolios. Except for 'Term Spread' the time variation in portfolio returns appears to be significantly related to the conditioning variables at the 5% level. This result justifies the use of the conditioning variables. Following the literature we consider all conditioning variables including ‘Term Spared’ for further analysis.

6. Test of Asset Pricing Models: Results and Discussion

6.1 Unconditional Factor Models

Panel A of Table 5 presents GMM parameter estimates $(\hat{b})$ of the stochastic discount factor of the unconditional CAPM and the associated risk premia $(\hat{\lambda})$ estimated from both the Fama-MacBeth cross-section regression and the GMM approach of Shanken and Zhou (2007). The test of model evaluation (J_T test and HJ-Distance) and parameter stability test (Sup LM) are also reported. The J_T test is the Hansen (1982) test of over identifying restrictions which follows a $\chi 2$ distribution with degrees of freedom as the number of moment conditions minus the number of parameter estimates in the SDF model. Unlike J_T statistics the HJ-Distance employs the second moment of asset returns as the weighting matrix which remains constant for all the models. This measure is thus appropriate for model comparison. The p-values are obtained by simulation following Hansen and Jagannathan (1996). Appendix A describes the procedure. The Sup-LM test is the Andrews (1993) test of structural stability of the parameters of the SDF model which assumes the alternative of single structural break at an unknown point in the sample range. The critical values are obtained from Andrews (1993). Appendix B describes the computational detail. The statistical significance of b implies that the corresponding factor is important explaining the pricing kernel. However the underlying factor may not necessarily earn an economic risk premia which are provided by estimated λ. The CAPM results indicate that the coefficient of market return factor is significantly different from zero with a high t-statistic value. This implies that the contribution of market factor cannot be ignored. However the market risk premium is not significant. This is not surprising if we consider similar findings in developed and emerging markets. See for example Harvey (1995) and Lettau and Ludvigson (2001). The absolute value and sign of risk premia differs for the Fama-MacBeth and GMM approaches. This could be explained by the fact that GMM uses the inverse of covariance matrix of the pricing errors which may be sensitive to the sample size employed as pointed out by Lettau and Ludvigson (2001). Nevertheless both GMM and Fama-MacBeth results agree on the statistical significance of the market risk premium. The J_T test and HJ-Distance both reject the model as a plausible explanation of expected returns. Among all the unconditional and conditional models employed the CAPM results in the largest J_T statistic. The HJ-Distance also attains one of the highest values among the competing models. Parameter stability is not a concern here as the LM statistic in insignificant.

Panel (a) in Figure 2 presents the pricing error of the CAPM. This is a graph of realized average portfolio returns vs the expected return predicted by the CAPM. The plot indicates that generally the pricing errors are big and the model explains only some large sized portfolios. Except for the largest growth portfolio (the portfolio with largest size and the highest book-to-market value) the CAPM over predicts the returns by as much as 2 % per month.

Panel B of Table 5 presents the results for the Fama-French model. In this case the market and the size factor (SMB) explain the pricing kernel at the 10 % level of significance. The OLS results show a significant risk price for the size and book-to-market factors. The GMM estimates of these risk premia agree in sign but not in statistical significance. The market factor is as usual not priced. The HJ-Distance is just 0.112 which is among the lowest in the models considered. The model parameters are also stable. The pricing error plot in Fig. 2, Panel (b) indicates that the pricing errors are smaller compared to the CAPM and the model satisfactorily explains three of the four smallest sized portfolios. A comparison with the pricing errors of the competing model indicates that the Fama-French model explains the small size portfolios better.

6.2 The conditional Fama-French model

In the previous section we reported that the unconditional Fama-French model clearly outperforms the unconditional CAPM. Hence we investigate whether conditional information provides further improvement in the performance of the Fama-French model. Panels A through F of Table 6 present the results for the conditional scaled factor Fama-French models each considered with a single conditioning variable. All six models seem to work as evident by the p-values of the HJ-Distance and J_T test and the statistical significance of the SDF parameters *b*. On this result the data do not provide evidence against the conditional Fama-French model. In terms of the HJ-Distance the best conditional model appears to be the one involving ‘Trading Volume’ as the scaling variable. Further, apart from ‘market’ and ‘size’ no other factor explains the pricing kernel significantly. In contrast the J_T test ranks the model with ‘Dividend Yield’ as the best conditional model. This model also results in a significant pricing kernel as four out of the six factors are significant. Moreover the GMM estimates yield significant risk prices for all the three scaled factors. For these two models the parameters also appear to be stable as evidenced by the Sup LM test.

The Pricing error plots of the conditional Fama-French model (Fig 3) indicates that the predictions of the conditional models are generally larger relative to what can be expected if the model were really true. This is true even for the best model i.e. the one scaled by ‘Trading Volume’. Fig 3, Panel (d) indicates that this model over predicts the portfolio returns by as much as about 1 % per month as seen by the error for portfolio 44. Overall it appears that the Fama-French factors scaled by ‘Trading Volume’ and ‘Dividend Yield’ explains time variation in SDF parameters and have some success in explaining portfolio returns. But generally their performance in explaining the cross section of size $\times$ book-to market is not good. Note that only the model scaled by ‘Trading Volume’ results in a smaller HJ-Distance compared to the unconditional Fama-French model. Three of the six conditional models also suffer from parameter instability problem as seen be the Sup-LM test at the 10% level of significance. The GMM estimates of risk premia for both conditional and unconditional models are not significant. This result is also consistent with Harvey (1995) which shows that his conditional model explains time variation in parameters but the associated risk premia are not significant.

Table 7 provide a formal test of the hypothesis that scaling variables do not provide improvement in the unscaled Fama-French model. Here the unrestricted model is

$$M_{t+1} = b_0 +_t + b_1 RM_{t+1} + b_2 SMB_{t+1} + b_3 HML_{t+1} + b_4 (z_t RM_{t+1}) + b_5 (z_t SMB_{t+1}) + b_6 (z_t HML_{t+1}) \quad (15)$$

The restrictions to be tested on this model are:

$$H_0 : b_4 = b_5 = b_6 = 0 \quad (16)$$

The test statistic is similar in principle to a Likelihood Ratio test and is suggested by Newey (1987) who calls it the D-test which is given as follows:

$$\begin{aligned} D &= TJ_T(Re\,stricted) - TJ_T(Unrestrictd) \quad \sim \quad \chi 2(Number\ of\ restrictions) \\ &= Tg_T(\hat{b})S^{-1}g_T(\hat{b}) - Tg_T(bu)S^{-1}g_T(\hat{bu}) \quad \sim \quad \chi 2(Number\ of\ restrictions) \end{aligned} \quad (17)$$

Note that in both restricted and unrestricted models that same unrestricted weighting matrix is employed. The D-test does not reject any of the scaled factor models implying that conditional information does not improve the fit of the unconditional

Fama-French factor model. Summing up the comparison of the unconditional and conditional Fama-French models it appears that conditional information represented by the information variables do not appear to improve the fit of the unconditional Fama-French model. However even the unconditional model does not provide satisfactory predictions of realized return as except for one largest-growth portfolio the expected return are generally over predicted by the model. Also the J_T test or the HJ-Distance tests fail to provide any further guidance as to why this may be the case.

