A Dynamic Asset Pricing Model with Time-Varying Factor and Idiosyncratic Risk[1]

Paskalis Glabadanidis[2]

Koç University

January 14, 2008

[1]I would like to thank James Bergin, Heber Farnsworth, John Scruggs, Jonathan Taylor, Yong Wang, Guofu Zhou and seminar participants at City University of Hong Kong, Koç University and Washington University in Saint Louis for their valuable help and suggestions. The usual disclaimer applies.

[2]Correspondence: Paskalis Glabadanidis, College of Administrative Sciences and Economics, Koç University, Rumelifeneri Yolu 34450, Sariyer, Istanbul, Turkey, tel: (++90) 212-338-1681, fax: (++90) 212-338-1651, email: pglabadanidis@ku.edu.tr.

A Dynamic Asset Pricing Model with Time-Varying Factor and Idiosyncratic Risk

Abstract

This paper utilizes a state-of-the-art multivariate GARCH model to account for time-variation of idiosyncratic risk in improving the performance of the single-factor CAPM, the three factor Fama-French model and the four-factor Carhart model. I show how to incorporate time-variation in the second moments of the residuals in a very general way. When applied to the Fama and French (1993) size/book-to-market portfolio returns, I document a 50% reduction in the average absolute pricing error of this dynamic Fama-French model over the static one. In addition, I find that market betas of growth stocks increase during recessions while market betas of value stocks decrease during recessions and that HML betas of value stocks increase during recessions while HML betas of growth stocks decrease during recessions. Finally, for the Fama and French industry portfolios I find that the single-factor model outperforms the three and four factor models substantially both in their unconditional *and* conditional forms.

Key Words: Dynamic Asset Pricing, Multivariate GARCH.

JEL Classification: G12 (Asset Pricing); C32 (Multiple Equation Time Series).

I. Introduction

The relationship between risk and return is one of the most important questions in finance. One of the first risk-return models is the classical Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). Early empirical tests of the CAPM by Black, Jensen and Scholes (1972) and Fama and MacBeth (1973), among others, have largely found substantial empirical support for it in the data. Gradually, over the next decade, studies began to document what appeared to be violations of the CAPM for certain portfolios of securities sorted by characteristics like market capitalization (Banz (1981)), for example. One possible explanation for these violations could be that they are the result of data snooping (Lo and MacKinlay (1990)). Another possibility is that the risk-return relationship is misspecified. If this is indeed the case, then a potential remedy would be to include new pervasive risk factors into the risk-return model. In a very important contribution in this direction, Fama and French (1993) introduce an empirically motivated three-factor model by adding a market capitalization factor and a book-to-market factor to the CAPM market factor. Carhart (1997) proposes a four-factor model by appending the three Fama-French factors with a momentum factor after the study by Jegadeesh and Titman (1993) on returns to momentum strategies.

The Fama-French and Carhart models appear to be substantially better than the CAPM at accurately describing the average returns of portfolios sorted by market capitalization and book-to-market (BM) ratios. The Carhart model appears to improve upon the Fama-French model in terms of reducing mean absolute pricing errors of mutual fund returns. By now the Fama-French and Carhart models have become quite popular and have been widely used for estimating costs of capital, computing optimal asset allocations and measuring performance evaluations. The lack of theoretical grounds for the Fama-French and Carhart's momentum factor-mimicking portfolios to be cross-sectionally priced risk factors has spawned a lot of research aimed at either identifying the economic reasons for these portfolios to be priced factors or discrediting the validity of the two multi-factor models on statistical grounds and risk-return relation mis-specifications.

Fama and French (1993, 1996) suggest that the book-to-market factor may be a proxy for a systematic factor related to distressed firms. Chung, Johnson and Schill (2001) find that the explanatory power of the book-to-market and size factors decreases or disappears as higher-order co-moments of stock returns with the market factor are added as additional risk factors. Lakonishok, Shleifer and Vishny (1994) propose that the book-to-market effect is related to a cognitive bias on behalf of investors that arises as they extrapolate firms' future earnings and growth potential from past values. Alternatively, Kothari, Shanken and Sloan (1995) point out a data-related selection bias associated with the COMPUSTAT dataset that might be driving the results of Fama and French (1993). Yet, Cohen and Polk (1995) and Davis (1994) attempt to fix the bias in the data and still find the presence of a book-to-market effect. Daniel and Titman (1997), on the other hand, argue that the size and book-to-market factors are picking up co-movements of stock returns that are related to stocks characteristics instead of some pervasive risk factors. More recently, Petkova (2006) finds that the Fama-French factors are correlated with innovations in instrumental variables that predict the return and volatility of a wide market index. Furthermore, Petkova and Zhang (2005) show that the empirically documented value premium is justified in a rational asset pricing framework by time-varying conditional betas of value and growth stocks over the business cycle. Finally, Moskowitz (2003) finds that the size premium is related to volatility and covariances while no such relation is present for the book-to-market and the momentum premium.

This heated debate over the economic rationale and the lack of theoretical motivation of the Fama and French (1993) and the Carhart (1997) models has spurred recent theoretical work on the subject. This research effort attempts to identify economic models that can justify and explain why the size effect and the book-to-market effect should have time series and cross-sectional explanatory power over asset returns. Berk, Green and Naik (1999) is an example of this research trend. They propose a microeconomic model of firm investment with irreversibility and explore its asset pricing implications. The authors show that the effect of investment irreversibility is to make book-to-market ratios of firms correlated with their equity returns. Kogan (2001, 2004) uses a general equilibrium model with irreversible investment to illustrate how conditional equity volatility could be time-varying in a way that is consistent with the "leverage effect". In a similar vein, Gomes, Kogan and Zhang (2003) explore a dynamic general equilibrium production economy with investment irreversibility and show that the size and book-to-market effect are entirely consistent with a single-factor conditional CAPM because they are correlated with the true market betas of equity returns.

In a very influential paper, Jagannathan and Wang (1997) show how unconditional tests of asset pricing models may fail even when their conditional version holds exactly. One major reason for these empirical rejections could be due to time-variation in factor-loadings and, in particular, the co-variation of the factor-loadings with the expected returns of the factors. If non-zero covariation of this sort is indeed present in the data, then the standard unconditional estimate of the pricing error (Jensen's α) for any portfolio will include the unconditional expectation of the covariance between the factor loading and the factor's expected rate of return. The authors show how addressing this issue in a framework with time-varying betas and factor expected returns helps (partially) re-establish the validity of the maintained risk-return relationship.

Another potentially contaminating effect arises due to the presence of autoregressive conditional heteroscedasticity (ARCH) in asset realized returns which has been well documented in the empirical literature on ARCH effects. If the amount of idiosyncratic risk injected into total excess return risk is changing over time, then the unconditional distribution of the innovation will be a mixture of the relevant time-varying distributions. This possibility may bias the results of statistical tests about pricing errors and the overall validity of asset pricing models if it is not addressed adequately in the estimation of a risk-return model.

The main claim in this paper is that empirical risk-return relationships should incorporate proper adjustments to account for potential serial autocorrelation in the volatility and time variation in the distribution of return innovations so that the results and tests can be meaningful with a reasonable degree of confidence. Specifically, I challenge the two popular multi-factor models of Fama and French (1993) and Carhart (1997) with two different sets of portfolios: the 25 Fama-French size/BM portfolios and 30 industry-sorted portfolios. The question this paper investigates is whether one model is robust for pricing both the characteristics-based size/BM portfolio returns *and* the industry-grouped portfolio returns. Unfortunately, at this stage it is still prohibitively difficult to attempt a joint tests using all 55 portfolios simultaneously. That is why I test both models with the two portfolio sets separately. I use a state-of-the-art model of time-varying multivariate generalized ARCH (GARCH) volatility and a less general GARCH model due to Bollerslev (1990) that restricts the conditional correlation between asset returns to be constant over time. It would appear that the latter is too restrictive and it is, in particular, with respect to modeling the dynamics of covariances between asset returns. Nevertheless, both GARCH models show little differences regarding the magnitudes of the absolute pricing errors that they produce.

In this paper, I document an important statistical problem with the static Fama-French and Carhart models which affects their performance as pricing tools. I show that there is a strong presence of autoregressive conditional heteroscedasticity (ARCH) in the portfolio returns used in Fama and French (1993) as well as in industry-sorted portfolio returns. This well-known feature of the financial return series represents a violation of a major assumption in the statistical analysis in that paper. Therefore, I propose to model jointly the risk-return relation of the Fama-French and Carhart models along with a multivariate Generalized ARCH (GARCH) volatility model to correct for the presence of GARCH effects. I adopt a recently developed flexible multivariate GARCH model (Ledoit, Santa-Clara and Wolf (2003), henceforth LSW) in order to estimate these new dynamic models. Then, I apply these dynamic models to price the 25 size and book-to-market portfolios of Fama and French (1993) as well as 30 industry portfolios. I find that I am able to reduce the presence of GARCH effects substantially. I find that the dynamic models produce more efficient estimates of assets factor loadings and pricing errors. I show that for the same sample size and 25 portfolios as in Fama and French (1993), the mean absolute pricing error is decreased by more than a half from 10 basis points per month to a level of 4.5 basis points per month. Similarly, for the same set of test assets, the dynamic CAPM reduces the mean absolute pricing error down to 10 basis points per month from the level of 29 basis points per month from the unconditional CAPM. For the 30 industry portfolios in the same sample period I find that the average absolute pricing error is reduced from 13 basis points to 4.14 basis points for the dynamic CAPM model. These results appear to indicate that there is either a risk-return mis-specification, a sample selection bias problem or data-mining problems associated with the way the two sets of portfolio returns are constructed. The reason for this conclusion is that in the absence of any of the three conditions previously mentioned we should be able to price any portfolio of financial securities very well (if not perfectly well, in an ideal setting). Unfortunately, the empirical models considered have little to no power against either of the three alternative possibilities so it would be difficult to decide which one is to blame for the fact that one set of data seems to prefer one dynamic model and another set of data prefers another dynamic model. Of course, this model ranking goes only as far as absolute pricing errors can be considered a suitable objective for a risk-return model and a sensible criterion for judging its empirical success.

Furthermore, I document some intriguing results on the time variation in the portfolios' loadings on the MKT, SMB and HML factors over the business cycle. I show that increases in the market dividend yield, default spread and term spread are subsequently followed by decreases in MKT betas and increases in SMB betas. This appears to be a counter-intuitive result at least within the standard macroeconomic results on how these quantities should be related. It also contradicts some of the findings in the pioneering study by Shanken (1990) which related the market factor loadings directly to these economic indicators in a linear fashion. Somewhat less paradoxically, market betas of growth stocks increase during recessions while market betas of value stocks decrease during recessions. At the same time, however, HML betas of value stocks increase during recessions while HML betas of growth stocks decrease during recessions. This last effect appears to conform better with economic intuition as well as with the empirical fact that average realized returns of value stocks are higher than the ones of growth stocks with the difference being bigger during economic contractions than expansions. The overall effect of these changes on the total amount of systematic portfolio risk varies with the values of a number of instrumental variable proxies for time variation in factor loadings.

Last but not least, I perform a test of the ability of the proposed dynamic Fama-French and Carhart models to account for the documented predictability of asset return variation over time using a set of instruments with demonstrated forecasting power. I show that the proposed models of conditional second moments of return innovations are able to explain only a portion of the asset return predictability present in the data.

The paper proceeds as follows. Section II presents the details of the econometric model and the estimation procedure. Section III discusses the empirical results. Section

IV offers a few concluding remarks and suggests possible avenues for future research.

II. Model

A. Preliminaries

The risk-return model introduced by Fama and French (1993, 1996) adds two more risk factors to the market risk factor of the CAPM:

$$r_{i,t} = \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the excess simple return of test asset i, MKT_t is the excess simple return on the market, SMB_t is the simple return on the SMB portfolio and HML_t is the simple return on the HML portfolio. The SMB portfolio is constructed as the simple difference in returns of an equal-weighted index of value, neutral and growth stocks with small market-capitalizations and an equal-weighted index of value, neutral and growth stock with large market-capitalizations. The HML portfolio is defined as the simple difference between the returns of an equal-weighted portfolio of small-cap and large-cap value stocks and an equal-weighted portfolio of small-cap and large-cap growth stocks. The cutoffs that define growth, neutrality and value stocks are the 70 and 30 percentiles, respectively, in a BM sort of the whole universe of available stocks in the CRSP database.[1]

In addition to the SMB and HML factor, Carhart (1997) proposes the addition of a momentum factor as follows:

$$r_{i,t} = \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + p_i \mathrm{PR1YR}_t + \epsilon_{i,t}, \tag{2}$$

where $\mathrm{PR1YR}_t$ is a factor-mimicking portfolio return for the momentum factor based on performance of individual stocks over the past 12 months. It is constructed as the simple difference between the return of an equal-weighted portfolio of stocks with the highest 30 per cent of past eleven month returns lagged one month and an equal-weighted portfolio of stocks with the smallest 30 per cent of past eleven month returns lagged one month. Instead of using the PR1YR factor from Carhart (1997), I choose to use the UMD factor constructed by French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/) in a very similar fashion. The UMD factor-mimicking portfolio return is based on the simple difference between the returns of a 50-50 strategy including small-cap and large-cap stocks with the highest 30 per cent of past eleven month returns lagged one month and a 50-50 strategy including small-cap and large-cap stocks with the lowest 30 per cent of past eleven month returns lagged one month. Therefore, the initial specification considered in this paper is (1) for the three-factor model and

$$r_{i,t} = \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + p_i \mathrm{UMD}_t + \epsilon_{i,t}, \tag{3}$$

for the four-factor model.

Before I turn to the discussion of dynamic versions of these static models, I will need to introduce some more notation. Let $r_N = [r_{1,.}, r_{2,.}, \ldots, r_{N,.}]$ be a $T \times N$ matrix of realized simple excess return vectors $r_{i,\cdot}$ of N test assets and $r_F = [\mathrm{MKT}_{\cdot}, \mathrm{SMB}_{\cdot}, \mathrm{HML}_{\cdot}]$ be a $T \times 3$ matrix of realized return vectors $\mathrm{MKT}_{\cdot}$, $\mathrm{SMB}_{\cdot}$, and $\mathrm{HML}_{\cdot}$ of the three Fama-French factors. Similarly, for the four-factor model $r_F = [\mathrm{MKT}_{\cdot}, \mathrm{SMB}_{\cdot}, \mathrm{HML}_{\cdot}, \mathrm{UMD}_{\cdot}]$. In a time-varying conditional framework, the factor loadings, factor covariance matrices and residual covariance matrices in (1) and (3) above may be changing over time. To allow for this possibility, let $\Sigma_{N,t}$ be an $N \times N$ covariance matrix the test assets excess returns at time period t, $\Sigma_{F,t}$ be a 3×3 (or 4×4 for the dynamic Carhart model) covariance matrix of the three Fama-French (four Carhart) factors at time period t, and $\Sigma_{\epsilon,t}$ be an $N \times N$ covariance matrix of the vector of residuals $\epsilon_{\cdot,t}$ at time t. Assuming that the true residual return innovation is uncorrelated with the time-varying factor returns and factor loadings, standard statistical results yield the following variance decomposition result for (1) and (3):

$$\Sigma_{N,t} = B_t \Sigma_{F,t} B_t' + \Sigma_{\epsilon,t}, \tag{4}$$

where B_t is an $N \times 3$ ($N \times 4$) matrix of factor loadings of the N assets onto the three Fama-French (four Carhart) factors at time t. Now, let Σ_t be the covariance matrix of the joint set of asset and factor returns $[r_{N,t}, r_{F,t}]$ and let us partition it conformably as follows:

$$\Sigma_t = \begin{pmatrix} \Sigma_{N,t} & \Sigma_{NF,t} \\ \Sigma_{FN,t} & \Sigma_{F,t} \end{pmatrix}, \tag{5}$$

where $\Sigma_{NF,t}$ is an $N \times 3$ ($N \times 4$) matrix of covariances between the asset and factor returns at time t. An estimate of the factor loadings B_t can now be obtained as

$$B_t = \Sigma_{NF,t}\Sigma_{F,t}^{-1}. \tag{6}$$

Using (4) and (6) we can express $\Sigma_{\epsilon,t}$ as

$$\Sigma_{\epsilon,t} = \Sigma_{N,t} - \Sigma_{NF,t}\Sigma_{F,t}^{-1}\Sigma_{FN,t}. \tag{7}$$

Intuitively, there is one important reason why estimating risk-return relations like (1) unconditionally may yield poor results and inferences about the Jensen α_is. As Jagannathan and Wang (1997) point out, if factor betas and factor premia are time-varying then the risk-return relationship may hold exactly conditionally. However, estimating it unconditionally one will obtain a non-zero Jensen α that will be equal to the unconditional covariance between the factor beta and its associated premium. This will happen even if the true value of α is exactly zero. This paper will focus on correcting the unconditional mis-specification and documenting the empirical performance of the conditional version of several multi-factor models with different sets of test assets.[2]

B. A Multivariate GARCH Model

The standard approach to estimating (1) is by the use of ordinary least squares (OLS). This produces consistent and efficient estimates only if the error term is homoscedastic and the parameters are constant. If the variance of the residual changes over time then a more efficient estimation procedure to use would be generalized least squares (GLS).