6.3 Considering thick tails and kurtosis

A possible reason for the biased prediction observed earlier may be that the discount factor for the Fama-French model may be misspecified. The literature on emerging markets indicates that the return generating process involving the square and the cubic market return factors capture skewness and excess kurtosis in the asset return. As Dittmar (2002) points out kurtosis is different from the variance. Variance measures the dispersion of observations from the mean whereas kurtosis captures the probability of outcomes that are highly divergent from the mean; that is, extreme outcomes. Considering kurtosis is especially useful in the case of emerging markets which are characterised by high frequency of extreme observations in either direction of the return distribution suggesting that thick tails relative to normal distribution. For example, Iqbal et al. (2007) for Pakistan’s market and Hwang and Satchel (1999) for a group of emerging markets demonstrate that kurtosis is an important factor in modelling emerging market returns. It can be argued that this factor is consistent with an asset pricing model which includes co-kurtosis as a factor. Dittmar (2002) captures kurtosis by including a cubic aggregate wealth term in the pricing kernel. Table 8 provides the parameter estimates and an evaluation of the unconditional CAPM and the Fama-French models in which the discount factors are augmented by a cubic market factor. For the case of the Fama-French model the augmented model is

$$M_{t+1} = b_0 +_t + b_1 RM_{t+1} + b_2 SMB_{t+1} + b_3 HML_{t+1} + b_4 RM^3_{t+1} \quad (18)$$

The results in Table 8 show that although the additional factor in the Fama-French model is not statistically significant the model fit is improved as seen by both the J_T test and the HJ-Distance measure. Fig 4 indicates that adding the cubic factor appears to reduce the bias in the predictions of both the CAPM and the Fama-French model. The Fama-French model augmented with the cubic market factor appears to provide the best unbiased predictions. Fig 4 Panel (B) indicates that inclusion of the cubic factor helps the Fama-French model in explaining the larger sized portfolios as well which were not explained by the three factor Fama-French model. Compared to the conditional models in Table 6 this model provides improvement. The associated HJ-Distance is even smaller than the best conditional model i.e. the model scaled by the 'Trading Volume'. Moreover model proposed in (18) compared to the scaled Fama-French model is also more parsimonious in terms of the number of parameters.

This analysis also demonstrates the usefulness of graphical tools in judging the asset pricing model selection. If one only relies on the numerical measures such as the HJ-Distance or the J_T statistic one may wrongly select the best model which gives the smallest of these measures. Reliance on these measures only may be dangerous if the model is to be used in investment analysis and asset allocation decision making. This point is not highlighted in previous studies.

7. Some Robustness Checks

In the analysis of conditional Fama-French models the term not involving the risk factor i.e. z_t was dropped following similar practice in the literature. This may mean that scaled factor model such as (15) may be misspecified. In the literature the consequences of this misspecification are not discussed. We investigate whether this misspecification leads to the biased prediction of expected return illustrated in Fig 3. We consider the two best conditional models i.e. the models when scaling variable are ‘Trading Volume’ and ‘Dividend Yield’. Figure 5 plots the pricing error for the case when the z_t term is included and when it is excluded from both models. Including the z_t term really matters for the case of Trading Volume variable but is ineffective for ‘Dividend Yield’. Although the HJ-Distance with the ‘Trading Volume’ variable including z_t term is 0.068 which is the smallest of all the models investigated the model suffers the worst in terms of parameter instability as indicated by the Sup LM statistic. The value of this statistic is more than doubled when z_t is included. For the case of other information variables the effect of including z_t is more adverse such as for the Term Spread variable the pricing errors are as large as 7 % per month.

We next investigate the relative importance of quadratic and cubic market return that need to be augmented in the unconditional Fama-French model to improve the model fit and reduce the prediction bias. The following table report the D-test for the zero restriction on the coefficient of the quadratic and cubic market return in the SDF model.

	D-Test	P-value
Zero Restriction on Quadratic Market Factor	1.602	0.203
Zero Restriction on Cubic Market Factor	7.495	0.006

The difference D-test strongly rejects the hypothesis that cubic market return is irrelevant in the pricing kernel. That is excess kurtosis needs to be considered when the modelling the risk return relationship. The quadratic term implying skewness may be ignored as supported in the test result.

8. Conclusion

Modelling risky asset prices has always been a daunting task as the prices are influenced by a variety of factors which are related to both microeconomic developments related to firm, microstructure of the market. Emerging markets have the added complexity that the institutional, political and macroeconomic conditions are generally volatile. This high volatility can have many implications for the tests of asset pricing models. In this paper we address two of these issues. (i) We compare asset pricing models where the model parameters are fixed with those where the parameters are allowed to vary with the business cycle and future expectations. (ii) Due to relatively high frequency of extreme observations related to institutional and political instability the asset returns may have thick tails therefore when modelling emerging market returns we need to consider excess kurtosis as well.

Using 16 Size $\times$ Book-to-Market portfolios as test assets from Pakistan's stock market it is found that the unconditional version of the CAPM is rejected. Adding size and book-to-market factors in the Fama French framework improves the performance of the benchmark CAPM as indicated by Hansen-Jagannathan distance measure. Some conditional models scaled by variables such as 'Trading Volume' and 'Dividend Yield' result in smaller prediction errors but generally conditional information variables do not improve the explanatory power of model significantly. The best conditional model is also the worst in terms of parameter stability. Moreover, all of the unconditional and conditional CAPM and Fama-French models appear to be upward biased. The model predictions are higher than the realized returns in most of the test portfolios. It is found that the unconditional Fama-French model augmented with a cubic market factor intended to capture excess kurtosis performs the best among the competing models. This model reduced the prediction bias and also results in smaller pricing errors. Additionally a comparison of the conditional models to the kurtosis augmented unconditional model shows that this model is also more parsimonious. In summary, we investigated two plausible improvements in the benchmark unconditional CAPM (i) accounting for the time variation in expected returns and parameters and (ii) allowing for thick tails and excess kurtosis relative to the normal distribution which is an inherent assumption of the CAPM. It is found that the Fama-French model that also incorporates excess kurtosis appears to explain the expected returns better for the emerging market under consideration.

Appendix A: Computation of HJ-Distance and P-values

Hansen and Jagannathan (1996) show that

$$THJ_T = Tg_T(b)'G_T^{-1}g_T(b) \quad \sim \ Asymptotically \ \sum_{j=1}^{N-k}\lambda_j\nu_j$$

Here $\nu_j \ (j=1,2,\dots,N-k)$ is a random variable distributed as Chi Square with 1 degree of freedom and $\lambda_j \ (j=1,2,\dots,N-k)$ are *N-k* positive eigenvalues of the following matrix:

$$A = S^{1/2}G^{-1/2}(I_N - (G^{-1/2})'D[D'G^{-1}D]^{-1}D'G^{-1/2})(G^{-1/2})'(S^{1/2})' \qquad (18)$$

Here $G_T = \frac{1}{T}\sum_{t=1}^{T}R_tR_t'$. $S^{1/2}$ and $G^{1/2}$ are the Cholesky factors of *S* and *G*[4] respectively.

S can D can be consistently estimated by $S_T = \frac{1}{T}\sum_{t=1}^{T}g_T(b)g_T(b)'$ and $D_T = \frac{1}{T}\sum_{t=1}^{T}R_tY_t'$,

where Y_t is a $k\times 1$ vector of one and the scaled and unscaled factors. Jagannathan and Wang describe the procedure for calculating the p-values. Let *M* denotes the number

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[4] Ahn and Gadarowski (2004, page 114) describe that $G^{-1/2}$ is the Cholesky factor of G^{-1} which is not consistent with the Jagannathan and Wang (1996, page 48) who describe that $G^{1/2}$ is the Cholesky factor of *G*. That is in eq. (18) Jagannathan and Wang employ inverse of the Cholesky factor of *G* while Ahn and Gadarowski appear to use the Cholesky factor of the inverse of *G*. However these two matrices are not the same!

of replications to compute the p-values. We draw an $M \times N-k$ matrix C of Chi Square (1) random variables and compute the $M \times 1$ vector $U = C\lambda$ where λ is a vector of *N*-*k* positive eigenvalues of A. Then p-values are computed as the count of the number of elements in *U* that exceed THJ_T divided by *M*. We set *M* = 10,000.

Appendix B: Computation of Sup LM statistic

The simplified Sup LM statistic in Andrews (1993, page 837) is given by

$$Sup\ LM(\pi) \cong max\ \frac{T}{\pi(1-\pi)} M_1{}' M_2{}^{-1} M_1$$

Here $M_1 = \bar{g}_T S_T^{-1} D_T$ and $M_2 = D_T' S_T^{-1} D_T$ where $\bar{g}_t = \frac{1}{T}\sum_{t=1}^{T} R_t F_T' b - 1$

Here π is allowed to vary between 0.2 and 0.8. In the computation full sample restricted estimates of the SDF parameters *b* are employed[5]. Critical values of the test are tabulated in Table 1 in Andrews (1993, page 840). The table provides the critical values for both symmetric interval (such as the one used in this paper) and non-symmetrical interval. We read critical values corresponding to row $\pi_0 = 0.2$ and column *p* that corresponds to the dimension of the vector of the SDF parameters *b* from Table 1 of the Andrews paper.

[5] In the formula for the LM test statistic given in eq. (19) and matrix C of Garcia and Ghysels (1998, page 471-472) there are several typos for instance the matrix M2 in the second row of matrix C is missing.

Table 1: Descriptive Statistics for the monthly portfolio returns- October 1992-March 2006

Portfolios	Mean	Standard Deviation	Skewness	Kurtosis	Jacque-Bera	P-value (JB)
P11	-0.470	12.35	1.369	7.331	177.2	0.000
P12	0.163	14.86	0.666	8.146	190.7	0.000
P13	0.465	9.585	0.418	8.755	99.87	0.000
P14	0.391	5.673	0.377	5.872	59.51	0.000
P21	0.699	8.842	0.163	3.650	3.567	0.168
P22	1.136	6.880	0.348	2.961	3.273	0.195
P23	0.897	9.059	0.440	3.554	7.304	0.026
P24	0.969	8.583	0.225	6.491	83.63	0.000
P31	0.073	10.63	0.282	2.724	2.667	0.264
P32	1.031	9.353	-0.134	3.729	4.070	0.131
P33	1.120	6.923	-0.068	3.056	0.144	0.930
P34	1.257	6.365	0.607	3.741	13.66	0.001
P41	0.691	10.33	0.277	3.671	5.105	0.078
P42	0.970	9.056	0.440	3.659	8.168	0.017
P43	0.769	9.007	-0.128	3.259	0.899	0.638
P44	1.746	12.35	-0.412	6.883	106.4	0.000
MKT	1.438	9.831	-0.422	4.694	24.33	0.000
SMB	-0.370	4.500	0.091	3.019	0.230	0.892
HML	0.586	5.477	-0.274	3.452	3.425	0.180

Note: This table present the summary statistics for the 4×4 portfolios constructed from the intersection of four size and four book-to-market sorted portfolios. The last two columns report the Jarque-Bera normality test. The first subscript in the portfolio notation P_{ij} represents the size quartile and the second denotes the book-to-market quartile. Normality is rejected in 11 out of 16 portfolios at 10 % level of significance. The non-normality appears to be caused by excess kurtosis.

Table 2: Tests for monthly seasonality of portfolio returns

Portfolios	$\mu_{Jan} - \mu_{Other}$	$\mu_{Jun} - \mu_{Other}$	$\mu_{Jul} - \mu_{Other}$
P11	3.875	-3.938	1.758
	(0.115)	(0.171)	(0.377)
P12	-0.139	-2.634	6.941
	(0.484)	(0.370)	(0.021)
P13	4.132	0.445	0.307
	(0.173)	(0.450)	(0.439)
P14	0.709	0.902	0.427
	(0.375)	(0.272)	(0.385)
P21	3.859	-0.611	-2.829
	(0.050)	(0.422)	(0.120)
P22	3.733	-2.499	-3.370
	(0.076)	(0.117)	(0.053)
P23	-1.570	-0.734	1.236
	(0.229)	(0.372)	(0.374)
P24	2.531	2.774	0.225
	(0.163)	(0.215)	(0.462)
P31	5.105	-1.597	-2.876
	(0.009)	(0.299)	(0.191)
P32	6.686	-3.967	-0.736
	(0.017)	(0.102)	(0.389)
P33	2.487	-0.507	-0.206
	(0.125)	(0.401)	(0.457)
P34	3.787	-4.716	1.260
	(0.028)	(0.001)	(0.187)
P41	4.534	-4.128	-0.273
	(0.032)	(0.115)	(0.461)
P42	4.622	-2.194	-0.660
	(0.056)	(0.225)	(0.358)
P43	4.391	-3.561	-3.350
	(0.055)	(0.126)	(0.116)
P44	6.095	-6.460	-3.635
	(0.022)	(0.109)	(0.211)
MKT	4.470	-4.478	-1.532
	(0.051)	(0.113)	(0.300)
SMB	-1.823	3.154	0.617
	(0.063)	(0.017)	(0.333)
HML	-1.358	0.666	0.593
	(0.155)	(0.348)	(0.364)

Note: This table presents the results of the hypothesis testing that the average difference in returns between a given month and the rest of the months is zero. In particular the return differences are compared for January, June and July with the rest of the months. The p-values of the t-test appear in parenthesis. The variances between the respective populations of returns are allowed to be different.