In order for GLS to be feasible one would need an estimate of the covariance matrix of the error term for every point in time. One particular way in which an estimate of $\Sigma_{\epsilon,t}$ can be obtained and correct the residual heteroscedasticity problem is through the use of a multivariate GARCH model.

A fairly general multivariate GARCH model, commonly referred to as the diagonal VECH model (DVECH), was proposed by Bollerslev et al. (1988). If Σ_t is the covariance matrix at time t and ϵ_t is the vector of residuals at time t, then the evolution of $\Sigma_t = [\sigma_{ij,t}]$ over time under the DVECH model has the following form

$$\sigma^2_{ii,t} = c_{ii} + b_{ii}\sigma^2_{ii,t-1} + a_{ii}\epsilon^2_{i,t-1}, \tag{8}$$

$$\sigma_{ij,t} = c_{ij} + b_{ij}\sigma_{ij,t-1} + a_{ij}\epsilon_{i,t-1}\epsilon_{j,t-1}, \tag{9}$$

or in matrix form

$$\Sigma_t = C + B \odot \Sigma_{t-1} + A \odot \epsilon_{t-1}\epsilon^T_{t-1}, \tag{10}$$

where C, B and A are symmetric matrices and $\odot$ denotes the Hadamard element by element multiplication operator. Every covariance and own variance element of the entire covariance matrix is allowed to depend in a unique way on its own lags and the cross-product of the associated lagged residuals. Unfortunately, the DVECH model is difficult to estimate with conventional numerical tools when the number of assets is bigger than 3. First, in order to keep Σ_t positive-definite in every time period one has to impose complicated nonlinear constraints on the parameters of the model. Second, the number of parameters to be estimated is a quadratic function of the number of assets.

These issues make this model difficult, if not impossible, to estimate for more than a few assets. The BEKK model was introduced by Engle and Kroner (1995) in order to address the first problem of positive-definiteness of the covariance matrix as well as to provide a good approximation to the DVECH model in (10). Their model has the following form:

$$\Sigma_t = C + B^T \Sigma_{t-1} B + A^T \epsilon_{t-1} \epsilon_{t-1}^T A, \tag{11}$$

where C is a positive-definite matrix. Notice that the two quadratic terms are positive-definite by construction and, thus, Σ_t is guaranteed to remain positive definite.

Despite the obvious advantages it offers, the BEKK model has too many parameters when systems larger than tri-variate are considered. In practice, parameter restrictions are typically needed before numerical optimization algorithms can be used to estimate this model in a feasible manner. The most common type of restriction is that the matrices A and B are diagonal which results in the so-called diagonal BEKK model (DBEKK). Occasionally, for larger systems, one has to constrain A and B even further by assuming that they have the same parameter along their diagonals (scalar BEKK). These practical considerations necessitate a sacrifice in terms of the generality of the dynamics of the covariance matrix of returns over time. Another GARCH model that has recently fallen out of fashion is the Bollerslev (1990) constant correlation GARCH model (CCORR). In this model, the dynamics of the conditional variances are of the same form as in (9) above. However, as the name of the model suggests, the covariances are modeled as if the conditional correlation between the return series is the same in every period:

$$\sigma_{ij,t} = \rho_{ij}\sigma_{ii,t}\sigma_{jj,t}. \tag{12}$$

A recent trend in the estimation of multivariate GARCH models has been the separation of the estimation process in stages. Initially, a series of univariate GARCH models are fitted to every individual asset to estimate the parameters associated with that asset's own variance. Next, a separate procedure is used to estimate the parameters driving the covariances of asset returns. One example of this approach is Engle (2002) which generalizes Bollerslev CCORR model. He introduces a dynamic conditional correlation model in which the correlation between any two assets is an exponentially smoothed function of past standardized residuals. In his model the correlation matrix is guaranteed to be positive definite and is combined with a set of univariate GARCH models for the individual assets variances to produce an estimate of the entire covariance matrix of returns.

Another such model is introduced by Ledoit et al. (2003). In their model, they also use a set of univariate GARCH models to estimate the own variance processes fist. Then, for every covariance element they estimate a separate univariate GARCH process much like the DVECH model above in (9). This procedure does not guarantee that the parameter matrices A and B (as well as the covariance matrix Σ_t itself) will be positive-definite. In a third and final step, Ledoit et al. (2003) show how to find the "closest" positive-semidefinite A and B to the ones estimated in the previous stage in a certain matrix norm.[3] This GARCH model is essentially a diagonal VECH model first proposed and estimated for a small set of assets in Bollerslev et al. (1988). It allows both own variances and every covariance element to have a life of its own. For comparison, the DCC model of Engle (2002) has 3 parameters that drive the entire evolution of the correlation matrix over time. My motivation in choosing to use the model of Ledoit et al. (2003) in this paper is, in part, based on its generality over the DCC model.

In this paper, I use the flexible multivariate GARCH model of Ledoit et al. (2003) in order to estimate Σ_t, the joint covariance matrix of the three Fama-French factors and the 25 size and book-to-market portfolios from Fama and French (1993,1996). Then I compute the matrix of factor loadings B_t and use (7) to compute $\Sigma_{\epsilon,t}$, the covariance matrix of the residuals in (1). Using this initial estimate of $\Sigma_{\epsilon,t}$, I employ a GLS procedure to estimate $\theta = [\alpha, \beta]$. Then I compute the fitted residuals from (1) again. Next, I use the flexible multivariate GARCH model and the multivariate CCORR GARCH model directly on the fitted residuals from the previous step to produce another estimate of $\Sigma_{\epsilon,t}$. Going back and forth, I repeat this process until the parameter vector θ has converged. This should result in a feasible GLS (FGLS) estimate which converges to the true GLS estimate under standard conditions. I adjust the standard errors of θ to correct for the fact that an estimate of $\Sigma_{\epsilon,t}$ is used in the FGLS procedure as well as for any mis-specification in the dynamics of the multivariate GARCH model using the results of Bollerslev and Wooldridge (1992).

III. Empirical Results

I use monthly simple excess returns for the 25 size and book-to-market sorted portfolios from Fama and French (1993), the 30 industry-sorted portfolios as well as the MKT, SMB, HML and UMD (Carhart (1997)) factor-mimicking portfolios for the sample period July 1963 to December 1993.[4]

A. Data Description

Table 1 provides descriptive statistics for the 25 size and book-to-market portfolios. The average excess returns are much larger for value (high book-to-market) than growth portfolios (low book-to-market). The difference is statistically significant for all pairs of such portfolios with the exception of the largest market capitalization one. This has been referred to as the value premium in the literature. The return series also exhibit significant departures from normality as indicated by the skewness and kurtosis tests. There also appear to be significant first-order autocorrelations in particular for smaller market capitalization stocks.

Insert Table 1 about here.

Summary statistics for the excess returns of the 30 industry portfolios are presented in Table 2. There are fewer average excess returns that are statistically significant for this set of assets as well as fewer deviations from the level of skewness for a normally distributed variable. However, the kurtosis tests show that the distribution of monthly excess returns is quite different from normal for all of the 30 assets. Finally, there are fewer significant first-order autocorrelations for industry than size and book-to-market portfolios' excess returns.

Insert Table 2 about here.

B. Asset Pricing Implications

In this section, I compare the performance of several unconditional pricing models with their conditional counterparts. Table 3 presents the OLS results for the unconditional CAPM model. One notable feature of these results is that this model substantially overprices growth stocks and underprices value stocks. The average absolute pricing error is 28.76 basis points per month which translates into more than 3% per annum. This is a substantial amount of mis-pricing. One popular measure of serial dependence in fitted residuals is the Ljung-Box statistic from Ljung and Box (1978). It is defined as a distributed lag function of the squared serial autocorrelations $\hat{\rho}_k^2$ of the fitted residuals at lags $k = 1, \ldots, m$. Formally, their test statistic for the hypothesis of no ARCH effects at lag m is computed in the following way:

$$\tilde{Q}(m) = T(T+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{T-k}, \tag{13}$$

where T is the sample size. If a test of serial dependence in squared fitted residuals $\tilde{Q}^2(m)$ is required, one should use $\hat{\rho}_k^2$ above where now the serial autocorrelation coefficient refers to the squared fitted residuals.[5] The values of the Ljung-Box diagnostic for serial correlation at lag 1 ($\tilde{Q}(1)$) indicates that there are significant GARCH effects for a few value and growth portfolio returns.

Insert Table 3 about here.

The unconditional three factor Fama-French model (Table 4) delivers a substantial improvement over previous risk-return models like the static CAPM in terms of reducing the pricing errors of the 25 size and book-to-market portfolios despite the marginal rejection of the model by the popular Gibbons, Ross and Shanken (1989) multivariate test statistic (Fama and French (1993)). Compared to the 28.76 basis points per month average absolute pricing error obtained by the classical CAPM model, the Fama-French model yields an average absolute pricing error of just over 10 basis points per month. This model is better able to price the growth and value portfolios that were so problematic for the unconditional CAPM. The goodness-of-fit statistics also improve quite a bit as indicated by the $\bar{R}^2$ of the regressions. However, the squared fitted residuals of the static Fama-French model display a significant amount of variation over time as evidenced by the $\tilde{Q}(1)$ statistic.

Insert Table 4 about here.

Next, Table 5 presents the results for the unconditional Carhart (1997) model. The average absolute pricing error is virtually unchanged by the addition of the momentum factor but the median absolute pricing error is now slightly lower compared with the one for the unconditional Fama-French model. The goodness-of-fit is marginally higher but there are still problems with pronounced GARCH effects for quite a few portfolios.

Insert Table 5 about here.

Turning to the unconditional models of industry portfolio returns, I uncover an interesting result. First, the unconditional CAPM (Table 6) delivers a mean absolute pricing error of 13.14 basis points, whereas the unconditional Fama-French model (Table 7) yields a mean absolute pricing error of 16.80 basis points and the unconditional Carhart model (Table 8) – 16.05 basis points. Among the notable diagnostics, the Durbin-Watson statistic for first order serial autocorrelation in the fitted residual shows up as significant most notably for the Household, Oil, Retail, Meals and Financial industry residuals. The Ljung-Box statistics indicates again that there are strong GARCH effects present at lag 1 for several industry portfolios.

Insert Table 6 about here.

Insert Table 7 about here.

Insert Table 8 about here.

Table 9 presents a summary of the mean absolute pricing errors by models. For all conditional models the flexible multivariate GARCH model of Ledoit et al. (2003) appears to slightly outperform the CCORR model of Bollerslev (1990). For the 25 size and book-to-market portfolios the conditional three-factor Fama-French model delivers the smallest mean absolute pricing error whereas for the 30 industry portfolios both the conditional and unconditional versions of the CAPM dominate their multifactor extensions. This is surprising given that the exact same factor realized excess returns are used to model the realized returns of the two sets of assets. One possible explanation for this inconsistency is that there are selection bias problems with the way the two sets of returns are constructed (i.e. the 25 portfolios exclude firm returns with negative book-to-market ratios). Another possibility is that the α_is are not so much indications of mis-pricing but are rather due to transactions costs and differential taxes on capital gains and interest income.

Insert Table 9 about here.

Next, I present the results of several hypothesis tests to judge the importance of the additional factors as well as the joint significance of the pricing errors. In Table 10, I present the results for the 25 size and book-to-market portfolios. The joint hypothesis that all the pricing errors are zero is strongly rejected for all three factor models in both their conditional and unconditional form. Next, the hypothesis that both the SMB and HML factors are jointly significant is rejected rather strongly for both multi-factor models. Finally, the significance of the UMD factor as well as joint significance of all three additional factors is very strongly rejected as well. It appears that the four-factor Carhart (1997) model is the most preferred one if the size and book-to-market portfolios are used as test assets. However, the results are quite different for the 30 industry portfolios. As Table 11 reports, the joint hypothesis that the regression intercepts are all zero cannot be rejected at any conventional levels both for the unconditional and the conditional version of the CAPM. However, adding SMB and HML as well as UMD completely reverses this result.

Insert Table 10 about here.

Insert Table 11 about here.

Once I make an adjustment for the time-variation in the variance of the residuals, there is significantly less evidence of serial dependence in the squared residuals. The results for the Lagrange multiplier and Ljung-Box tests on the fitted residuals of the time-varying Fama-French model are reported in the Tables 15 and 16, respectively. Compared to the results for the static Fama-French model above, now there are only 4 out of the 25 assets for which there is significant evidence of serial dependence at lag 1. Furthermore, the average absolute pricing error has decreased substantially to about 4.4 basis points per month (Table 9).

Insert Table 15 about here.

Insert Table 16 about here.

Intuitively, one could see where the gain from using feasible GLS comes from. The fitted variances of the three Fama-French factors (Figure 1), the 25 size and book-to-market portfolios (Figure 2) and the fitted residuals (Figure 3) all estimated using the flexible multivariate GARCH model of Ledoit et al. (2003), show how persistent volatilities are and, furthermore, how correlated they are cross-sectionally. The latter phenomenon is apparent from the commonality of movements in the variances of asset excess returns. This suggests that a feasible GLS procedure would produce an efficiency gain over an OLS procedure. However, this efficiency gain has no bearing on the size of the parameters only on their standard errors. Therefore, the improvement in the pricing errors of the 25 portfolios is not a direct result of the FGLS. Rather, the FGLS improves the precision of the estimates and it appears that the dynamic Fama-French model has an even better ability to price the size and book-to-market portfolios than the static one. However, for the industry portfolios the conditional as well as unconditional CAPM outperform the multi-factor models as far as mean absolute pricing errors are concerned. In an ideal world, it is inconceivable that having the right pricing model and the right factors certain portfolios of individual securities will be priced a lot better than others. Hence, there are several possible explanations for the conflicting empirical results reported above. Either, the factors in these models are mis-specified or they leave a lot of non-tradable assets out like human capital, for example. Another potential explanation is that the models themselves are mis-specified. Finally, it is also quite possible that there is something wrong with the way the portfolios are constructed, raising possible issues about data-mining or selection/survivorship bias. This paper cannot resolve these issues per se but can point towards the fact that the time-varying volatility models proposed here go only part of the way towards explaining the puzzle documented above.

Insert Figure 1 about here.

Insert Figure 2 about here.

Insert Figure 3 about here.

C. Specification Tests on Residuals

Next, I test whether the OLS residuals from the static Fama-French model and their squares are predictable using a set of instrumental variables. I use instrumental variables with demonstrated power to predict asset returns and volatility. My set of instrumental variables includes: the long-term government bond return in excess of the 30-day U.S. Treasury bill, the dividend yield (Fama and French (1988)), the difference in yields between Moody's Baa- and Aaa-rated corporate bonds (Keim and Stambaugh (1986)) and the difference in yields between ten-year and one-year U.S. Treasury securities.[6] These variables are lagged to make sure that they are available at the beginning of every month.

The results from the regression of the OLS residuals on a constant and the set of instrumental variables are reported in Table 12. They show that there is some predictability in the residuals from the static Fama-French model. The adjusted R^2s range from 0.0066 to 0.0565. The probability values of the F tests of the null hypotheses of no relation between the OLS residuals and the instruments indicate that 8 out of the 25 portfolio residuals are predictable at the 5% significance level. These assets are comprised of both small and large market capitalization stocks. For 7 of the 25 portfolios the effect of the long term government bond excess return on the fitted residuals is significant, for 6 out of the 25 portfolios the dividend yield and the default spread have a significant effect, and for 3 out of the 25 portfolios the term slope has a significant effect. The results are similar for the regressions of the squared OLS residuals on the same set of instrumental variables (Table 13).

Insert Table 12 about here.

Insert Table 13 about here.

Now I turn to the results from the regression of the GLS residuals from the dynamic Fama-French model and their squares on a constant and the instrumental variables. These are presented in Tables 17 and 18, respectively. The regression results for the GLS residuals show a slight improvement over the ones for the OLS residuals. The adjusted R^2 now range between 0.0040 and 0.0517. There is now one less asset for which the excess long term government bond return has a significant return. There are also three less assets for which the default premium has a significant effect. The results for the squared GLS residuals show a slightly bigger improvement over the ones for the squared OLS residuals. Now there are only 3 instead of 5 assets for which the instruments have any significant ability to forecast the squared GLS residuals.

Insert Table 17 about here.

Insert Table 18 about here.

Overall, these predictability tests show that time-variation in the conditional factor and residual covariance matrices can account for some but not all of the predictability of asset returns.