Table 3: Predictive ability of conditioning variables

Size Quartiles	Book-to-market Quartiles			
	B1 (Low)	B2	B3	B4 (High)
S1 (Small)	7.321	9.544	13.437	5.931
	(0.292)	(0.145)	(0.036)	(0.430)
S2	14.236	22.803	16.640	5.158
	(0.027)	(0.001)	(0.010)	(0.523)
S3	13.446	16.762	8.359	9.503
	(0.036)	(0.010)	(0.212)	(0.147)
S4 (Large)	19.942	12.284	11.074	1.618
	(0.003)	(0.055)	(0.086)	(0.951)

Note: This table report the Wald tests of predictive ability of the conditioning variables employed in the paper (p-values in parenthesis). The sample period from October 1992 to March 2006 comprises 162 monthly observations. The conditioning variables are
TERM: Term Spread (Difference between 10 year government bond yield rate and 30 days repurchase option rate)
RF: 30 day repo rate percent per year
DY: Dividend Yield percent per year
VOL: Trading volume turnover million of shares
CY: Cyclical component of manufacturing production (filtered by HP filter)
JAN: A dummy variable taking value one for January and zero elsewhere

The Wald test is the test of joint restriction $(H_0: b = 0)$ in the following regression.

$$R^{i}_{t+1} = a + b'z_t + \varepsilon_{t+1}$$

The test statistic is asymptotically distributed as Chi-Square with number of degrees of freedom as number of restrictions in each equation which is 6 in this case corresponding to number of conditioning variables.

Table 4: Relative importance of conditioning variables

	Term Spread	Short Term Interest Rate	Dividend Yield	Trading Volume	Cyclical Component of Manufacturing Production	January Dummy
Wald	7.984	28.128	53.529	52.863	28.030	37.075
P-value $\chi 2(16)$	(0.949)	(0.030*)	(0.000*)	(0.000*)	(0.031)	(0.002)

Note: This table report the tests of relevance and importance of the conditioning variables employed in the paper. The sample period from October 1992 to April 2006 comprises 162 monthly observations. The conditioning variables are
* indicates that p-value is less than 0.05 therefore the associated conditioning variable is significant at 5 % level..

Table 5: Estimating of Parameters of Unscaled SDF model and Risk Premium via OLS and GMM

Panel A: Unconditional CAPM				
Parameters of SDF	const	b_m		
coefficients	0.158*	0.013*		
(t-stats)	(3.311)	(5.144)		
Factor Risk Premium	const	λ_m		
Risk Premia (OLS)	0.347	0.748		
(t-stats)	(0.945)	(1.147)		
Risk Premia (GMM)	0.879*	-0.162		
(t-stats)	(2.672)	(-0.186)		
Model Specification Tests	$J_T -$ test	HJ-Dist	Sup-LM	
Statistic	23.897	0.149	5.074	
(p-value)	(0.047)	(0.015)		
Panel B : Unconditional Fama-French Model				
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}
coefficients	0.211	0.015*	0.021**	0.009
(t-stats)	(1.511)	(2.589)	(1.827)	(1.064)
Factor Risk Premium	const	λ_m	λ_{SMB}	λ_{HML}
Risk Premia (OLS)	0.982*	0.197	-0.487*	0.736*
(t-stats)	(3.449)	(0.377)	(-3.716)	(4.072)
Risk Premia(GMM)	1.000*	-0.592	-0.353	0.557
(t-stats)	(1.923)	(0.388)	(-0.736)	(1.254)
Model Specification Tests	$J_T -$ test	HJ-Dist	Sup-LM	
Statistic	13.185	0.112	6.229	
(p-value)	(0.355)	(0.243)		

* and ** indicate significance at 5 and 10 % level respectively

This table presents parameters GMM estimates of SDF and associated risk premia of unconditional CAPM (Panel A), Fama-French 3 factor model (Panel B), and a model that includes a cubic market factor in addition to the market return (Panel C) and Fama French model with a cubic factor term (Panel D). The parameters estimates of the risk premia are obtained using both the Fama-Macbeth and GMM approach and the approach in Shanken and Zhou (2007). The test assets are 4×4 size and book-to-market sorted portfolios. The sample comprises monthly portfolio data from October 1992 to March 2006. The last two rows in each panel also present the model specification tests. The J_T test is the Hansen (1982) test of over identifying restriction which follows a $\chi 2$(# moment conditions - # parameters estimates in the SDF model). This test is the minimized value of the GMM objective function which is a quadratic form in the pricing errors with matrix of quadratic form i.e. the weighting matrix as the Hansen (1982) optimal weighting matrix. HD-Dist is the Hansen and Jagannathan (1997) measure of model evaluation and specification. The p-values are obtained by simulation using Hansen and Jagannathan (1996). Sup-LM test is the Andrews (1993) test of structural stability of the parameters of the SDF model. The critical values are obtained from Andrews (1993) Table 1.

Table 6: Estimation of Parameters of 3-Factor SDF model and Risk Premium via OLS and GMM

Panel A: FF scaled by Term Spread (TERM)							
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	$b_{TERM.m}$	$b_{TERM.SMB}$	$b_{TERM.HML}$
coefficients	0.151	0.021*	0.024*	0.013**	0.013	0.001	-0.009
(t-stats)	(1.292)	(3.840)	(2.159)	(1.744)	(1.244)	(0.013)	(-0.018)
Factor Risk Premium	Const	λ_m	λ_{SMB}	λ_{HMLB}	$\lambda_{TERM.m}$	$\lambda_{TERM.SMB}$	$\lambda_{TERM.HML}$
Risk Premia (OLS)	1.498*	-0.360	-0.503*	0.714*	-1.250	-0.392	0.590
(t-stats)	(2.594)	(-0.445)	(-3.649)	(3.739)	(-0.843)	(-0.624)	(0.632)
Risk Premia (GMM)	1.002	-1.141	-0.797	0.486	-1.291	-0.020	-0.081
(t-stats)	(1.345)	(-0.525)	(-1.235)	(0.751)	(-0.907)	(-1.242)	(-0.293)
Model Specification Tests	$J_T -$ test			HJ-Dist		Sup LM	
Statistic	10.603			0.124		19.697**	
(p-value)	(0.304)			(0.208)			
Panel B : FF scaled by Short Interest Rate (RF)							
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	$b_{RF.m}$	$b_{RF.SMB}$	$b_{RF.HML}$
coefficients	0.239*	0.017*	0.021*	0.001**	-0.007	0.018	0.003
(t-stats)	(2.896)	(2.275)	(2.208)	(0.191)	(-0.636)	(0.829)	(0.205)
Factor Risk Premium	Const	λ_m	λ_{SMB}	λ_{HMLB}	$\lambda_{RF.m}$	$\lambda_{RF.SMB}$	$\lambda_{RF.HML}$
Risk Premia (OLS)	1.227**	-0.131	-0.464*	0.716*	1.396	-0.101	-1.185
(t-stats)	(2.048)	(-0.125)	(-3.270)	(3.703)	(0.875)	(-0.115)	(-1.243)
Risk Premia (GMM)	1.215*	-0.997	-0.082	0.428	-0.635	-0.010	-0.025
(t-stats)	(2.162)	(-0.489)	(-0.132)	(0.857)	(-0.436)	(-0.614)	(-1.243)
Model Specification Tests	$J_T -$ test			HJ-Dist		Sup LM	
Statistic	11.616			0.122		19.553**	
(p-value)	(0.235)			(0.669)			
Panel C: FF scaled by Dividend Yield (DY)							
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	$b_{DY.m}$	$b_{DY.SMB}$	$b_{DY.HML}$
coefficients	0.311	0.028*	0.025*	0.009	-0.035**	-0.037	-0.042**
(t-stats)	(1.533)	(2.708)	(2.179)	(0.623)	(-1.766)	(-0.697)	(-1.850)
Factor Risk Premium	Const	λ_m	λ_{SMB}	λ_{HMLB}	$\lambda_{DY.m}$	$\lambda_{DY.SMB}$	$\lambda_{DY.HML}$
Risk Premia (OLS)	1.280*	-0.180	-0.481*	0.721*	1.316	0.131	1.168
(t-stats)	(3.166)	(-0.277)	(-3.450)	(3.902)	(0.719)	(0.118)	(1.390)
Risk Premia (GMM)	1.403*	-1.853	-0.499	0.775	3.599*	0.043*	0.580*
(t-stats)	(2.154)	(-0.757)	(-0.860)	(0.925)	(2.560)	(2.090)	(2.373)
Model Specification Tests	$J_T -$ test			HJ-Dist		Sup LM	
Statistic	6.896			0.126		10.513	
(p-value)	(0.648)			(0.613)			

Table 6 (continue): Estimation of Parameters of 3-Factor SDF model and Risk Premium via OLS and GMM

Panel D : FF scaled by Trading Volume (VOL)							
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	$b_{VOL.m}$	$b_{VOL.SMB}$	$b_{VOL.HML}$
coefficients	0.371*	0.015*	0.026*	-0.005	-0.001	-0.033	-0.023
(t-stats)	(3.193)	(2.720)	(2.106)	(-0.581)	(-0.116)	(-1.237)	(-1.371)
Factor Risk Premium	Const	λ_m	λ_{SMB}	λ_{HMLB}	$\lambda_{VOL.m}$	$\lambda_{VOL.SMB}$	$\lambda_{VOL.HML}$
Risk Premia (OLS)	1.068*	0.281	-0.478*	0.703*	1.012	0.387	1.062
(t-stats)	(2.289)	(0.317)	(-3.713)	(4.008)	(0.364)	(0.439)	(1.458)
Risk Premia (GMM)	0.919**	-1.624	-0.624	0.508	1.542*	0.013	0.432**
(t-stats)	(1.654)	(-1.293)	(-1.355)	(0.867)	(2.539)	(1.030)	(1.88)
Model Specification Tests	$J_T -$ test			HJ-Dist		Sup LM	
Statistic	8.495			0.109		16.546	
(p-value)	(0.485)			(0.864)			
Panel E: FF scaled by Cyclical Component of GDP (CY)							
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	$b_{CY.m}$	$b_{CY.SMB}$	$b_{CY.HML}$
coefficients	0.219**	0.018*	0.031*	0.004	0.001	-0.001	0.0001
(t-stats)	(1.891)	(2.952)	(3.906)	(0.421)	(0.934)	(-0.376)	(0.134)
Factor Risk Premium	Const	λ_m	λ_{SMB}	λ_{HMLB}	$\lambda_{CY.m}$	$\lambda_{CY.SMB}$	$\lambda_{CY.HML}$
Risk Premia (OLS)	1.121**	0.177	-0.416*	0.693*	-5.049	3.329	8.148
(t-stats)	(2.097)	(0.220)	(-2.961)	(3.685)	(-0.364)	(0.592)	(1.098)
Risk Premia (GMM)	1.178*	-0.367	-0.614	0.894	3.550	0.181**	0.716
(t-stats)	(1.971)	(-0.194)	(-1.010)	(1.307)	(0.420)	(1.724)	(0.314)
Model Specification Tests	$J_T -$ test			HJ-Dist		Sup LM	
Statistic	9.988			0.131		21.212*	
(p-value)	(0.351)			(0.310)			
Panel F : FF scaled by January Dummy (JAN)							
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	$b_{JAN.m}$	$b_{JAN.SMB}$	$b_{JAN.HML}$
coefficients	0.269**	0.010	0.013	0.004	0.047	0.049	0.066
(t-stats)	(1.750)	(1.126)	(0.937)	(0.360)	(0.749)	(0.379)	(0.602)
Factor Risk Premium	Const	λ_m	λ_{SMB}	λ_{HMLB}	$\lambda_{JAN.m}$	$\lambda_{JAN.SMB}$	$\lambda_{JAN.HML}$
Risk Premia (OLS)	0.859*	0.445	-0.492*	0.669*	-0.783	0.431	-0.110
(t-stats)	(2.357)	(0.673)	(-3.507)	(3.445)	(-1.068)	(1.049)	(-0.327)
Risk Premia (GMM)	0.938**	0.630	-0.247	1.094**	-0.511	-0.002	-0.151**
(t-stats)	(1.812)	(0.257)	(-0.404)	(1.866)	(-1.359)	(-0.374)	(-1.879)
Model Specification Tests	$J_T -$ test			HJ-Dist		Sup LM	
Statistic	16.730			0.124		18.582	
(p-value)	(0.053)			(0.286)			

* and ** indicate significance at 5 and 10 % level respectively

This table presents parameters GMM estimates of SDF and associated risk premia of the conditional Fama-French model. The time variation in the SDF parameters is allowed using scaling the fundamental factor with the set of information variables. The scaling variables are Term Spread, 30 day repo rate (a measure of risk free rate) Dividend Yield, Trading volume, the HP-filtered cyclical component of manufacturing production and a January dummy. This is a three factor model with the fundamental factors being the market returns, size (SMB) and book-to-market factor (HML). The parameters estimates of risk premia are obtained using both Fama-Macbeth and GMM approach and the approach in Shanken and Zhou (2007). The test assets are 4*4 size and book-to-market sorted portfolios. The sample is monthly portfolio data from October 1992 to March 2006. The last two rows in each panel also present the model specification tests. The J_T test is the Hansen (1982) test of over identifying restriction which follows a $\chi 2$(# moment conditions -# parameters estimates in the SDF model). This test is the minimized value of the GMM objective function which is quadratic form in the pricing errors with matrix of quadratic form i.e. the weighting matrix is the Hansen (1982) optimal weighting matrix. HD-Dist is the Hansen and Jagannathan (1997) measure of model evaluation and specification. This is the square root of the quadratic form in the pricing errors. The weighting g matrix the second moment matrix of gross asset returns. The p-values are obtained by simulation using Hansen and Jagannathan (1996). Sup-LM test is the Andrews (1993) test of structural stability of the parameters of the SDF model which assumes the alternative of single structural break at unknown point in the sample range. The critical values are obtained from Andrews (1993).