D. Time Series Predictability of Factor Loadings

Finally, I investigate the time-variation of factor loadings $\hat{B}_t$ estimated at the first stage of the dynamic Fama-French model with the flexible multivariate GARCH model of Ledoit et al. (2003). Similar results obtain for the fitted factor loadings estimated using the constant conditional correlation model of Bollerslev (1990) and are, therefore, not reported here.[7] I take the fitted values of $\hat{\beta}_i$, $\hat{s}_i$ and $\hat{h}_i$ and regress them on a set of instruments that includes a constant, the dividend yield, the term spread and a recession dummy variable which takes a value of 1 during recessions and zero otherwise.[8] I would like to emphasize that these time-varying exposures were *not* used explicitly in the risk-return relations tested in the previous subsections because of numerical difficulties associated with estimating such a complicated system even in stages let alone jointly. Needless to say these fitted factor risk exposures are contemporaneous but noisy estimates of the true factor exposures. They are provided here solely for completeness and to highlight some potential problems and counter-intuitive behavior they exhibit over the business cycle. These counter-indications may serve as a warning that we either have mis-specified the factors, the GARCH model or both. Even worse, they may indicate that our current understanding of macroeconomic variables and how they relate to each as well as with financial risk measures over time is, at best, poor.

First, I report the results of the regressions of the estimated market factor loadings $\hat{beta}_i$ on the instruments in Table 19. The market betas of the 25 portfolios appear to be negatively correlated with the dividend yield. Of these, 18 have a significantly negative coefficient on D/P. This suggests that a market-wide decrease in the dividend yield is followed by increases in the exposure of the 25 Fama-French portfolios to the market risk factor. Turning to the default premium, virtually all (23 out of 25) portfolios market betas have negative coefficients on this instrumental variable. An increase in the term premium has a significantly negative correlation with subsequent market betas for only six portfolios without any pattern across the size and book-to-market dimension. The recession dummy variable is significant for 18 of the 25 portfolios with a mostly negative sign. The only exception are most growth portfolios which have a positive coefficient on REC. This implies that the exposures of growth stocks to the market risk factor increase during recessions while the exposures of value stocks decrease during recessions regardless of market capitalization. The average R^2 of these regressions across all 25 portfolios is quite high at 0.4113 with a minimum of 0.0167 for the large-cap median book-to-market portfolio (FF53) and a maximum of 0.5841 for the small-cap median-to-high book-to-market portfolio (FF14).

Insert Table 19 about here.

Next, I turn to the results of the regressions of the estimated SMB factor loadings $\hat{s}_i$ on the instruments which are reported in Table 20. In this case, the dividend yield has the opposite effect. Of the 18 significant D/P coefficients, 17 are positive. Similarly, an increase in the default spread is followed by increases in SMB factor exposures for 22 of the 25 portfolios. An increase in the term spread has a small positive but mostly insignificant effect on $\hat{s}_i$s. The recession indicator has mixed effects on the SMB factor loadings. The coefficient of the REC instrument has a negative sign for mid-cap portfolios and a positive sign for large-cap value and growth portfolios. Overall, the signs of D/P, DEF and TERM coefficients for the SMB factor are virtually exactly the opposite ones of those for the market factor. These results suggest that increases in the aggregate dividend yield as well as increases in the default and term spreads are followed by increases in assets exposures to the SMB factor and decreases in assets exposures to the market factor. The average R^2 of these regression over all 25 portfolios is 0.2011 and is about half as large as the one from the fitted market betas regressions. The smallest R^2 in this case is 0.0239 for the small-cap growth portfolio (FF11) and the highest R^2 is 0.3193 for the medium-cap value portfolio (FF35).

Insert Table 20 about here.

Lastly, I report the results of the regressions of the HML factor loadings $\hat{h}_i$ in Table 21. In this case, an increase in the market dividend yield is subsequently followed by a decrease of the HML exposures of value stocks and an increase of the HML exposures of growth stocks. The statistical significance of these results is stronger for stocks with larger market capitalizations. The impact of an increase in the default spread is negative and significant for almost all of the 25 portfolios as was the case for the market factor exposures. The term spread appears to have a positive impact on the HML exposures of value stocks and a negative impact on the HML exposures of growth stocks. However, this result has to be treated with caution since very few of the TERM coefficients are significant. Finally, the coefficients of the recession dummy variable suggest that HML exposures increase for value stocks and decrease for growth stocks when the economy is in a recession. The average R^2 of these regressions is 0.1105 with a minimum of 0.0107 for the median-to-large capitalization growth portfolio (FF41) and a maximum of 0.2655 for the median-cap value portfolio (FF35). The average goodness-of-fit of the HML regressions is half as big as the average one of the SMB beta regressions and only a quarter of the one from the market beta regressions. These results suggest that if the Fama-French factor loadings are to be modelled as a reduced form linear function of lagged instrumental variables, this approach will be more powerful for market betas, less powerful for SMB betas and least powerful for HML betas, at least for this set of test assets and within the sample period under consideration. This casts some doubt on these popular modeling approaches of time-varying factor exposures.

Insert Table 21 about here.

IV. Conclusion

In this paper, I adapt a recently developed flexible multivariate GARCH model to generalize the well known and, by now, standard Fama and French (1993) and Carhart (1997) models by incorporating time varying idiosyncratic volatility. I initially replicate the results of the static Fama and French (1993) model for the 25 size and book-to-market portfolios and analyze the residuals to check whether they satisfy the assumptions that validate the use of OLS in their paper. I show that there is one serious statistical problem with the static Fama-French model. The squared fitted residuals from their regressions exhibit very substantial serial correlation which violates the homoscedasticity assumption of OLS. This is evidence of what has become known as a GARCH effect in the literature. The presence of GARCH effects in the size and book-to-market portfolios is not surprising as most financial returns series that have been examined exhibit GARCH effects. However, this suggests an avenue for improvement of the static Fama-French model by allowing the volatility of factor and asset returns to change over time. One parsimonious way to achieve this goal is to incorporate a multivariate GARCH model into the linear three factor risk-return relation of Fama and French (1993) and the linear four-factor Carhart (1997) model. To this end, I use a multivariate GARCH model proposed by Ledoit et al. (2003) as well as a two-stage constant correlation GARCH model (Bollerslev (1990)).

These new dynamic Fama-French and Carhart models appear to do a very good job at eliminating the GARCH effects present in the size and book-to-market as well as industry portfolios. The serial correlation in the squared fitted residuals is substantially reduced as evidenced by the Lagrange multiplier and the Ljung-Box test. Moreover, the dynamic models produce a dramatic improvement in the pricing errors of the 25 size and book-to-market and 30 industry portfolios. In the static model of Fama and French (1993), the average absolute pricing error is 10 basis points per month. Once I adjust the estimation process to allow for the time-variation of the volatility of the residuals, I obtain an average absolute pricing error of 4.5 basis points per month. This is a reduction in excess of 50% compared to the results of the static Fama-French model. For the industry portfolios, the improvement is even bigger – from just over 13% for the unconditional CAPM down to 4% for the conditional CAPM. However, I am unable to identify a single risk-return relationship that prices both sets of portfolios reasonably well.

In addition, I investigate whether time variation of the conditional second moments of the Fama-French factors and their 25 portfolios can account for the predictability of asset returns. I find that this time variation explains only a small portion of the predictable variation in the size and book-to-market portfolio returns. After controlling for a majority of the documented GARCH effects, the residuals from the dynamic Fama-French model are still forecastable using popular instrumental variables like the dividend yield, the default spread and the term spread.

Finally, I characterize the correlations between several instrumental variables and the assets' factor loadings in the framework of the proposed dynamic Fama-French model. I show that, increases in the market dividend yield, the default spread and the term spread are followed by a decrease in market betas. This result is at odds with the results of Shanken (1990). It raises a red flag about the modeling of factor loadings as linear combinations of instrumental variables without investigating the economic forces that might be driving the actual relationship between instruments and factor loadings. At the same time, the same changes in these instrumental variables are followed by the exact opposite changes in the SMB betas. This result conforms better with economic intuition. I also document important business cycle effects in the time variation of the factor loadings. Market betas of growth stocks tend to increase during recessions while market betas of value stocks tend to decrease during recessions. Loadings on the HML factor, however, increase for value stocks and decrease for growth stocks during recessions. Unlike the former result about market betas, the latter result about HML exposures conforms nicely with the empirical fact that average returns of value stocks are higher than average returns of growth stocks, particularly so during recessions than during economic booms. The net result of these effects varies widely from an overall increase to an overall decrease in the total amount of systematic portfolio risk depending on the exact values of the instrumental variables. Overall, the *ad hoc* analysis of the time-variation of the estimated factor loadings suggests that there may be a variety of forces at play and merits a more in-depth study. Such an investigation is beyond the scope of this paper and is left for future study.

A potential extension of these dynamic multi-factor models would be to incorporate asymmetric volatility effects (Engle and Ng (1993)) into the flexible multivariate GARCH part of the model. This may mitigate even further the GARCH effects documented above. Furthermore, it would be instructive to investigate whether the good in-sample pricing performance of the proposed models persists in out-of-sample dynamic tests. It is left for further research to determine the effects of these extensions on the performance of the dynamic Fama-French and Carhart models proposed in this paper.

Footnotes

[1]See Fama and French (1993) for more details on the complete set of sample selection criteria as well as the exclusion of negative BM stocks, etc.

[2]First-pass estimates of the time-varying factor exposures exhibit small in-sample covariances with the realized factor returns indicating that the Jagannathan and Wang (1997) correction in this case will be small which is why I have omitted this correction from the analysis that is to follow. Details are available from the author upon request.

[3]I am grateful to P. Santa-Clara for providing the computer code used in Ledoit et al. (2003).

[4]I obtained the return series data from K. French's website and I am grateful to him for providing it publicly.

[5]Tims and Mahieu (2003) refer to this statistic as the McLeod and Li (1983) test.

[6]The Treasury yields are from the CRSP Treasury Bill Term Structure files. The dividend yield on the CRSP value-weighted index of NYSE and AMEX stocks. The long term government bond returns are from Ibbotson Associates *Stocks, Bonds, Bills and Inflation 1998 Yearbook*.

[7]Details are available from the author upon request.

[8]The dates for troughs and peaks that determine recession periods are taken from the National Bureau of Economic Research.

Bibliography

[1] Banz, R., 1981, The Relationship Between Return and Market Value of Common Stocks, *Journal of Financial Economics* 9, 3–18.

[2] Basu, S., 1983, The Relationship Between Earnings' Yield, Market Value and Return for NYSE Common Stocks: Further Evidence, *Journal of Financial Economics*, 12, 129–156.

[3] Berk, J., R. Green and V. Naik, 1999, Optimal Investment, Growth Options and Security Returns, *Journal of Finance* 54, 1153–1607.

[4] Black, F., M. C. Jensen and M. Scholes, 1972, The Capital Asset Pricing Model: Some Empirical Tests, in M. Jensen (ed.) *Studies in the Theory of Capital Markets* (Praeger).

[5] Bollerslev, T., 1990, Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model, *Review of Economics and Statistics* 72, 498–505.

[6] Bollerslev, T. and J. Wooldridge, 1992, Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances, *Econometric Review* 11, 143–172.

[7] Bolleslev, T., R. F. Engle and J. Wooldridge, 1988, Capital Asset Pricing Model with Time-Varying Covariances, *Journal of Political Economy* 96, 116–131.

[8] Carhart, M. M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.

[9] Chung, Y. P., H. Johnson and M. J. Schill, 2001, Asset Pricing When Returns are Non-Normal: Fama-French Factors vs. Higher-Order Systematic Co-Moments, Working paper, University of California, Riverside.

[10] Cohen, R. B. and C. K. Polk, 1995, COMPUSTAT Selection Bias in Tests of the Sharpe-Lintner-Black CAPM, Working paper, University of Chicago.

[11] Daniel, K. and S. Titman, 1997, Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *Journal of Finance* 52, 1–34.

[12] Davis, J. L., 1994, The Cross-Section of Realized Stock Returns: The pre-COMPUSTAT Evidence, *Journal of Finance* 50, 1579–1593.

[13] Engle, R. F., 2002, Dynamic Conditional Correlation – A Simple Class of Multivariate GARCH Models, *Journal of Business and Economic Statistics* Vol. 17, No. 5.

[14] Engle, R. F. and K. F. Kroner, 1995, Multivariate Simultaneous GARCH, *Econometric Theory* 11, 122-150.

[15] Engle, R. F. and V. K. Ng, 1993, Measuring and Testing the Impact of News on Volatility, *Journal of Finance* 48, 1749–1778.

[16] Fama, E. F. and K. R. French, 1988, Dividend Yields and Expected Returns on Stocks and Bonds, *Journal of Financial Economics* 22, 3–25.

[17] Fama, E. F. and K. R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427–465.

[18] Fama, E. F. and K. R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

[19] Fama, E. F. and K. R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance* 51, 55–84.

[20] Fama, E. F. and J. D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

[21] Gibbons, M. R., S. A. Ross and J. Shanken, 1989, A Test of the Efficiency of a Given Portfolio, *Econometrica* 57, 1121–1152.

[22] Gomes, J., L. Kogan and L. Zhang, 2003, Equilibrium Cross-Section of Returns, *Journal of Political Economy* 111, 693–732.

[23] Jagannathan, R. and Z. Wang, 1997, The Conditional CAPM and the Cross-Section of Expected Returns, *Journal of Finance* 51, 3–53.

[24] Jegadeesh, N. and S. Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

[25] Keim, D. B. and R. F. Stambaugh, 1986, Predicting Returns in the Stock and Bond Markets, *Journal of Financial Economics* 17, 357–390.

[26] Kogan, L., 2001, An Equilibrium Model of Irreversible Investment, *Journal of Financial Economics* 62, 201–245.

[27] Kogan, L., 2004, Asset Prices and Real Investment, *Journal of Financial Economics* 73, 411–432.

[28] Kothari, S. P., J. Shanken and R. Sloan, 1995, Another Look at the Cross-Section of Expected Returns, *Journal of Finance* 50, 185–224.

[29] Lakonishok, J., A. Schleifer and R. W. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance* 49, 1541–1578.

[30] Ledoit, O., P. Santa-Clara and M. Wolf, 2003, Flexible Multivariate GARCH Modeling With an Application to International Stock Markets, *Review of Economics and Statistics* 85, Issue 3, 735–747.

[31] Lintner, J., 1965, The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics* 47, 13–37.

[32] Lo, A., and A. C. MacKinlay, 1990, Data Snooping Biases in Tests of Financial Asset Pricing Models, *Review of Financial Studies* 3, 431–468.

[33] Ljung, G. and G. Box, 1978, On a Measure of Lack of Fit in Time Series Models, *Biometrika* 65, 297–303.

[34] McLeod, A. L. and W. K. Li, 1983, Diagnostic Checking ARMA Time Series Models Using Squared-Residual Autocorrelations, *Journal of Time Series Analysis* 4, 269–273.

[35] Moskowitz, T. J., 2003, An Analysis of Covariance Risk and Pricing Anomalies, *Review of Financial Studies* 16, No. 2, pp. 417–457.

[36] Petkova, R., 2006, Do the Fama-French Factors Proxy for Innovations in Predictive Variables?, *Journal of Finance* 61, 581–612.

[37] Petkova, R. and L. Zhang, 2005, Is Value Riskier than Growth?, *Journal of Financial Economics* 78, 187–202.

[38] Shanken, J., 1990, Intertemporal Asset Pricing: An Empirical Investigation, *Journal of Econometrics* 45, 99-120.

[39] Sharpe, W. F., 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance* 19, 425–442.

[40] Tims, B. and R. Mahieu, 2003, International Portfolio Choice: A Spanning Approach, Working Paper, Rotterdam School of Management, Erasmus University.

Table 1: Summary Statistics MKT, SMB, HML and UMD Factors and 25 Size/BM Portfolios

This table presents the summary statistics for the MKT, SMB, HML, UMD factors and the 25 size and book-to-market portfolios of Fama and French (1993). The simple excess mean returns are in per cent per month, SD is the monthly standard deviation in per cent, SK is the third central moment of returns standardized by the third power of SD, KT is the fourth central moment of returns standardized by the fourth power of SD, ρ_1, ρ_2 and ρ_3 are the first, second and third order sample autocorrelation of returns. * and ** indicate statistical significance at the 5% and 1% level, respectively. The data sample covers 1963:07 until 1993:12.

Portfolio	Mean	SD	SK	KT	ρ_1	ρ_2	ρ_3
MKT	0.4102	4.4398	-0.4030**	5.5217**	0.0576	-0.0344	-0.0082
SMB	0.2627	2.8577	0.1578	4.1831**	0.1768**	0.0554	-0.0245
HML	0.4548**	2.5610	0.0166	3.9877**	0.1903**	0.0702	-0.0162
UMD	0.8437**	3.4258	-0.5715**	5.3584**	0.0363	-0.0332	-0.0591
FF11	0.2648	7.6381	-0.3402**	4.8743**	0.2306**	0.0308	0.0052
FF12	0.6933*	6.7025	-0.2944*	5.6156**	0.2173**	0.0040	-0.0171
FF13	0.7283*	6.1360	-0.2658*	5.9520**	0.2132**	-0.0022	-0.0051
FF14	0.9223**	5.8304	-0.1439	6.5554**	0.2120**	-0.0148	-0.0066
FF15	1.0848**	6.1754	-0.0240	7.1204**	0.2363**	-0.0099	-0.0247
FF21	0.3818	7.1665	-0.4226**	4.8001**	0.1767**	-0.0085	-0.0454
FF22	0.6318	6.1707	-0.5009**	6.0447**	0.1716**	-0.0292	-0.0267
FF23	0.8949**	5.5798	-0.4451**	6.7232**	0.1810**	-0.0325	-0.0308
FF24	0.9245**	5.2757	-0.2793*	6.9431**	0.1553**	-0.0449	-0.0314
FF25	1.0484**	5.8902	-0.1710	7.2398**	0.1466**	-0.0630	-0.0651
FF31	0.4112	6.5404	-0.3584**	4.6411**	0.1481**	-0.0072	-0.0363
FF32	0.7153*	5.5636	-0.6272**	6.2506**	0.1656**	-0.0151	0.0126
FF33	0.6773*	5.0902	-0.5873**	5.8809**	0.1550**	-0.0461	-0.0372
FF34	0.8870**	4.8006	-0.2794*	5.9456**	0.1551**	-0.0305	-0.0136
FF35	0.9428**	5.5181	-0.2989*	6.9318**	0.1320*	-0.0882	-0.0722
FF41	0.4659	5.7886	-0.2888*	4.4792**	0.1103*	-0.0164	-0.0143
FF42	0.3704	5.2958	-0.5148*	6.1762**	0.1251*	-0.0266	-0.0324
FF43	0.6320*	4.9277	-0.3797**	6.1552**	0.0715	-0.0393	-0.0146
FF44	0.7897**	4.7541	0.1295**	5.2974**	0.0673	-0.0122	-0.0131
FF45	0.9505**	5.5689	-0.1626	5.6373**	0.0497	-0.0318	-0.0253
FF51	0.3245	4.7954	-0.0754	5.2269**	0.0602	-0.0072	-0.0069
FF52	0.3559	4.5923	-0.2674	5.0292**	0.0346	-0.0640	-0.0018
FF53	0.4151	4.2892	-0.1044*	5.8279**	-0.0465	-0.0596	0.0009
FF54	0.5184*	4.2055	0.1979	4.7633**	-0.0685	0.0032	0.0541
FF55	0.6067*	4.7472	-0.0472	4.0856**	0.0269	-0.0035	-0.0543

Table 2: Summary Statistics 30 Industry Portfolios

This table presents the summary statistics for the 30 industry portfolios (K. French website). The simple excess mean returns are in per cent per month, SD is the monthly standard deviation in per cent, SK is the third central moment of returns standardized by the third power of SD, KT is the fourth central moment of returns standardized by the fourth power of SD, ρ_1, ρ_2 and ρ_3 are the first, second and third order sample autocorrelation of returns. * and ** indicate statistical significance at the 5% and 1% level, respectively. The data sample covers 1963:07 until 1993:12.

Industry	Mean	SD	SK	KT	ρ_1	ρ_2	ρ_3
Food	0.6561**	4.5826	0.0035	5.4625**	0.0659	-0.0394	-0.0002
Beer	0.5003	5.4399	0.1616	5.3070**	0.0226	0.0087	0.0336
Smoke	0.9100**	5.5592	0.1175	4.7698**	0.0483	-0.0079	-0.0495
Games	0.7501*	7.2644	-0.2464	5.0077**	0.1338*	0.0014	-0.0141
Books	0.6372*	5.8842	-0.2648*	4.4333**	0.2146**	0.0373	-0.0597
Hshld	0.4333	4.9912	-0.2728*	4.7547**	0.0904	0.0105	0.0103
Clths	0.4976	6.6955	-0.0335	5.8916**	0.1985**	0.0812	-0.0183
Hlth	0.5853*	5.2692	0.1756	5.8762**	0.0083	0.0121	-0.0988
Chems	0.4118	5.3795	-0.1930	5.7075**	-0.0015	-0.0625	0.0624
Txtls	0.6534*	6.2080	-0.4732**	5.9888**	0.1947**	0.0224	0.0595
Cnstr	0.5118	5.9026	-0.1440	5.4192**	0.1171*	-0.0457	-0.0230
Steel	0.2016	6.1351	-0.1638	5.1778**	-0.0125	-0.0528	-0.0802
FabPr	0.3850	5.7714	-0.3515**	5.7209**	0.0947	-0.0107	-0.0308
ElcEq	0.5299	5.9958	-0.1260	5.2821**	0.0472	-0.0017	-0.0336
Autos	0.4363	5.8206	-0.0875	5.1640**	0.1285*	-0.0128	-0.0206
Carry	0.5994	6.6329	-0.0984	4.2915**	0.1480**	0.0259	-0.0803
Mines	0.5562	6.9702	-0.1974	4.5041**	0.0637	-0.0059	-0.0167
Coal	0.5623	7.7765	0.5727**	6.8363**	-0.0098	0.0341	0.0088
Oil	0.5214	5.2671	0.0283	4.9913**	-0.0112	-0.0508	0.0477
Util	0.3196	3.9360	0.2987*	4.5005**	0.0240	-0.0940	-0.0380
Telcm	0.4553*	4.1112	-0.0928	3.6227**	-0.0126	0.0021	0.0243
Servs	0.5770	6.6656	-0.0923	4.4621**	0.1269*	0.0042	-0.0014
BusEq	0.3066	5.7125	-0.0667	4.2212**	0.1104*	-0.0074	0.0009
Paper	0.4683	5.1624	-0.1731	5.8660**	-0.0078	-0.0824	-0.0313
Trans	0.4561	6.3139	-0.2348	4.1195**	0.1036*	-0.0262	-0.0586
Whlsl	0.6712*	6.3144	-0.3605**	5.1370**	0.1474**	-0.0124	-0.0318
Rtail	0.5981*	5.7545	-0.1642	5.6382**	0.1724**	0.0097	-0.0731
Meals	0.8370*	7.0659	-0.4987**	5.0777**	0.2092**	0.0486	0.0022
Fin	0.4655	5.1017	-0.1318	4.2213**	0.1358**	-0.0386	-0.0566
Other	0.4118	6.0398	-0.2775*	4.1850**	0.1223*	-0.0284	-0.0184

Table 3: OLS Results for the Capital Asset Pricing Model with Fama-French 25 Size/BM Portfolios

This table presents the OLS results for the CAPM with the 25 Size/BM portfolios. $\hat{\alpha}_i$ is the Jensen α, $\hat{\beta}_i$ is the MKT loading of asset i, $\sigma(\hat{\epsilon})$ is the standard error of the fitted residual, $\tilde{Q}^2(1)$ is the Ljung-Box statistic for serial first order autocorrelation in the fitted squared residuals, DW is the Durbin-Watson statistic for first order serial autocorrelation in the fitted residuals and $\bar{R}^2$ is the goodness-of-fit measure adjusted for the extra degrees of freedom. * and ** indicate statistical significance at the 5% and 1% level, respectively. † superscript by the Durbin-Watson statistic indicates that the value falls into the inconclusive region. The data sample covers 1963:07 until 1993:12.

$\hat{\alpha}_i$	Low	2	3	4	High	Statistics	
Small	-0.3191	0.1783	0.2532	0.4799**	0.6337**		
2	-0.2075	0.1240	0.4371**	0.4955**	0.5853**	Min	0.0388
3	-0.1468	0.2399*	0.2502*	0.4867**	0.5034**	Mean	0.2876
4	-0.0388	-0.0940	0.2071*	0.3932**	0.5022**	Median	0.2495
Large	-0.0879	-0.0473	0.0556	0.1738	0.2495	Max	0.6337
$\hat{\beta}_i$	Low	2	3	4	High	Statistics	
Small	1.4235**	1.2556**	1.1583**	1.0786**	1.0998**		
2	1.4367**	1.2379**	1.1161**	1.0458**	1.1291**	Min	0.8402
3	1.3602**	1.1589**	1.0412**	0.9760**	1.0714**	Mean	1.1049
4	1.2305**	1.1320**	1.0357**	0.9666**	1.0928**	Median	1.0928
Large	1.0053**	0.9830**	0.8764**	0.8402**	0.8706**	Max	1.4367
$\sigma(\hat{\epsilon})$	Low	2	3	4	High	Statistics	
Small	4.2894	3.7210	3.3476	3.3260	3.7805		
2	3.2669	2.8053	2.5650	2.5046	3.0923	Min	1.4297
3	2.5109	2.1165	2.1309	2.0660	2.7970	Mean	2.5655
4	1.9137	1.6689	1.7712	2.0455	2.7332	Median	2.5109
Large	1.7534	1.4297	1.8050	1.9423	2.7559	Max	4.2894
$\tilde{Q}^2(1)$	Low	2	3	4	High	Statistics	
Small	1.1061	2.1426	4.0255*	4.3876*	7.9018**		
2	1.1467	7.7362**	2.4553	2.8843	3.4311	Min	0.0311
3	4.0396*	0.0853	1.5992	1.7395	3.5413	Mean	5.2522
4	10.9672**	30.2124**	20.3337**	3.2190	3.0535	Median	3.2190
Large	9.2150**	0.0311	4.5892*	1.3491	0.1139	Max	30.2124
DW	Low	2	3	4	High	Statistics	
Small	1.6856	1.8264	1.8559	1.8984	1.7889		
2	1.7070	1.9598	2.0607	1.9363	1.8324	Min	1.6856
3	1.8067	1.9857	1.9426	1.9824	1.7555	Mean	1.8850
4	1.7740	1.9366	1.9910	1.8620	1.9148	Median	1.8981
Large	1.8981	1.8169	1.7853	2.1111	2.0105	Max	2.1111
$\bar{R}^2$	Low	2	3	4	High	Statistics	
Small	0.6838	0.6909	0.7015	0.6737	0.6242		
2	0.7916	0.7928	0.7881	0.7740	0.7236	Min	0.6242
3	0.8522	0.8549	0.8243	0.8143	0.7424	Mean	0.7842
4	0.8904	0.9004	0.8704	0.8144	0.7584	Median	0.7916
Large	0.8659	0.9028	0.8224	0.7861	0.6621	Max	0.9028

Table 4: OLS Results for the Fama-French Three Factor Model with Fama-French 25 Size/BM Portfolios

This table presents the OLS results for the Fama-French three factor model with the 25 Size/BM portfolios. $\hat{\alpha}_i$ is the Jensen α, $\hat{\beta}_i$ is the MKT loading of asset i, $\hat{s}_i$ is the SMB loading of asset i, $\hat{h}_i$ is the HML loading of asset i, $\sigma(\hat{\epsilon})$ is the standard error of the fitted residual, $\tilde{Q}^2(1)$ is the Ljung-Box statistic for serial first order autocorrelation in the fitted squared residuals, DW is the Durbin-Watson statistic for first order serial autocorrelation in the fitted residuals and $\bar{R}^2$ is the goodness-of-fit measure adjusted for the extra degrees of freedom. * and ** indicate statistical significance at the 5% and 1% level, respectively. † superscript by the Durbin-Watson statistic indicates that the value falls into the inconclusive region. The data sample covers 1963:07 until 1993:12.

$\hat{\alpha}_i$	Low	2	3	4	High	Statistics	
Small	-0.4100**	-0.0968	-0.0759	0.0852	0.0832		
2	-0.1223	-0.0497	0.1586*	0.1145	0.0701	Min	0.0040
3	-0.0259	0.1193	-0.0156	0.1480*	0.0183	Mean	0.1002
4	0.1552*	-0.1613*	-0.0040	0.0703	0.0531	Median	0.0834
Large	0.1936**	-0.0143	-0.0062	-0.0834	-0.1709	Max	0.4100
$\hat{\beta}_i$	Low	2	3	4	High	Statistics	
Small	1.0392**	0.9846**	0.9466**	0.9026**	0.9594**		
2	1.1059**	1.0298**	0.9810**	0.9851**	1.0780**	Min	0.9026
3	1.1106**	1.0252**	0.9804**	0.9767**	1.0777**	Mean	1.0233
4	1.0661**	1.0811**	1.0487**	1.0351**	1.1582**	Median	1.0298
Large	0.9555**	1.0313**	0.9792**	0.9997**	1.0440**	Max	1.1582
$\hat{s}_i$	Low	2	3	4	High	Statistics	
Small	1.4212**	1.2772**	1.1463**	1.1108**	1.1929**		
2	1.0107**	0.9321**	0.8206**	0.7021**	0.8442**	Min	-0.2682
3	0.6890**	0.6104**	0.5520**	0.4387**	0.6103**	Mean	0.5515
4	0.3046**	0.2604**	0.2309**	0.1882**	0.3634**	Median	0.6103
Large	-0.1976**	-0.2068**	-0.2682**	-0.2060**	-0.0404	Max	1.4212
$\hat{h}_i$	Low	2	3	4	High	Statistics	
Small	-0.2744**	0.1116**	0.2525**	0.3850**	0.6479**		
2	-0.4728**	0.0314	0.2602**	0.4869**	0.6912**	Min	-0.4728
3	-0.4385**	0.0333	0.3202**	0.4906**	0.7083**	Mean	0.2189
4	-0.4544**	0.0435	0.3192**	0.5395**	0.7187**	Median	0.2602
Large	-0.4599**	0.0034	0.1981**	0.5406**	0.7914**	Max	0.7914
$\sigma(\hat{\epsilon})$	Low	2	3	4	High	Statistics	
Small	1.9335	1.4510	1.1720	1.1244	1.2092		
2	1.5191	1.2909	1.1469	1.1296	1.2380	Min	1.1244
3	1.3939	1.3463	1.3103	1.2001	1.4623	Mean	1.4062
4	1.3697	1.5123	1.4653	1.4934	1.8652	Median	1.3581
Large	1.2461	1.3190	1.5944	1.3581	2.0048	Max	2.0048
$\tilde{Q}^2(1)$	Low	2	3	4	High	Statistics	
Small	11.5159**	7.4775**	8.9265**	0.1180	15.1209**		
2	1.4334	14.8031**	0.0027	6.9858**	1.0052	Min	0.0019
3	6.3073*	0.5826	0.0019	1.1625	0.0455	Mean	6.4040
4	6.6723**	7.4752**	13.5350**	18.6398**	1.8521	Median	6.3073
Large	20.5243**	1.2620	11.8713**	0.8407	1.9381	Max	20.5243
DW	Low	2	3	4	High	Statistics	
Small	1.9545	2.1637	1.9028	1.9244	1.8481		
2	2.0285	2.0719	1.9496	1.9781	1.9716	Min	1.7946
3	1.9567	1.9381	2.0004	1.9725	1.9430	Mean	1.9820
4	1.9349	1.9172	2.0100	1.9648	2.2306	Median	1.9567
Large	1.8958	1.9025	1.7946†	2.1255	2.1713	Max	2.2306
$\bar{R}^2$	Low	2	3	4	High	Statistics	
Small	0.9354	0.9527	0.9632	0.9625	0.9613		
2	0.9547	0.9559	0.9574	0.9538	0.9555	Min	0.8202
3	0.9542	0.9410	0.9332	0.9370	0.9292	Mean	0.9292
4	0.9435	0.9178	0.9108	0.9005	0.8869	Median	0.9370
Large	0.9319	0.9168	0.8607	0.8949	0.8202	Max	0.9632

Table 5: OLS Results for the Carhart Four Factor Model with Fama-French 25 Size/BM Portfolios

This table presents the OLS results for the Carhart four factor model with the 25 Size/BM portfolios. $\hat{\alpha}_i$ is the Jensen α, $\hat{\beta}_i$ is the MKT loading of asset i, $\hat{s}_i$ is the SMB loading of asset i, $\hat{h}_i$ is the HML loading of asset i, $\hat{p}_i$ is the UMD loading of asset i, $\sigma(\hat{\epsilon})$ is the standard error of the fitted residual, $\tilde{Q}^2(1)$ is the Ljung-Box statistic for serial first order autocorrelation in the fitted squared residuals, DW is the Durbin-Watson statistic for first order serial autocorrelation in the fitted residuals and $\bar{R}^2$ is the goodness-of-fit measure adjusted for the extra degrees of freedom. * and ** indicate statistical significance at the 5% and 1% level, respectively. † superscript by the Durbin-Watson statistic indicates that the value falls into the inconclusive region. The data sample covers 1963:07 until 1993:12.