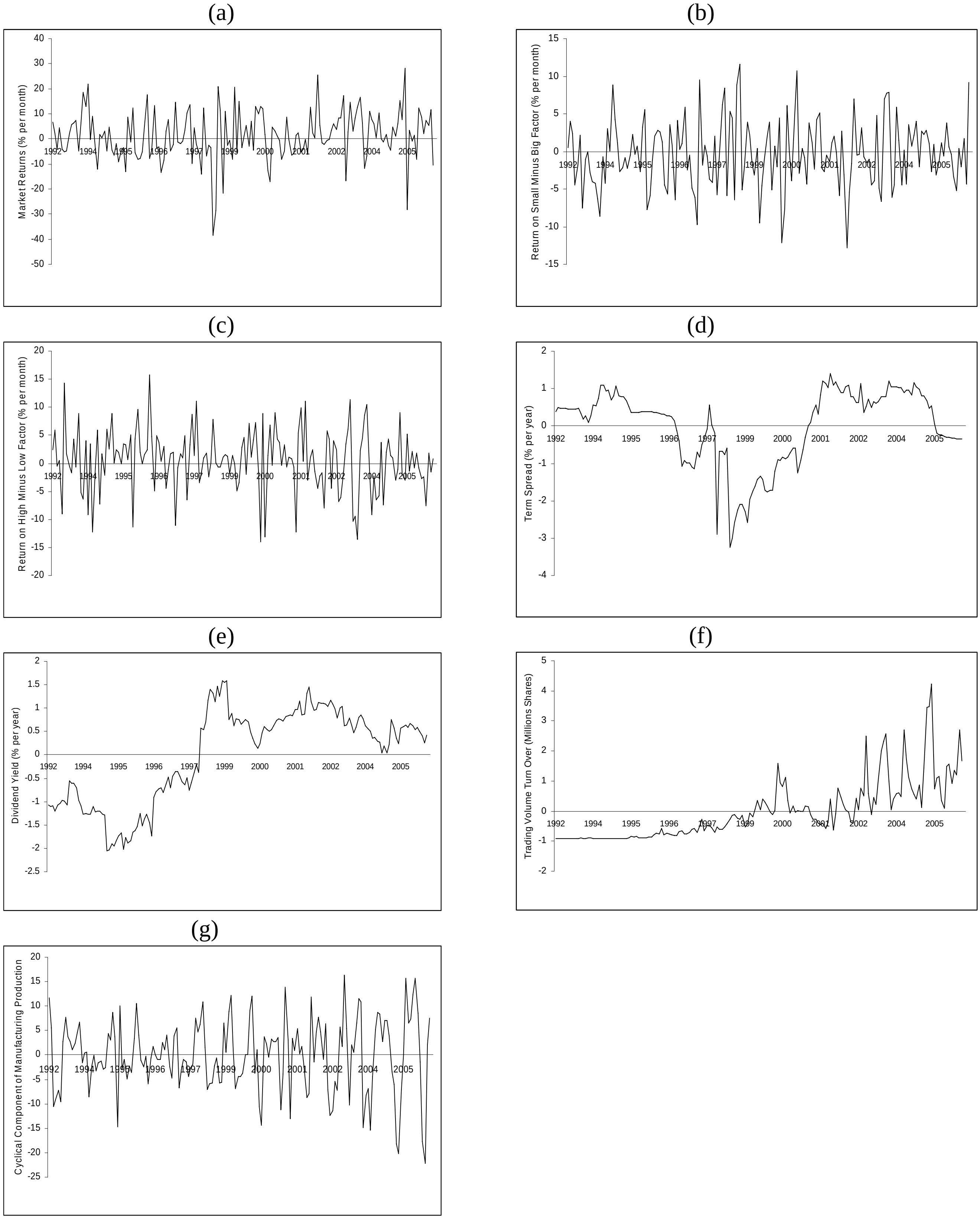


Figure 1: Time Series Behaviours of Factors and Conditioning Variables. The conditioning variables are mean centred. The factors are the market return, and the factors mimicking size and book-to-market.

(a) (b)

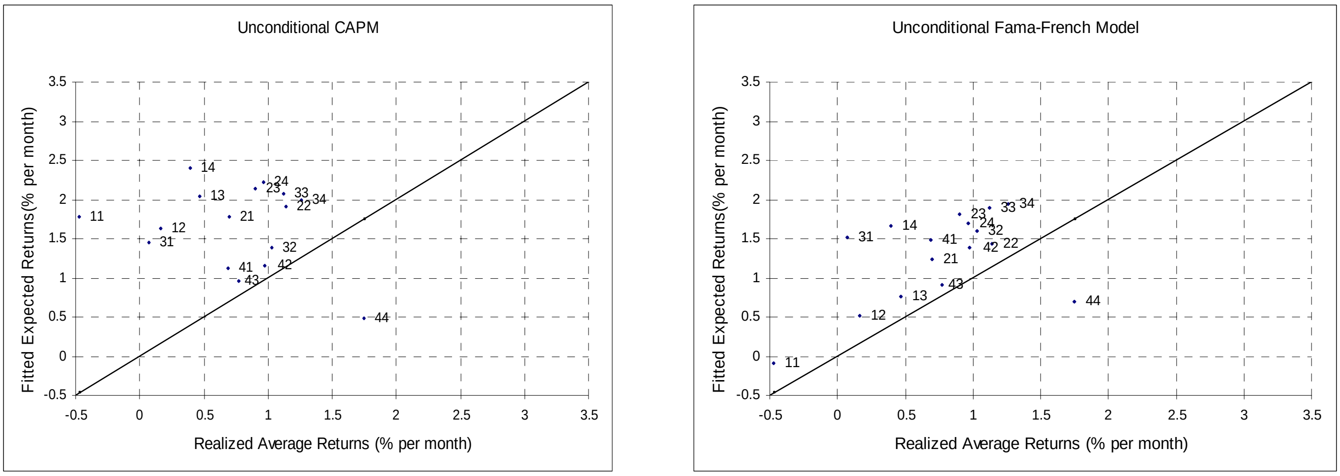


Figure 2: Realized vs. fitted returns of the 16 size $\times$ book-to-market portfolios in percent per month for the four unconditional factor models. The figure present the pricing error plots for different specifications of the four unconditional models namely the CAPM, the cubic factor model that includes a cubic market return in addition to the market return, the Fama French three factor models and the Fama-French model with a cubic factor term. The first digit of the data labels represent the size quartile (1 = small, 4 = Big) and the second digit refers to the book-to-market quartile (1 = Low, 4= High) .The sample range is October 1992 to March 2006. The pricing errors are generated using SDF parameters estimates from the HJ GMM estimation to ensure the results of different models are comparable.