$\hat{\alpha}_i$	Low	2	3	4	High	Statistics	
Small	-0.4619**	-0.0662	-0.0570	0.0927	0.0734		
2	-0.1309	0.0231	0.1879**	0.1120	0.0577	Min	0.0019
3	0.0094	0.1129	0.0313	0.1751**	0.0019	Mean	0.1030
4	0.1516*	-0.0767	0.0279	0.1236	0.0684	Median	0.0767
Large	0.2248**	-0.0023	-0.0784	-0.0449	-0.1839	Max	0.4619
$\hat{\beta}_i$	Low	2	3	4	High	Statistics	
Small	1.0389**	0.9848**	0.9467**	0.9026**	0.9593**		
2	1.1058**	1.0302**	0.9812**	0.9851**	1.0779**	Min	0.9026
3	1.1108**	1.0252**	0.9808**	0.9769**	1.0776**	Mean	1.0234
4	1.0661**	1.0816**	1.0489**	1.0355**	1.1583**	Median	1.0302
Large	0.9557**	1.0314**	0.9788**	1.0000**	1.0439**	Max	1.1583
$\hat{s}_i$	Low	2	3	4	High	Statistics	
Small	1.4298**	1.2721**	1.1431**	1.1095**	1.1945**		
2	1.0121**	0.9200**	0.8157**	0.7025**	0.8463**	Min	-0.2563
3	0.6832**	0.6115**	0.5442**	0.4342**	0.6130**	Mean	0.5492
4	0.3052**	0.2464**	0.2256**	0.1794**	0.3608**	Median	0.6115
Large	-0.2027**	-0.2088**	-0.2563**	-0.2124**	-0.0382	Max	1.4298
$\hat{h}_i$	Low	2	3	4	High	Statistics	
Small	-0.2622**	0.1044**	0.2481**	0.3832**	0.6503**		
2	-0.4708**	0.0143	0.2533**	0.4875**	0.6941**	Min	-0.4708
3	-0.4469**	0.0348	0.3092**	0.4842**	0.7122**	Mean	0.2158
4	-0.4535**	0.0235	0.3116**	0.5269**	0.7151**	Median	0.2533
Large	-0.4673**	0.0006	0.2151**	0.5316**	0.7944**	Max	0.7944
$\hat{p}_i$	Low	2	3	4	High	Statistics	
Small	0.0524	-0.0309	-0.0191	-0.0075	0.0099		
2	0.0087	-0.0735**	-0.0296	0.0026	0.0125	Min	-0.0854
3	-0.0357	0.0065	-0.0473*	-0.0273	0.0166	Mean	-0.0137
4	0.0036	-0.0854**	-0.0323	-0.0537**	-0.0154	Median	-0.0154
Large	-0.0315	-0.0121	0.0729**	-0.0389	0.0131	Max	0.0729
$\sigma(\hat{\epsilon})$	Low	2	3	4	High	Statistics	
Small	1.9256	1.4473	1.1703	1.1241	1.2087		
2	1.5188	1.2673	1.1427	1.1296	1.2373	Min	1.1241
3	1.3888	1.3461	1.3007	1.1966	1.4612	Mean	1.4008
4	1.3696	1.4850	1.4613	1.4825	1.8645	Median	1.3518
Large	1.2417	1.3184	1.5757	1.3518	2.0043	Max	2.0043
$\tilde{Q}^2(1)$	Low	2	3	4	High	Statistics	
Small	14.6681**	8.0945**	6.4378*	0.0937	15.2212**		
2	1.4277	11.8160**	0.0125	7.3166**	1.1108	Min	0.0004
3	4.5351*	0.5587	0.0004	0.6958	0.0931	Mean	5.3127
4	6.7339**	7.2605**	11.1433**	13.6820**	1.5267	Median	4.5351
Large	9.2293**	1.2999	6.7335**	1.4237	1.7027	Max	15.2212
DW	Low	2	3	4	High	Statistics	
Small	1.9891	2.1319	1.8991	1.9182	1.8529		
2	2.0242	2.1011	1.9552	1.9763	1.9691	Min	1.8101
3	1.9714	1.9333	2.0023	1.9814	1.9453	Mean	1.9874
4	1.9337	1.9615	2.0265	1.9829	2.2263	Median	1.9714
Large	1.8919	1.8966	1.8101	2.1327	2.1721	Max	2.2263
$\bar{R}^2$	Low	2	3	4	High	Statistics	
Small	0.9357	0.9529	0.9632	0.9624	0.9613		
2	0.9546	0.9574	0.9576	0.9536	0.9554	Min	0.8198
3	0.9544	0.9408	0.9340	0.9372	0.9291	Mean	0.9296
4	0.9434	0.9205	0.9111	0.9017	0.8867	Median	0.9372
Large	0.9322	0.9167	0.8636	0.8955	0.8198	Max	0.9632

Table 6: OLS Results for the Capital Asset Pricing Model with 30 Industry Portfolios

This table presents the OLS results for the CAPM model with 30 industry portfolios (K. French website). $\hat{\alpha}_i$ is the Jensen α, $\hat{\beta}_i$ is the MKT loading of asset i, $\sigma(\hat{\epsilon})$ is the standard error of the fitted residual, $\tilde{Q}^2(1)$ is the Ljung-Box statistic for serial first order autocorrelation in the fitted squared residuals, DW is the Durbin-Watson statistic for first order serial autocorrelation in the fitted residuals and $\bar{R}^2$ is the goodness-of-fit measure adjusted for the extra degrees of freedom. * and ** indicate statistical significance at the 5% and 1% level, respectively. † superscript by the Durbin-Watson statistic indicates that the value falls into the inconclusive region. The data sample covers 1963:07 until 1993:12.

Industry	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\sigma(\hat{\epsilon})$	$\tilde{Q}^2(1)$	DW	$\bar{R}^2$
Food	0.2981*	0.8728**	2.4463	8.0400**	1.7903	0.7143
Beer	0.1078	0.9570**	3.3970	0.0445	2.0232	0.6090
Smoke	0.5694**	0.8304**	4.1606	0.5873	1.7446	0.4383
Games	0.1925	1.3593**	4.0437	4.6557*	1.8191	0.6893
Books	0.1678	1.1444**	2.9682	0.9478	1.9391	0.7449
Hshld	0.0255	0.9941**	2.3305	0.0587	1.7141	0.7814
Clths	-0.0044	1.2237**	3.9130	4.3686*	1.8852	0.6575
Hlth	0.1870	0.9710**	3.0298	11.8812**	1.8506	0.6685
Chems	-0.0277	1.0715**	2.5113	8.9015**	1.8801	0.7815
Txtls	0.2062	1.0902**	3.8870	5.3910*	1.7705	0.6069
Cnstr	0.0076	1.2292**	2.2489	1.9980	1.8361	0.8544
Steel	-0.2385	1.0728**	3.8667	0.8249	1.9456	0.6017
FabPr	-0.0985	1.1788**	2.4323	7.3328**	1.6994	0.8219
ElcEq	0.0455	1.1809**	2.9085	2.6715	2.0425	0.7640
Autos	0.0250	1.0026**	3.7504	0.1459	1.7887	0.5837
Carry	0.0971	1.2245**	3.8003	2.8854	1.8611	0.6708
Mines	0.1508	0.9884**	5.4156	6.1768*	1.8149	0.3947
Coal	0.0931	1.1438**	5.8895	10.6338**	1.7575	0.4249
Oil	0.1702	0.8563**	3.6456	24.6127**	1.6700*	0.5196
Util	0.0631	0.6253**	2.7899	0.0339	1.7678	0.4962
Telcm	0.1880	0.6517**	2.9204	0.0666	1.9328	0.4940
Servs	0.0253	1.3451**	2.9610	1.5224	1.7887	0.8021
BusEq	-0.1466	1.1047**	2.9284	0.1257	1.8859	0.7365
Paper	0.0453	1.0311**	2.3862	0.5653	2.0513	0.7858
Trans	-0.0394	1.2078**	3.3331	4.4717*	1.8743	0.7206
Whlsl	0.1545	1.2596**	2.9319	7.5583**	1.8743	0.7838
Rtail	0.1453	1.1040**	3.0151	0.1938	1.7314	0.7247
Meals	0.2951	1.3212**	3.9397	7.4116**	1.5776**	0.6883
Fin	0.0336	1.0528**	2.0444	10.6416**	1.5958**	0.8390
Other	-0.0931	1.2310**	2.5707	0.0415	1.9962	0.8183
Statistics						
Min	0.0044	0.6253	2.0444	0.0339	1.5776	0.3947
Mean	0.1314	1.0775	3.2822	4.4930	1.8303	0.6748
Median	0.1032	1.0971	2.9916	2.7785	1.8313	0.7018
Max	0.5694	1.3593	5.8895	24.6127	2.0513	0.8544

Table 7: OLS Results for the Fama-French Three Factor Model with 30 Industry Portfolios

This table presents the OLS results for the Fama-French three factor model with 30 industry portfolios (K. French website). $\hat{\alpha}_i$ is the Jensen α, $\hat{\beta}_{i,m}$ is the MKT loading of asset i, $\hat{s}_i$ is the SMB loading of asset i, $\hat{h}_i$ is the HML loading of asset i, $\sigma(\hat{\epsilon})$ is the standard error of the fitted residual, $\tilde{Q}^2(1)$ is the Ljung-Box statistic for serial first order autocorrelation in the fitted squared residuals, DW is the Durbin-Watson statistic for first order serial autocorrelation in the fitted residuals and $\bar{R}^2$ is the goodness-of-fit measure adjusted for the extra degrees of freedom. * and ** indicate statistical significance at the 5% and 1% level, respectively. † superscript by the Durbin-Watson statistic indicates that the value falls into the inconclusive region. The data sample covers 1963:07 until 1993:12.

Industry	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{s}_i$	$\hat{h}_i$	$\sigma(\hat{\epsilon})$	$\tilde{Q}^2(1)$	DW	$\bar{R}^2$
Food	0.3278*	0.8952**	-0.1146*	-0.0194	2.4264	7.3327**	1.8240	0.7173
Beer	0.0777	0.9288**	0.1347*	0.0138	3.3777	0.1445	2.0009	0.6113
Smoke	0.6394**	0.8691**	-0.2220**	-0.0605	4.1150	0.2961	1.7613	0.4475
Games	0.1114	1.1687**	0.7518**	-0.0840	3.5087	3.1587	1.8930	0.7648
Books	0.1019	1.0562**	0.3847**	0.0023	2.7849	0.2626	1.8930	0.7741
Hshld	0.1761	0.9754**	-0.1327**	-0.2376**	2.2296	3.6998	1.7084	0.7988
Clths	-0.2338	1.0841**	0.7720**	0.1844*	3.2890	0.7894	1.9137	0.7567
Hlth	0.5307**	0.8960**	-0.1933**	-0.5765**	2.6405	9.0872**	1.8593	0.7468
Chems	-0.0858	1.1207**	-0.0910	0.1360*	2.4792	10.1676**	1.8991	0.7858
Txtls	-0.0844	0.9846**	0.7363**	0.3087**	3.2582	2.5086	1.8885	0.7223
Cnstr	-0.1612	1.1815**	0.3816**	0.1939**	1.9436	0.1246	1.8042	0.8907
Steel	-0.5485**	1.1106**	0.2755**	0.4884**	3.6051	0.6285	1.9852	0.6518
FabPr	-0.1329	1.1158**	0.2585**	-0.0169	2.3325	1.8969	1.7281	0.8353
ElcEq	0.0745	1.0899**	0.2709**	-0.1383*	2.8004	6.3504*	2.0333	0.7800
Autos	-0.2827	1.0843**	0.1236	0.5314**	3.5098	0.0075	1.8057	0.6334
Carry	0.0215	1.1241**	0.4386**	0.0033	3.6155	3.7849	1.8994	0.7004
Mines	0.0087	0.9035**	0.4727**	0.1159	5.2573	4.8089*	1.7910	0.4264
Coal	0.0474	1.0837**	0.2632*	0.0027	5.8474	8.8439**	1.7489	0.4299
Oil	0.1492	0.9764**	-0.3800**	0.1572*	3.4849	38.3652**	1.6326**	0.5586
Util	-0.1177	0.7735**	-0.2671**	0.4181**	2.5141	0.0912	1.7789	0.5886
Telcm	0.0585	0.7752**	-0.2499**	0.3176**	2.7457	0.0412	2.0319	0.5503
Servs	0.0751	1.1220**	0.6915**	-0.3078**	2.2146	2.1292	1.9538	0.8887
BusEq	-0.0004	0.9808**	0.2297**	-0.3424**	2.7496	0.0094	1.8567	0.7664
Paper	0.0267	1.0614**	-0.0785	0.0590	2.3732	0.3118	2.0471	0.7869
Trans	-0.2158	1.1494**	0.4278**	0.1935**	3.0920	1.9533	1.9924	0.7582
Whlsl	0.1350	1.0551**	0.7187**	-0.1877**	2.1839	10.6149**	2.1232	0.8794
Rtail	0.1366	1.0448**	0.2117**	-0.0500	2.9600	0.2329	1.6894*	0.7332
Meals	0.2705	1.1272**	0.6897**	-0.1693*	3.4663	21.6614**	1.6694*	0.7574
Fin	-0.1099	1.0889**	0.0644	0.2457**	1.9492	8.8742**	1.5860*	0.8528
Other	-0.0987	1.0986**	0.4562**	-0.1317**	2.2474	0.4139	2.1626	0.8604
Statistics								
Min	0.0004	0.7735	-0.3800	-0.5765	1.9436	0.0075	1.5860	0.4264
Mean	0.1680	1.0309	0.2342	0.0350	3.0334	4.9531	1.8680	0.7151
Median	0.1145	1.0726	0.2609	0.0030	2.7927	2.0412	1.8739	0.7570
Max	0.6394	1.1815	0.7720	0.5314	5.8474	38.3652	2.1626	0.8907

Table 8: OLS Results for the Carhart Four Factor Model with 30 Industry Portfolios

This table presents the OLS results for the Carhart four factor model with 30 industry portfolios (K. French website). $\hat{\alpha}_i$ is the Jensen α, $\hat{\beta}_{i,m}$ is the MKT loading of asset i, $\hat{s}_i$ is the SMB loading of asset i, $\hat{h}_i$ is the HML loading of asset i, $\hat{p}_i$ is the UMD loading of asset i, $\sigma(\hat{\epsilon})$ is the standard error of the fitted residual, $\tilde{Q}^2(1)$ is the Ljung-Box statistic for serial first order autocorrelation in the fitted squared residuals, DW is the Durbin-Watson statistic for first order serial autocorrelation in the fitted residuals and $\bar{R}^2$ is the goodness-of-fit measure adjusted for the extra degrees of freedom. * and ** indicate statistical significance at the 5% and 1% level, respectively. † superscript by the Durbin-Watson statistic indicates that the value falls into the inconclusive region. The data sample covers 1963:07 until 1993:12.

Industry	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{s}_i$	$\hat{h}_i$	$\hat{p}_i$	$\sigma(\hat{\epsilon})$	$\tilde{Q}^2(1)$	DW	R^2
Food	0.3777**	0.8955**	-0.1229*	-0.0311	-0.0503	2.4206	6.1773*	1.8367	0.7179
Beer	0.0448	0.9286**	0.1402*	0.0215	0.0332	3.3759	0.1219	1.9919	0.6106
Smoke	0.7477**	0.8698**	-0.2400**	-0.0860	-0.1094	4.0987	0.3190	1.7685	0.4504
Games	0.0617	1.1684**	0.7601**	-0.0722	0.0502	3.5046	3.4539	1.8985	0.7647
Books	0.1670	1.0567**	0.3739**	-0.0131	-0.0658	2.7762	0.3762	1.9727	0.7749
Hshld	0.2002	0.9756**	-0.1367**	-0.2433**	-0.0243	2.2281	2.6900	1.7133*	0.7985
Clths	-0.0306	1.0854**	0.7383**	0.1366	-0.2052**	3.2165	1.4236	1.9361	0.7667
Hlth	0.5224**	0.8960**	-0.1920**	-0.5745**	0.0084	2.6404	9.6207**	1.8609	0.7461
Chems	0.0111	1.1213**	-0.1071*	0.1132*	-0.0979*	2.4575	12.1782**	1.9072	0.7890
Txtls	0.0028	0.9852**	0.7219**	0.2882**	-0.0880	3.2449	3.8601*	1.9085	0.7238
Cnstr	-0.0783	1.1821**	0.3678**	0.1744**	-0.0837**	1.9233	0.0694	1.8068	0.8927
Steel	-0.4987*	1.1109**	0.2672**	0.4766**	-0.0503	3.6012	0.8210	1.9842	0.6516
FabPr	-0.0872	1.1161**	0.2510**	-0.0277	-0.0462	2.3273	1.9710	1.7331	0.8356
ElcEq	0.0745	1.0899**	0.2709**	-0.1383*	0.0001	2.8004	6.3493*	2.0333	0.7794
Autos	-0.0768	1.0856**	0.0894	0.4829**	-0.2079**	3.4400	0.1498	1.8190	0.6468
Carry	-0.0667	1.1235**	0.4533**	0.0241	0.0891	3.6031	4.1241*	1.9230	0.7016
Mines	-0.0493	0.9031**	0.4823**	0.1295	0.0586	5.2537	4.9851*	1.7972	0.4256
Coal	0.0258	1.0836**	0.2668*	0.0078	0.0218	5.8470	8.6750**	1.7508	0.4284
Oil	0.0184	0.9755**	-0.3583**	0.1880*	0.1321*	3.4567	23.9662**	1.6281**	0.5645
Util	-0.0428	0.7740**	-0.2795**	0.4005**	-0.0757	2.5013	0.2213	1.7774	0.5917
Telcm	0.1454	0.7757**	-0.2643**	0.2972**	-0.0878*	2.7299	0.0140	2.0408	0.5542
Servs	0.1116	1.1222**	0.6854**	-0.3164**	-0.0369	2.2112	2.1152	1.9522	0.8887
BusEq	0.0086	0.9809**	0.2282**	-0.3445**	-0.0091	2.7494	0.0067	1.8551	0.7658
Paper	0.0598	1.0616**	-0.0840	0.0512	-0.0335	2.3705	0.2880	2.0592	0.7868
Trans	-0.2064	1.1494**	0.4263**	0.1913**	-0.0095	3.0918	1.8977	1.9920	0.7576
Whlsl	0.1260	1.0551**	0.7202**	-0.1856**	0.0091	2.1837	11.0959**	2.1252	0.8791
Rtail	0.3535*	1.0463**	0.1758**	-0.1011	-0.2190**	2.8677	0.1183	1.7010*	0.7489
Meals	0.3957*	1.1280**	0.6690**	-0.1988**	-0.1265*	3.4403	22.8007**	1.6778*	0.7603
Fin	-0.0213	1.0895**	0.0497	0.2249**	-0.0894**	1.9260	9.6614**	1.5610**	0.8559
Other	-0.2013	1.0979**	0.4732**	-0.1076*	0.1035**	2.2204	0.2193	2.1675	0.8633
Statistics									
Min	0.0028	0.7740	-0.3583	-0.5745	-0.2190	1.9233	0.0067	1.5610	0.4256
Mean	0.1605	1.0311	0.2275	0.0256	-0.0403	3.0169	4.6590	1.8726	0.7174
Median	0.0755	1.0726	0.2589	0.0146	-0.0415	2.7883	2.0431	1.8797	0.7589
Max	0.7477	1.1821	0.7601	0.4829	0.1321	5.8470	23.9662	2.1675	0.8927

Table 9: Mean Absolute Pricing Errors

This table presents the average absolute pricing errors (in basis points) of the dynamic asset pricing models in the paper. CAPM is the Capital Asset Pricing Model, FF3 is the three-factor Fama and French (1993) model, FF3+MOM is the Carhart (1997) four-factor model, CONST means that the variance-covariance matrix of the residuals is an intertemporal constant, CCORR is Bollerslev (1990) constant correlation multivariate GARCH model estimated in two-stages (see text for details) and FLEXM is the Ledoit et al. (2003) flexible multivariate GARCH model similarly estimated in stages. FF25 refers to the 25 size and book-to-market portfolios, IND30 indicates the 30 industry portfolios. The sample used in the estimation is 1963:07 until 1993:12.

APM	GARCH	FF25	IND30
CAPM	CONST	28.76	13.14
	CCORR	21.14	4.65
	FLEXM	10.42	4.14
FF3	CONST	10.02	16.80
	CCORR	7.52	6.22
	FLEXM	4.39	5.68
FF3+MOM	CONST	10.30	16.05
	CCORR	7.30	5.97
	FLEXM	4.10	5.54

Table 10: Hypotheses Tests with Fama-French 25 Size/BM Portfolios

This table presents the hypotheses test results for three factor models using the 25 size and book-to-market portfolios as test assets. CAPM is the Capital Asset Pricing Model, FF3 is the three-factor Fama and French (1993) model, FF3+MOM is the Carhart (1997) four-factor model, CONST means that the variance-covariance matrix of the residuals is an intertemporal constant, CCORR is Bollerslev (1990) constant correlation multivariate GARCH model estimated in two-stages (see text for details) and FLEXM is the Ledoit et al. (2003) flexible multivariate GARCH model similarly estimated in stages. The Wald statistic used to perform the tests has a χ^2 asymptotic distribution with the indicated number of degrees of freedom. The sample used in the estimation is 1963:07 until 1993:12.

APM	GARCH	H_0	df	Wald	p-value
CAPM	CONST	$\alpha = 0$	25	144.84	0.0000
	CCORR	$\alpha = 0$	25	588.39	0.0000
	FLEXM	$\alpha = 0$	25	556.88	0.0000
FF3	CONST	$\alpha = 0$	25	65.75	0.0000
	CCORR	$\alpha = 0$	25	71.77	0.0000
	FLEXM	$\alpha = 0$	25	96.11	0.0000
	CONST	$s = h = 0$	50	25803.13	0.0000
	CCORR	$s = h = 0$	50	96667.91	0.0000
	FLEXM	$s = h = 0$	50	93892.49	0.0000
FF3+MOM	CONST	$\alpha = 0$	25	68.93	0.0000
	CCORR	$\alpha = 0$	25	70.88	0.0000
	FLEXM	$\alpha = 0$	25	64.50	0.0000
	CONST	$s = h = 0$	50	25103.04	0.0000
	CCORR	$s = h = 0$	50	97105.58	0.0000
	FLEXM	$s = h = 0$	50	93809.10	0.0000
	CONST	$p = 0$	25	70.90	0.0000
	CCORR	$p = 0$	25	5703.53	0.0000
	FLEXM	$p = 0$	25	4953.86	0.0000
	CONST	$s = h = p = 0$	75	11606.75	0.0000
	CCORR	$s = h = p = 0$	75	102209.11	0.0000
	FLEXM	$s = h = p = 0$	75	98852.96	0.0000

Table 11: Hypotheses Tests with 30 Industry Portfolios

This table presents the hypotheses test results for three factor models using the 30 industry portfolios as test assets. CAPM is the Capital Asset Pricing Model, FF3 is the three-factor Fama and French (1993) model, FF3+MOM is the Carhart (1997) four-factor model, CONST means that the variance-covariance matrix of the residuals is an intertemporal constant, CCORR is Bollerslev (1990) constant correlation multivariate GARCH model estimated in two-stages (see text for details) and FLEXM is the Ledoit et al. (2003) flexible multivariate GARCH model similarly estimated in stages. The Wald statistic used to perform the tests has a χ^2 asymptotic distribution with the indicated number of degrees of freedom. The sample used in the estimation is 1963:07 until 1993:12.

APM	GARCH	H_0	df	Wald	p-value
CAPM	CONST	$\alpha = 0$	30	27.78	0.5823
	CCORR	$\alpha = 0$	30	36.55	0.1906
	FLEXM	$\alpha = 0$	30	33.87	0.2861
FF3	CONST	$\alpha = 0$	30	57.57	0.0018
	CCORR	$\alpha = 0$	30	62.96	0.0004
	FLEXM	$\alpha = 0$	30	64.30	0.0003
	CONST	$s = h = 0$	60	2138.27	0.0000
	CCORR	$s = h = 0$	60	25230.52	0.0000
	FLEXM	$s = h = 0$	60	25729.96	0.0000
FF3+MOM	CONST	$\alpha = 0$	30	58.49	0.0014
	CCORR	$\alpha = 0$	30	63.11	0.0004
	FLEXM	$\alpha = 0$	30	62.97	0.0004
	CONST	$s = h = 0$	60	2067.42	0.0000
	CCORR	$s = h = 0$	60	25601.01	0.0000
	FLEXM	$s = h = 0$	60	26010.15	0.0000
	CONST	$p = 0$	30	126.26	0.0000
	CCORR	$p = 0$	30	460.77	0.0000
	FLEXM	$p = 0$	30	480.95	0.0000
	CONST	$s = h = p = 0$	90	3687.39	0.0000
	CCORR	$s = h = p = 0$	90	26601.79	0.0000
	FLEXM	$s = h = p = 0$	90	26491.10	0.0000

Table 12: Instrumental Variable Regressions for OLS Residuals from of the 25 Size/BM Portfolios

This table presents the results from the regression of the OLS residuals of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged long-term government bond return SBBI (LTGB), the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF) and the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Residual	Const.	LTGB	D/P	DEF	TERM	$\bar{R}^2$	p-val.
$\hat{\epsilon}_{11}$	0.6092	-0.1322*	-0.0445	-0.2853	-0.1953*	0.0565	0.0003*
$\hat{\epsilon}_{12}$	0.4210	-0.0820*	-0.1545	0.2191	-0.1244	0.0343	0.0131*
$\hat{\epsilon}_{13}$	-0.0285	-0.0543*	-0.1067	0.4373*	-0.0721	0.0369	0.0086*
$\hat{\epsilon}_{14}$	0.7596*	-0.0175	-0.3185*	0.4667*	-0.1311*	0.0469	0.0016*
$\hat{\epsilon}_{15}$	0.9623*	-0.0507*	-0.3565*	0.3739*	-0.0631	0.0429	0.0032*
$\hat{\epsilon}_{21}$	-0.1532	-0.0787*	0.0907	-0.1399	-0.0393	0.0267	0.0438*
$\hat{\epsilon}_{22}$	-0.7087*	-0.0258	0.1141	0.2576	0.0124	0.0233	0.0734
$\hat{\epsilon}_{23}$	0.4566	-0.0028	-0.2185*	0.2985	0.0502	0.0191	0.1377
$\hat{\epsilon}_{24}$	-0.5028	0.0205	0.1091	0.0531	0.0608	0.0125	0.3368
$\hat{\epsilon}_{25}$	0.2008	0.0006	-0.0173	-0.1271	0.0020	0.0032	0.8865
$\hat{\epsilon}_{31}$	-0.2643	-0.0339	0.0604	0.0571	-0.0305	0.0079	0.5801
$\hat{\epsilon}_{32}$	-0.3345	0.0559*	0.0248	0.2025	0.0275	0.0234	0.0723
$\hat{\epsilon}_{33}$	-0.0889	0.0698*	0.0156	-0.0095	0.0557	0.0252	0.0556
$\hat{\epsilon}_{34}$	0.4673	0.0325	-0.1311	0.0356	-0.0354	0.0135	0.2938
$\hat{\epsilon}_{35}$	-0.1808	-0.0279	0.1319	-0.2737	-0.0151	0.0095	0.4854
$\hat{\epsilon}_{41}$	-0.1925	-0.0350	0.0537	0.0001	-0.0058	0.0066	0.6626
$\hat{\epsilon}_{42}$	-0.6377	0.0525	0.1573	0.0067	0.0660	0.0174	0.1748
$\hat{\epsilon}_{43}$	-0.0741	0.0227	0.0226	0.0102	-0.0371	0.0040	0.8368
$\hat{\epsilon}_{44}$	0.4081	0.0164	-0.0472	-0.1619	-0.0940	0.0097	0.4736
$\hat{\epsilon}_{45}$	0.1893	-0.0650	-0.0491	0.0445	-0.0787	0.0116	0.3777
$\hat{\epsilon}_{51}$	0.8039*	-0.0183	-0.3164*	0.3745*	-0.0538	0.0252	0.0551
$\hat{\epsilon}_{52}$	-0.6411	-0.0012	0.1263	0.1133	0.0790	0.0131	0.3118
$\hat{\epsilon}_{53}$	-0.6204	0.0397	0.3521*	-0.6863*	0.0870	0.0310	0.0225*
$\hat{\epsilon}_{54}$	-0.0992	-0.0414	0.0860	-0.1070	-0.1607*	0.0295	0.0283*
$\hat{\epsilon}_{55}$	0.9473	-0.0624	-0.4159*	0.5716*	-0.0274	0.0223	0.0861

Table 13: Instrumental Variable Regressions of Squared OLS Residuals of the 25 Size/BM Portfolios

This table presents the results from the regression of the squared OLS residuals of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged long-term government bond return SBBI (LTGB), the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF) and the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Sq. Res.	Const.	LTGB	D/P	DEF	TERM	$\bar{R}^2$	p-val.
$\hat{\epsilon}_{11}^2$	3.3397*	-0.0642	-0.6832	2.6302*	0.1229	0.0261	0.0480*
$\hat{\epsilon}_{12}^2$	3.4867*	0.0643	-0.4597	0.4087	-0.2085	0.0198	0.1244
$\hat{\epsilon}_{13}^2$	2.7192*	-0.0124	-0.4059*	0.2293	-0.1441	0.0180	0.1597
$\hat{\epsilon}_{14}^2$	1.4022*	0.0262	-0.0150	-0.0750	-0.0112	0.0023	0.9342
$\hat{\epsilon}_{15}^2$	1.6785*	0.0263	-0.0374	-0.0456	-0.0556	0.0023	0.9342
$\hat{\epsilon}_{21}^2$	4.8297*	-0.0208	-0.4094	-0.7194	-0.3613*	0.0286	0.0327*
$\hat{\epsilon}_{22}^2$	0.7369	-0.0349	0.3471	-0.2841	-0.0844	0.0087	0.5338
$\hat{\epsilon}_{23}^2$	1.4025*	0.0016	-0.0033	-0.0313	-0.0714	0.0016	0.9639
$\hat{\epsilon}_{24}^2$	0.6325	-0.0262	0.2132	-0.1178	-0.0343	0.0087	0.5339
$\hat{\epsilon}_{25}^2$	2.4181*	0.0394	-0.4351*	0.6780	-0.0213	0.0162	0.2055
$\hat{\epsilon}_{31}^2$	3.9195*	-0.0248	-0.6541*	0.3885	0.0455	0.0235	0.0717
$\hat{\epsilon}_{32}^2$	2.2672*	-0.0845	0.0462	-0.4678	-0.1853	0.0202	0.1166
$\hat{\epsilon}_{33}^2$	2.6669*	-0.1115*	-0.3089	0.3569	-0.2964*	0.0262	0.0478*
$\hat{\epsilon}_{34}^2$	0.5961	-0.1270*	0.2168	0.1211	-0.1355	0.0402	0.0051*
$\hat{\epsilon}_{35}^2$	1.4964	-0.0442	0.0723	0.2875	0.0959	0.0046	0.7976
$\hat{\epsilon}_{41}^2$	3.7230*	-0.0884	-0.5455*	0.1547	0.0235	0.0263	0.0469*
$\hat{\epsilon}_{42}^2$	3.0834*	0.0172	-0.0771	-0.3572	-0.2094	0.0061	0.6990
$\hat{\epsilon}_{43}^2$	1.5814	-0.0767	0.0086	0.7292	-0.4121*	0.0273	0.0401*
$\hat{\epsilon}_{44}^2$	0.9110	-0.1848*	0.2929	0.2365	-0.0222	0.0213	0.0996
$\hat{\epsilon}_{45}^2$	5.6233*	-0.0115	-1.0060*	1.3300	0.2250	0.0197	0.1261
$\hat{\epsilon}_{51}^2$	0.2707	-0.1439*	0.2088	0.4819	-0.0115	0.0417	0.0039*
$\hat{\epsilon}_{52}^2$	0.6436	-0.0485	-0.0804	1.1490*	0.2368*	0.0550	0.0004*
$\hat{\epsilon}_{53}^2$	0.1294	-0.2396*	0.0183	1.8587*	0.5508*	0.0397	0.0055*
$\hat{\epsilon}_{54}^2$	1.8851*	-0.1003	-0.2585	0.9022*	-0.0893	0.0211	0.1024
$\hat{\epsilon}_{55}^2$	3.8050	-0.0097	-0.0742	0.4706	-0.0506	0.0008	0.9913