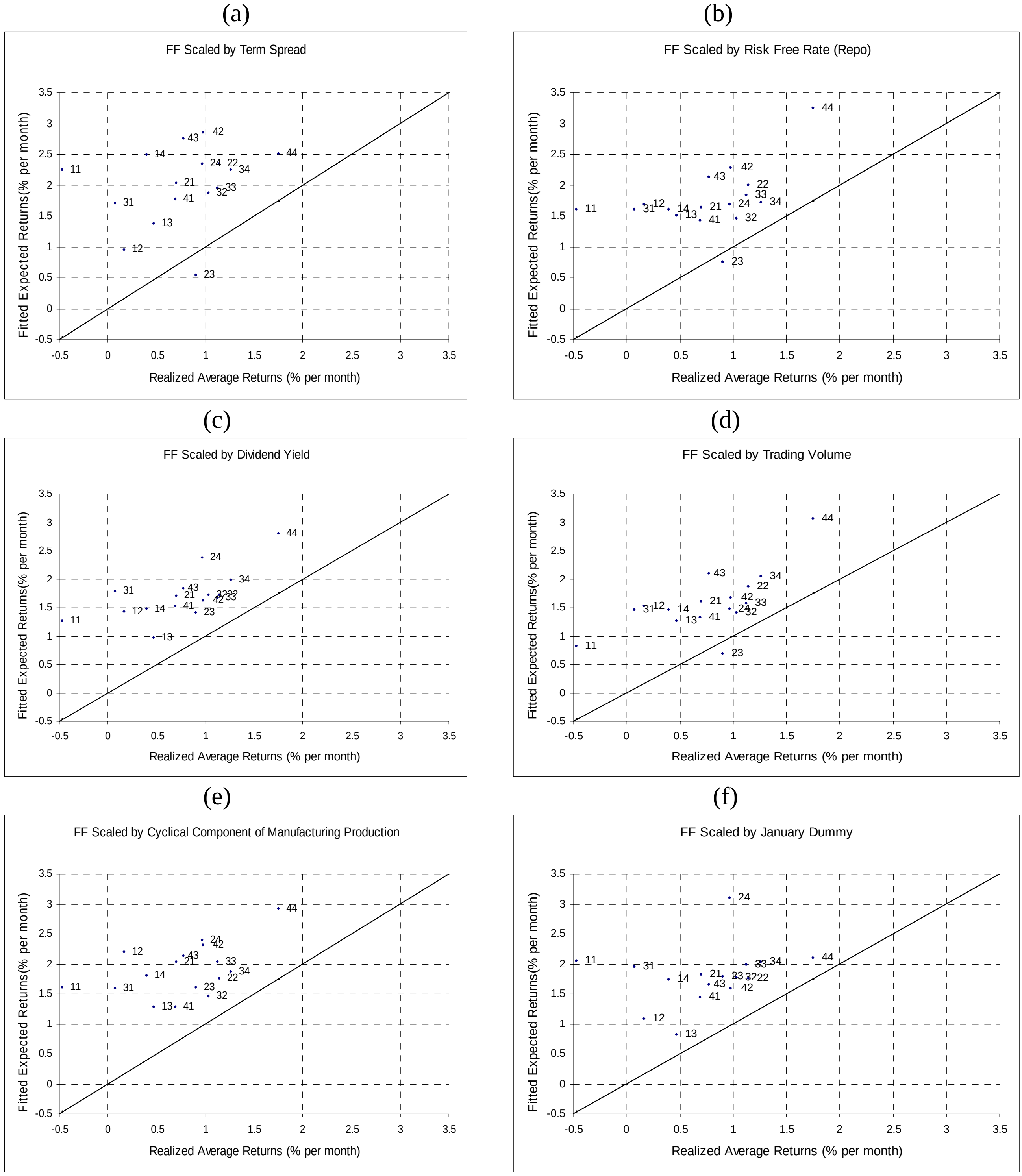


Figure 3: Realized vs. fitted returns of the 16 size $\times$ book-to-market portfolios in percent per month for the conditional three factor Fama-French model. The figure present the pricing error plots for different specifications of the FF model scaled by the each of the six information variables. The first digit of the data labels represent the size quartile (1 = small, 4 = Big) and the second digit refers to the book-to-market quartile (1 = Low, 4= High). The pricing errors are generated using SDF parameters estimates HJ GMM to make the results comparable across models.

Table 7: Testing whether marginally scaling factors conditional information help FF

Conditioning Variable	D-Statistic	P-value (D test)
Term Spread	3.103	0.376
Risk Free Rate	2.246	0.523
Dividend Yield	1.455	0.693
Trading Volume	2.762	0.429
Cyclical Comp. Manufacturing Production	1.527	0.676
January Dummy	2.554	0.466

This table presents the Newey (1987) test of Difference test to test the significance of coefficient of the factors scaled by conditioning variables. The test has an asymptotic Chi Square distribution with number of degrees of freedom equal to the number of restrictions tested which is 2 in this case.

Table 8: Estimating of Parameters of Unscaled SDF CAPM and Fama-French model augmented by a cubic market factor and the Risk Premium via OLS and GMM

Panel A: Unconditional Cubic Return Model			
Parameters of SDF	const	b_m	$b_{rm\wedge 3}$
coefficients	0.098*	0.026*	-3.52×10^{-5}*
(t-stats)	(2.110)	(6.901)	(-4.047)
Factor Risk Premium	const	λ_m	$\lambda_{rm\wedge 3}$
Risk Premia (OLS)	0.382	0.689	0.331×10^{-3}
(t-stats)	(0.806)	(0.979)	(0.605)
Risk Premia(GMM)	0.818**	-0.007	-100.737
(t-stats)	(1.926)	(-0.005)	(-0.107)
Model Specification Tests	$J_T -$ test	HJ-Dist	Sup-LM
Statistic	16.518	0.145	7.215
(p-value)	(0.222)	(0.024)	

Panel B : Unconditional Fama-French Cubic Factor Model					
Parameters of SDF	const	b_m	b_{SMB}	b_{HML}	bm^3
coefficients	0.185	0.025*	0.029*	0.008	-2.21×10^{-5}
(t-stats)	(1.885)	(3.536)	(3.512)	(1.511)	(-1.452)
Factor Risk Premium	const	λ_m	λ_{SMB}	λ_{HML}	$\lambda_m{}^3$
Risk Premia (OLS)	1.422*	-0.427	-0.512*	0.738*	22.842
(t-stats)	(2.878)	(-0.564)	(-3.837)	(4.071)	(0.812)
Risk Premia(GMM)	1.178*	-2.381	-0.593	0.457	924.695
(t-stats)	(2.144)	(-1.035)	(-1.120)	(1.016)	(0.422)
Model Specification Tests	$J_T -$ test	HJ-Dist	Sup-LM		
Statistic	12.836	0.101	9.490		
(p-value)	(0.304)	(0.319)			

* and ** indicate significance at 5 and 10 % level respectively

This table presents parameters GMM estimates of SDF and associated the risk premia of unconditional CAPM (Panel A), Fama-French factor model (Panel B) each augmented by a cubic market factor. The parameters estimates of risk premia are obtained using both Fama-Macbeth and GMM approach and the approach in Shanken and Zhou (2007). The test assets are 4×4 size and book-to- market sorted portfolios. The sample comprises monthly portfolio data from October 1992 to March 2006. The last two rows in each panel also present the model specification tests. The J_T test is the Hansen (1982) test of over identifying restriction which follows a $\chi 2$ (# moment conditions - # parameters estimates in the SDF model). The p-values are obtained by simulation using Hansen and Jagannathan (1996). Sup-LM test is the Andrews (1993) test of structural stability of the parameters of the SDF model which assumes the alternative of single structural break at unknown point in the sample range. The critical values are obtained from Andrews (1993) Table 1.