Table 14: GLS Pricing Errors for the 25 Size/BM Portfolios

This table presents the pricing errors obtained for the 25 Fama-French portfolios using an ordinary least squares regression as in Fama and French (1996). The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Portfolio	Intercept	Standard Deviation	t Statistic
FF11	-0.1442*	0.0360	-4.0101
FF12	-0.0324	0.0266	-1.2186
FF13	-0.0258	0.0242	-1.0665
FF14	0.0346	0.0226	1.5300
FF15	0.0334	0.0205	1.6346
FF21	-0.0590	0.0331	-1.7832
FF22	-0.0339	0.0298	-1.1360
FF23	0.0654*	0.0235	2.7812
FF24	0.0425	0.0246	1.7287
FF25	0.0226	0.0218	1.0352
FF31	-0.0081	0.0388	-0.2100
FF32	0.0475	0.0317	1.4999
FF33	-0.0047	0.0325	-0.1433
FF34	0.0575*	0.0275	2.0921
FF35	0.0112	0.0269	0.4168
FF41	0.0961*	0.0432	2.2261
FF42	-0.0849	0.0484	-1.7527
FF43	-0.0084	0.0378	-0.2232
FF44	0.0261	0.0323	0.8079
FF45	0.0146	0.0294	0.4957
FF51	0.1196*	0.0385	3.1104
FF52	-0.0130	0.0361	-0.3586
FF53	0.0145	0.0420	0.3461
FF54	-0.0366	0.0300	-1.2213
FF55	-0.0608	0.0360	-1.6866

Table 15: Lagrange Multiplier Homoscedasticity Tests of the GLS Residuals of the 25 Size/BM Portfolios

This table presents the results from the LM homoscedasticity test on the GLS residuals of the 25 Fama-French portfolios. The statistic is the sample size times the R^2 from the regression of $\hat{\epsilon}_{ij}^2$ on a constant and q lags and is distributed as χ_q^2. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Residual	$q = 1$	$q = 2$	$q = 3$	$q = 6$	$q = 12$
$\hat{\epsilon}_{11}$	4.3306*	4.6073	4.5360	14.3275*	24.9943*
$\hat{\epsilon}_{12}$	6.8179*	7.4231*	7.5253	8.1820	12.4373
$\hat{\epsilon}_{13}$	0.3392	6.3461*	13.7411*	16.9801*	26.1068*
$\hat{\epsilon}_{14}$	0.2589	0.6699	0.6852	2.2324	12.8876
$\hat{\epsilon}_{15}$	6.5180*	7.4645*	9.1024*	9.6496	17.8447
$\hat{\epsilon}_{21}$	0.0723	0.6064	0.6285	7.9176	21.1001*
$\hat{\epsilon}_{22}$	0.6800	0.6505	0.7296	1.4413	10.7868
$\hat{\epsilon}_{23}$	1.8282	2.4152	2.8160	4.5701	8.1479
$\hat{\epsilon}_{24}$	0.1696	5.4519	5.5873	9.2401	15.0357
$\hat{\epsilon}_{25}$	0.0008	0.5293	1.8431	2.8016	5.4483
$\hat{\epsilon}_{31}$	1.0542	2.0589	6.0873	7.5648	9.3155
$\hat{\epsilon}_{32}$	0.3794	0.9323	0.3695	1.5098	20.7107
$\hat{\epsilon}_{33}$	1.6643	2.1184	2.2591	14.0902*	21.1948*
$\hat{\epsilon}_{34}$	0.1118	0.5634	0.5399	12.0180	18.2710
$\hat{\epsilon}_{35}$	0.0000	2.1414	2.1613	2.7647	5.3965
$\hat{\epsilon}_{41}$	0.0001	0.3730	0.4217	1.6864	4.9101
$\hat{\epsilon}_{42}$	0.0394	0.1402	2.6598	5.2021	32.2501*
$\hat{\epsilon}_{43}$	5.2523*	5.1914	5.5840	6.4157	13.2634
$\hat{\epsilon}_{44}$	0.0989	0.0926	0.2509	4.6401	9.5098
$\hat{\epsilon}_{45}$	0.2837	0.3018	0.2258	1.8647	13.4640
$\hat{\epsilon}_{51}$	0.5796	1.4476	2.7149	10.8532	22.0274*
$\hat{\epsilon}_{52}$	0.3530	0.4087	3.5736	4.9830	11.0128
$\hat{\epsilon}_{53}$	1.6410	1.9976	2.5107	2.6847	8.6959
$\hat{\epsilon}_{54}$	0.6267	2.0818	2.0967	1.9165	8.3342
$\hat{\epsilon}_{55}$	0.3321	7.0992*	11.0183*	13.5718*	17.0493

Table 16: Ljung-Box Homoscedasticity Tests of GLS Residuals of the 25 Size/BM Portfolios

This table presents the results from the LB homoscedasticity test on the GLS residuals of the 25 Fama-French portfolios. The statistic is a weighted-average of the sample autocorrelations of the fitted squared residuals at lags $1, \ldots, q$ and is distributed as χ^2_q. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Residual	$q = 1$	$q = 2$	$q = 3$	$q = 6$	$q = 12$
$\hat{\epsilon}_{11}$	4.3781*	4.4877	4.5052	13.5172*	25.6609*
$\hat{\epsilon}_{12}$	6.8928*	7.1062*	7.1698	7.9238	12.1445
$\hat{\epsilon}_{13}$	0.3430	6.5375*	14.6878*	18.0922*	27.5555*
$\hat{\epsilon}_{14}$	0.2618	0.6950	0.7197	2.2907	15.2019
$\hat{\epsilon}_{15}$	6.5895*	8.3463*	9.3093*	10.7893	17.9956
$\hat{\epsilon}_{21}$	0.0731	0.6187	0.6347	7.8249	26.1563*
$\hat{\epsilon}_{22}$	0.6874	0.6877	0.7980	1.4953	11.2553
$\hat{\epsilon}_{23}$	1.8482	2.5677	2.7964	4.4565	8.2605
$\hat{\epsilon}_{24}$	0.1715	5.5744	5.6366	9.1143	14.9036
$\hat{\epsilon}_{25}$	0.0008	0.5374	1.8817	2.7850	5.6025
$\hat{\epsilon}_{31}$	1.0657	2.2352	5.8781	7.6096	12.3455
$\hat{\epsilon}_{32}$	0.3836	1.0587	1.0605	1.9449	21.5009*
$\hat{\epsilon}_{33}$	1.6826	2.2868	2.4085	16.1388*	23.6286*
$\hat{\epsilon}_{34}$	0.1130	0.5065	0.5123	11.8612	17.5314
$\hat{\epsilon}_{35}$	0.0000	2.1767	2.2989	3.1256	6.7161
$\hat{\epsilon}_{41}$	0.0001	0.3783	0.3957	1.7159	3.8929
$\hat{\epsilon}_{42}$	0.0399	0.1237	2.6872	5.0755	36.4105*
$\hat{\epsilon}_{43}$	5.3099*	5.3430	5.6979	6.6775	15.9990
$\hat{\epsilon}_{44}$	0.1000	0.1001	0.2598	4.9315	10.6745
$\hat{\epsilon}_{45}$	0.2868	0.2870	0.3052	2.0535	12.6036
$\hat{\epsilon}_{51}$	0.5860	1.4459	2.8867	12.4933	24.0242*
$\hat{\epsilon}_{52}$	0.3569	0.3984	3.5724	4.5503	11.6818
$\hat{\epsilon}_{53}$	1.6590	2.1405	2.8159	3.2161	9.5210
$\hat{\epsilon}_{54}$	0.6336	2.2106	2.3499	2.6343	10.1641
$\hat{\epsilon}_{55}$	0.3357	7.1507*	11.6710*	16.1791*	24.2419*

Table 17: Instrumental Variable Regressions of GLS Residuals of the 25 Size/BM Portfolios

This table presents the results from the regression of the GLS residuals of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged long-term government bond return SBBI (LTGB), the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF) and the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Residual	Const.	LTGB	D/P	DEF	TERM	$\bar{R}^2$	p-val.
$\hat{\epsilon}_{11}$	0.1640	-0.0452*	-0.0104	-0.0745	-0.0645*	0.0517	0.0007*
$\hat{\epsilon}_{12}$	0.1141	-0.0244*	-0.0410	0.0605	-0.0405	0.0272	0.0406*
$\hat{\epsilon}_{13}$	-0.0393	-0.0169*	-0.0283	0.1476*	-0.0231	0.0281	0.0354*
$\hat{\epsilon}_{14}$	0.2601*	-0.0056	-0.1043*	0.1437*	-0.0454*	0.0364	0.0093*
$\hat{\epsilon}_{15}$	0.2952*	-0.0133	-0.1032*	0.0903	-0.0139	0.0353	0.0113*
$\hat{\epsilon}_{21}$	-0.0692	-0.0320*	0.0360	-0.0473	-0.0165	0.0265	0.0451*
$\hat{\epsilon}_{22}$	-0.3156*	-0.0110	0.0475	0.1253	0.0068	0.0261	0.0482*
$\hat{\epsilon}_{23}$	0.1774	-0.0009	-0.0822*	0.1071	0.0187	0.0184	0.1507
$\hat{\epsilon}_{24}$	-0.2132	0.0082	0.0477	0.0189	0.0239	0.0130	0.3149
$\hat{\epsilon}_{25}$	0.0747	0.0003	-0.0062	-0.0477	0.0004	0.0041	0.8300
$\hat{\epsilon}_{31}$	-0.1415	-0.0167	0.0312	0.0339	-0.0154	0.0076	0.5981
$\hat{\epsilon}_{32}$	-0.1311	0.0234*	0.0109	0.0732	0.0145	0.0200	0.1200
$\hat{\epsilon}_{33}$	-0.0109	0.0294*	0.0048	-0.0208	0.0208	0.0206	0.1098
$\hat{\epsilon}_{34}$	0.2342	0.0122	-0.0627	0.0074	-0.0169	0.0144	0.2624
$\hat{\epsilon}_{35}$	-0.0455	-0.0106	0.0364	-0.0783	-0.0059	0.0086	0.5347
$\hat{\epsilon}_{41}$	-0.0444	-0.0205	0.0232	-0.0295	-0.0124	0.0064	0.6776
$\hat{\epsilon}_{42}$	-0.3368	0.0316	0.0829	0.0031	0.0362	0.0161	0.2094
$\hat{\epsilon}_{43}$	0.0086	0.0103	0.0005	0.0025	-0.0229	0.0040	0.8329
$\hat{\epsilon}_{44}$	0.2032	0.0044	-0.0244	-0.0798	-0.0422	0.0123	0.3445
$\hat{\epsilon}_{45}$	0.0462	-0.0189	-0.0083	0.0012	-0.0236	0.0117	0.3736
$\hat{\epsilon}_{51}$	0.5322*	-0.0107	-0.1854*	0.1612	-0.0279	0.0265	0.0457*
$\hat{\epsilon}_{52}$	-0.4098*	0.0006	0.0717	0.1079	0.0418	0.0218	0.0918
$\hat{\epsilon}_{53}$	-0.3390	0.0133	0.1688*	-0.2913*	0.0436	0.0251	0.0562
$\hat{\epsilon}_{54}$	-0.0059	-0.0150	0.0254	-0.0429	-0.0650*	0.0261	0.0483*
$\hat{\epsilon}_{55}$	0.2733	-0.0210	-0.1263*	0.1891	-0.0122	0.0201	0.1189

Table 18: Instrumental Variable Regressions of the Squared GLS Residuals of the 25 Size/BM Portfolios

This table presents the results from the regression of the squared GLS residuals of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged long-term government bond return SBBI (LTGB), the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF) and the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

Sq. Res.	Const.	LTGB	D/P	DEF	TERM	$\bar{R}^2$	p-val.
$\hat{\epsilon}^2_{11}$	0.5995*	-0.0072	-0.0639	0.0719	0.0096	0.0042	0.8251
$\hat{\epsilon}^2_{12}$	0.5777*	0.0076	-0.0547	-0.1078	-0.0244	0.0454	0.0021*
$\hat{\epsilon}^2_{13}$	0.5267*	-0.0001	-0.0535	-0.1041	-0.0227	0.0413	0.0042*
$\hat{\epsilon}^2_{14}$	0.2919*	0.0038	-0.0090	-0.0753	-0.0026	0.0222	0.0867
$\hat{\epsilon}^2_{15}$	0.2465*	0.0030	-0.0154	-0.0414	-0.0014	0.0164	0.2004
$\hat{\epsilon}^2_{21}$	0.9007*	0.0017	-0.0579	-0.2525*	-0.0551	0.0527	0.0006*
$\hat{\epsilon}^2_{22}$	0.3890*	-0.0083	0.0214	-0.1400	-0.0170	0.0173	0.1776
$\hat{\epsilon}^2_{23}$	0.2922*	0.0012	-0.0141	-0.0440	-0.0036	0.0091	0.5098
$\hat{\epsilon}^2_{24}$	0.2242*	-0.0005	0.0278	-0.1098*	-0.0013	0.0155	0.2273
$\hat{\epsilon}^2_{25}$	0.3445*	0.0057	-0.0468*	-0.0036	-0.0055	0.0220	0.0902
$\hat{\epsilon}^2_{31}$	1.1358*	-0.0056	-0.1402*	-0.0929	0.0089	0.0385	0.0066*
$\hat{\epsilon}^2_{32}$	0.6975*	-0.0158	-0.0397	-0.1748*	-0.0229	0.0419	0.0038*
$\hat{\epsilon}^2_{33}$	0.8092*	-0.0237*	-0.0973	-0.0397	-0.0643*	0.0406	0.0047*
$\hat{\epsilon}^2_{34}$	0.2992*	-0.0190*	0.0126	-0.0633	-0.0250	0.0253	0.0549
$\hat{\epsilon}^2_{35}$	0.3175*	-0.0014	-0.0043	-0.0563	0.0129	0.0092	0.5016
$\hat{\epsilon}^2_{41}$	1.4015*	-0.0205	-0.1438	-0.2177	0.0273	0.0461	0.0018*
$\hat{\epsilon}^2_{42}$	1.6956*	-0.0046	-0.1727	-0.2040	-0.0398	0.0226	0.0824
$\hat{\epsilon}^2_{43}$	0.6689*	-0.0172	-0.0364	0.0159	-0.0930*	0.0173	0.1776
$\hat{\epsilon}^2_{44}$	0.4086*	-0.0217	0.0109	-0.0807	-0.0030	0.0134	0.3003
$\hat{\epsilon}^2_{45}$	0.6170*	0.0030	-0.0936*	0.0144	0.0193	0.0356	0.0107*
$\hat{\epsilon}^2_{51}$	0.4348*	-0.0410*	0.0450	-0.0692	-0.0248	0.0252	0.0552
$\hat{\epsilon}^2_{52}$	0.6445*	-0.0094	-0.0471	-0.0256	0.0149	0.0107	0.4219
$\hat{\epsilon}^2_{53}$	0.3876	-0.0440	0.0092	0.0946	0.1419*	0.0247	0.0601
$\hat{\epsilon}^2_{54}$	0.4652*	-0.0125	-0.0454	0.0121	0.0010	0.0122	0.3504
$\hat{\epsilon}^2_{55}$	0.7433*	0.0037	-0.0675	-0.0541	0.0196	0.0108	0.4130

Table 19: Instrumental Variable Regressions of the Estimated Market Factor Loadings of the 25 Size/BM Portfolios

This table presents the results from the regression of the estimated market factor loadings of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF), the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM) and a dummy variable that takes the value of 1 during recessions and 0 during booms (REC). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

$\hat{\beta}_i$	Const.	D/P	DEF	TERM	REC	$\bar{R}^2$	p-val.
$\hat{\beta}_{11}$	1.3131*	-0.0176	-0.0995*	-0.0106*	0.0091	0.2148	0.0000*
$\hat{\beta}_{12}$	1.3185*	-0.0317*	-0.1712*	-0.0072	-0.0675*	0.4702	0.0000*
$\hat{\beta}_{13}$	1.2147*	-0.0309*	-0.1350*	-0.0039	-0.0510*	0.4870	0.0000*
$\hat{\beta}_{14}$	1.1675*	-0.0396*	-0.1381*	-0.0063	-0.0611*	0.5841	0.0000*
$\hat{\beta}_{15}$	1.1378*	-0.0255*	-0.1596*	-0.0041	-0.0825*	0.5433	0.0000*
$\hat{\beta}_{21}$	1.4048*	-0.0151	-0.1487*	-0.0075	0.0155	0.3286	0.0000*
$\hat{\beta}_{22}$	1.2718*	-0.0251*	-0.1333*	-0.0007	-0.0254*	0.5316	0.0000*
$\hat{\beta}_{23}$	1.1852*	-0.0183*	-0.1571*	-0.0104*	-0.0350*	0.4789	0.0000*
$\hat{\beta}_{24}$	1.1945*	-0.0393*	-0.1303*	-0.0102*	-0.0317*	0.5408	0.0000*
$\hat{\beta}_{25}$	1.3268*	-0.0323*	-0.2034*	-0.0041	-0.0998*	0.5773	0.0000*
$\hat{\beta}_{31}$	1.3688*	-0.0296*	-0.0919*	0.0014	0.0487*	0.3040	0.0000*
$\hat{\beta}_{32}$	1.2982*	-0.0313*	-0.1718*	0.0010	-0.0421*	0.5302	0.0000*
$\hat{\beta}_{33}$	1.1546*	-0.0327*	-0.1066*	-0.0060	0.0227	0.4480	0.0000*
$\hat{\beta}_{34}$	1.1556*	-0.0300*	-0.1544*	-0.0102*	-0.0516*	0.5147	0.0000*
$\hat{\beta}_{35}$	1.3091*	-0.0341*	-0.1962*	-0.0054	-0.0597*	0.5635	0.0000*
$\hat{\beta}_{41}$	1.1310*	-0.0034	0.0059	0.0027	0.0527*	0.0656	0.0001*
$\hat{\beta}_{42}$	1.0390*	-0.0014	0.0306*	0.0007	0.0765*	0.1773	0.0000*
$\hat{\beta}_{43}$	1.1912*	-0.0147*	-0.1419*	-0.0027	0.0078	0.4975	0.0000*
$\hat{\beta}_{44}$	1.1308*	-0.0209*	-0.1232*	-0.0102*	-0.0320*	0.4645	0.0000*
$\hat{\beta}_{45}$	1.2460*	-0.0337*	-0.1345*	0.0043	-0.0825*	0.4759	0.0000*
$\hat{\beta}_{51}$	0.9818*	0.0022	-0.0417*	0.0036	-0.0311*	0.1788	0.0000*
$\hat{\beta}_{52}$	0.7801*	0.0062	0.1312*	0.0151*	0.0327	0.3207	0.0000*
$\hat{\beta}_{53}$	0.8677*	0.0061	0.0107	0.0033	-0.0127	0.0167	0.1923
$\hat{\beta}_{54}$	1.0433*	-0.0237*	-0.1101*	-0.0090*	-0.0230	0.4550	0.0000*
$\hat{\beta}_{55}$	1.2941*	-0.0344*	-0.2334*	-0.0010	-0.0969*	0.5257	0.0000*