(a) (b)

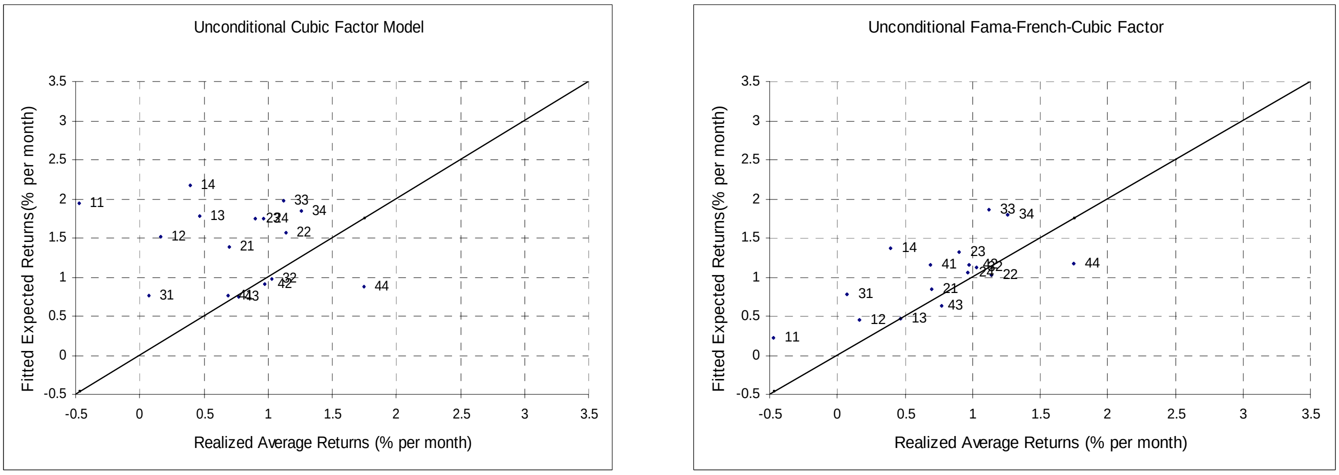
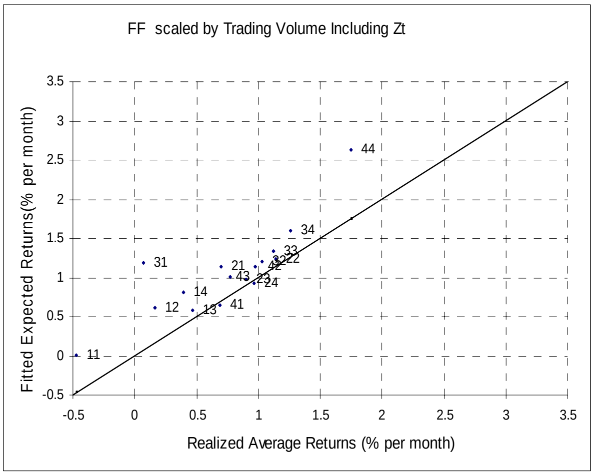


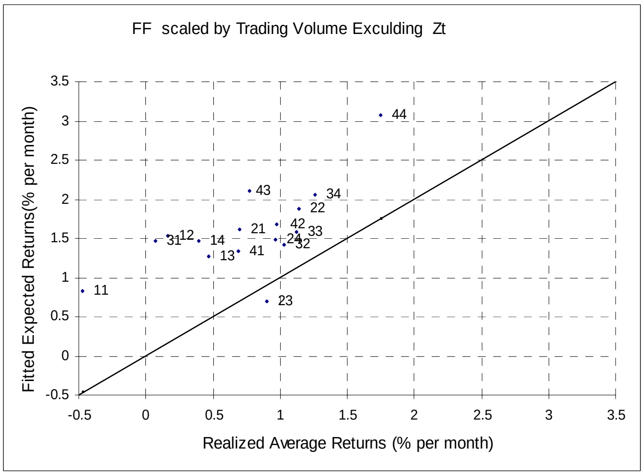
Figure 4: Realized vs. fitted returns of the 16 size $\times$ book-to-market portfolios in percent per month for the two unconditional factor models augmented by a cubic market factor. The figure present the pricing error plots for different specifications of the two unconditional models namely the CAPM and the Fama-French model with a cubic factor term. The first digit of the data labels represent the size quartile (1 = small, 4 = Big) and the second digit refers to the book-to-market quartile (1 = Low, 4= High) .The sample range is October 1992 to March 2006. The pricing errors are generated using SDF parameters estimates from the HJ GMM estimation to ensure the results of different models are comparable.

(a)



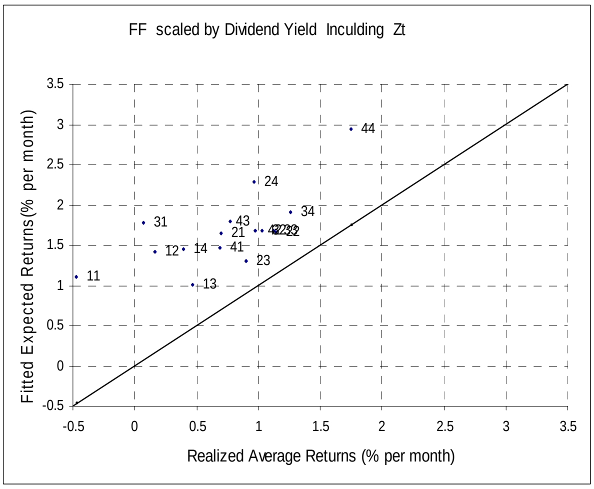
HJ-Distance = 0.068 (0.975)
Sup LM = 37.518*

(b)



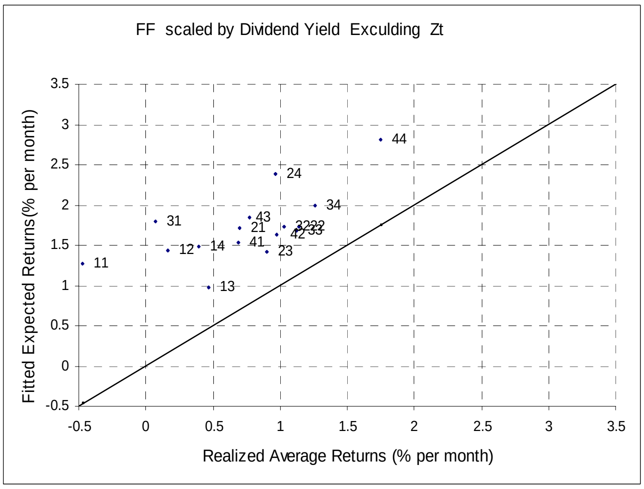
HJ-Distance = 0.109 (0.863)
Sup LM = 16.546

(c)



HJ-Distance = 0.125 (0.583)
Sup LM = 17.285

(d)



HJ-Distance = 0.126 (0.613)
Sup LM = 10.513

Figure 5: Realized vs. fitted returns of the 16 size $\times$book-to-market portfolios in percent per month for the conditional three factor Fama-French model with and without including the term involving the conditional variable z_t in the discount factor model. The figure present the pricing error plots for specifications of the FF model scaled by the each of the two information variables. The first digit of the data labels represent the size quartile (1 = small, 4 = Big) and the second digit refers to the book-to-market quartile (1 = Low, 4= High). The pricing errors are generated using SDF parameters estimates HJ GMM to make the results comparable across models.

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