Table 20: Instrumental Variable Regressions of the Estimated SMB Factor Loadings of the 25 Size/BM Portfolios

This table presents the results from the regression of the estimated SMB factor loadings of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF), the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM) and a dummy variable that takes the value of 1 during recessions and 0 during booms (REC). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

$\hat{s}_i$	Const.	D/P	DEF	TERM	REC	$\bar{R}^2$	p-val.
$\hat{s}_{11}$	1.0837*	0.0119	0.0064	0.0069	-0.0314	0.0239	0.0674
$\hat{s}_{12}$	0.8009*	0.0167*	0.0683*	0.0100*	0.0106	0.1731	0.0000*
$\hat{s}_{13}$	0.6953*	0.0182*	0.0653*	-0.0025	0.0150	0.2288	0.0000*
$\hat{s}_{14}$	0.6877*	0.0294*	0.0617*	0.0041	-0.0292	0.1826	0.0000*
$\hat{s}_{15}$	0.7392*	0.0316*	0.0610*	0.0068	0.0135	0.1764	0.0000*
$\hat{s}_{21}$	0.6214*	0.0301*	0.0245*	0.0030	-0.0529*	0.1164	0.0000*
$\hat{s}_{22}$	0.5356*	0.0346*	0.0374*	0.0045	0.0321*	0.2449	0.0000*
$\hat{s}_{23}$	0.4128*	0.0201*	0.0581*	0.0013	0.0229	0.2331	0.0000*
$\hat{s}_{24}$	0.3345*	0.0429*	0.0394*	0.0044	-0.0243	0.2130	0.0000*
$\hat{s}_{25}$	0.3840*	0.0477*	0.0865*	0.0054	-0.0190	0.2947	0.0000*
$\hat{s}_{31}$	0.4304*	0.0182*	0.0165	0.0002	-0.0051	0.0757	0.0000*
$\hat{s}_{32}$	0.2048*	0.0456*	0.0777*	0.0060	-0.0476*	0.2862	0.0000*
$\hat{s}_{33}$	0.2461*	0.0424*	0.0267*	0.0033	-0.0013	0.2483	0.0000*
$\hat{s}_{34}$	0.1618*	0.0380*	0.0627*	0.0067	-0.0232	0.2578	0.0000*
$\hat{s}_{35}$	0.2155*	0.0489*	0.0640*	-0.0052	-0.0170	0.3193	0.0000*
$\hat{s}_{41}$	0.1998*	0.0222*	-0.0471*	-0.0052	-0.0114	0.0700	0.0000*
$\hat{s}_{42}$	0.1751*	0.0047	-0.0296*	0.0048	0.0313*	0.0282	0.0349*
$\hat{s}_{43}$	0.0311	0.0223*	0.0793*	0.0057	-0.0559*	0.2430	0.0000*
$\hat{s}_{44}$	0.0053	0.0248*	0.0342*	-0.0034	0.0012	0.2754	0.0000*
$\hat{s}_{45}$	0.1906*	0.0072	0.0773*	-0.0126*	0.0322*	0.3107	0.0000*
$\hat{s}_{51}$	-0.1372*	-0.0242*	0.0518*	0.0021	0.0110	0.1450	0.0000*
$\hat{s}_{52}$	-0.0674*	-0.0089	-0.0744*	-0.0090	0.0802*	0.1150	0.0000*
$\hat{s}_{53}$	-0.0902*	-0.0061	0.0032	0.0010	-0.0462*	0.0613	0.0001*
$\hat{s}_{54}$	-0.2038*	0.0097	0.0749*	0.0086*	-0.0228*	0.2583	0.0000*
$\hat{s}_{55}$	-0.2150*	0.0102	0.1411*	0.0056	0.0023	0.4002	0.0000*

Table 21: Instrumental Variable Regressions of the Estimated HML Factor Loadings of the 25 Size/BM Portfolios

This table presents the results from the regression of the estimated HML factor loadings of the 25 Fama-French portfolios on a set of instrumental variables. The instrumental variables include a constant, the lagged dividend yield on the NYSE/AMEX value-weighted index from CRSP (D/P), the lagged default spread defined as Moody's Baa corporate bond yield minus the Aaa yield (DEF), the lagged term spread defined as the 10 year Treasury bond yield minus the 1 month Treasury bill yield (TERM) and a dummy variable that takes the value of 1 during recessions and 0 during booms (REC). P-value is the probability value of the F test of the null hypothesis that all the coefficients in the linear regression are equal to zero. The monthly returns cover the period 1963:07 to 1993:12. Stars indicate significance at the 5% level.

$\hat{h}_i$	Const.	D/P	DEF	TERM	REC	$\bar{R}^2$	p-val.
$\hat{h}_{11}$	-0.2232*	-0.0011	-0.0299*	0.0019	0.0538*	0.0396	0.0055*
$\hat{h}_{12}$	-0.0400	-0.0017	-0.0440*	0.0040	0.0373*	0.0553	0.0004*
$\hat{h}_{13}$	0.0661*	-0.0004	-0.0398*	-0.0001	0.0053	0.0739	0.0000*
$\hat{h}_{14}$	0.1493*	0.0036	-0.0526*	-0.0003	-0.0074	0.1345	0.0000*
$\hat{h}_{15}$	0.3014*	0.0035	-0.0716*	-0.0019	-0.0328*	0.2519	0.0000*
$\hat{h}_{21}$	-0.3867*	-0.0080	-0.0247	0.0037	0.0577*	0.0414	0.0041*
$\hat{h}_{22}$	-0.1214*	-0.0007	-0.0249*	0.0043	0.0425*	0.0401	0.0051*
$\hat{h}_{23}$	0.0002	0.0085	-0.0422*	0.0005	0.0219	0.0537	0.0005*
$\hat{h}_{24}$	0.2485*	0.0044	-0.0611*	-0.0035	-0.0108	0.2147	0.0000*
$\hat{h}_{25}$	0.3772*	0.0168*	-0.0979*	-0.0067	-0.0430*	0.2359	0.0000*
$\hat{h}_{31}$	-0.4051*	-0.0169*	0.0218	0.0065	0.0652*	0.0551	0.0004*
$\hat{h}_{32}$	-0.1926*	0.0099	-0.0300*	0.0092	0.0480*	0.0326	0.0174*
$\hat{h}_{33}$	0.1268*	0.0063	-0.0448*	-0.0014	0.0112	0.0982	0.0000*
$\hat{h}_{34}$	0.2132*	0.0127*	-0.0721*	-0.0028	-0.0085	0.1707	0.0000*
$\hat{h}_{35}$	0.3537*	0.0159*	-0.0970*	-0.0036	-0.0233*	0.2655	0.0000*
$\hat{h}_{41}$	-0.2476*	0.0087	-0.0107	0.0002	0.0088	0.0107	0.4218
$\hat{h}_{42}$	0.0852*	-0.0073	-0.0201	-0.0059	0.0314*	0.0500	0.0010*
$\hat{h}_{43}$	0.1466*	0.0089	-0.0591*	-0.0001	0.0180	0.1312	0.0000*
$\hat{h}_{44}$	0.2713*	0.0217*	-0.0746*	-0.0077*	-0.0183	0.1727	0.0000*
$\hat{h}_{45}$	0.4191*	0.0141	-0.0929*	-0.0068	-0.0386*	0.1786	0.0000*
$\hat{h}_{51}$	-0.4708*	-0.0095	0.0491*	0.0123*	0.0199	0.0797	0.0000*
$\hat{h}_{52}$	0.1317*	-0.0207*	0.0090	-0.0033	0.0308*	0.0290	0.0309*
$\hat{h}_{53}$	0.1825*	0.0135*	-0.0298*	-0.0049	0.0017	0.0327	0.0171*
$\hat{h}_{54}$	0.2654*	0.0196*	-0.0634*	-0.0030	-0.0070	0.0801	0.0000*
$\hat{h}_{55}$	0.4619*	0.0213*	-0.1197*	-0.0068	-0.0516*	0.2120	0.0000*

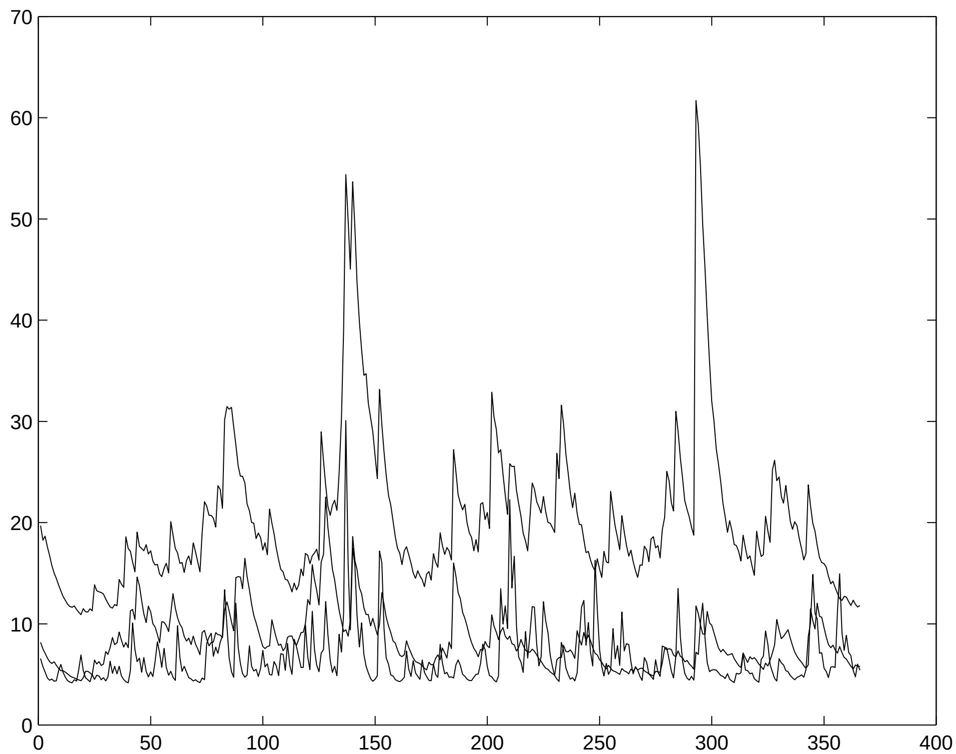

Figure 1: Time series of the three Fama-French factors own variances.

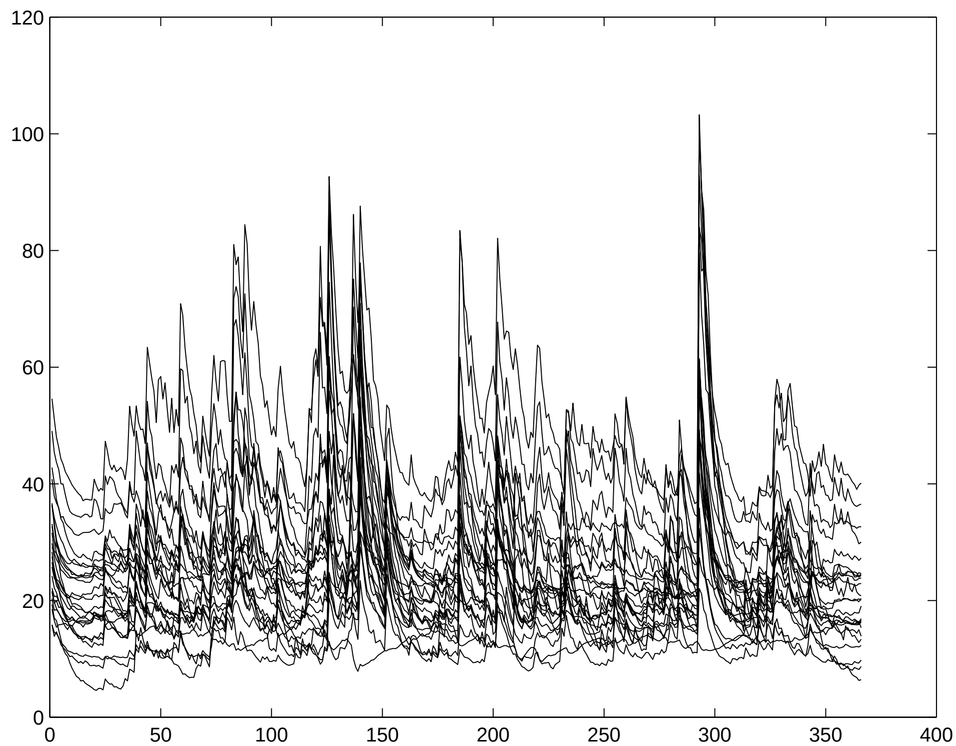

Figure 2: Time series of the 25 Fama-French portfolios own variances.

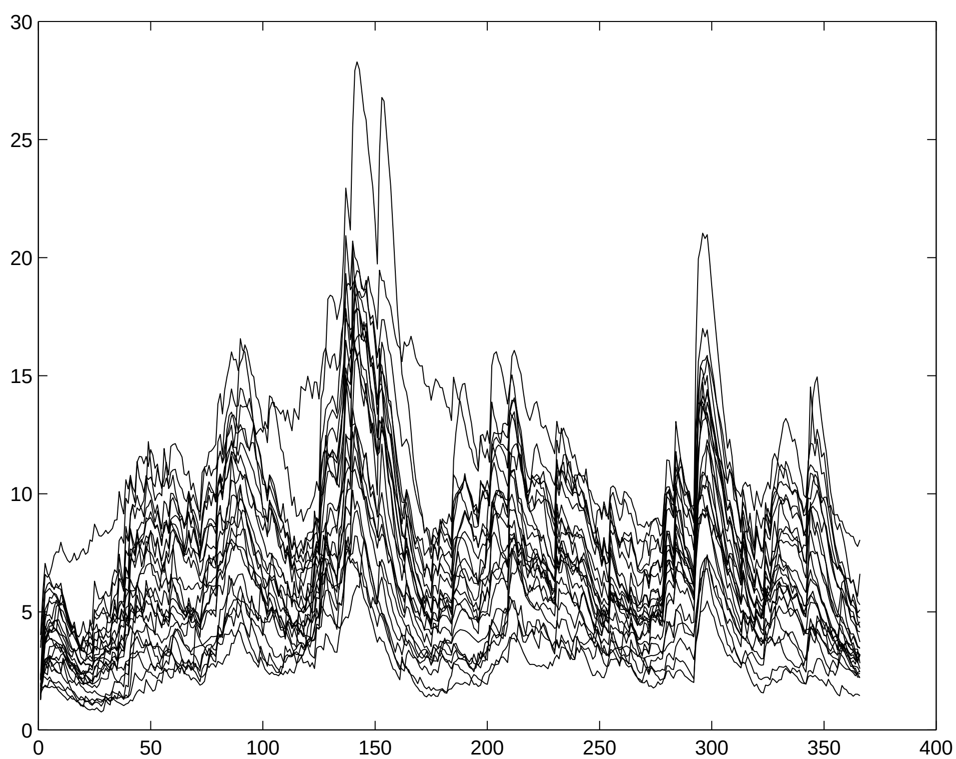

Figure 3: Time series of the 25 Fama-French portfolios idiosyncratic (residual) variances.