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兩階段估計 Fama-French 三因子模型－台灣股市之研究

On the Two-Stage Estimation of the Fama-French Three Factor Model: Evidence from Taiwan

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摘要：關於因子模型的參數估計問題，文獻中常以兩階段迴歸處理。本文以台灣股票市場為例，檢驗一些常用的兩階段估計方法在 Fama-French 三因子模型參數估計的影響。證據大多顯示支持市場因子，而支持高--低淨值市價比的證據微弱。風險貼水的顯著程度取決於分組與逐年更新的程序；誤差變項與非同步交易的調整並對結果不會造成太大的影響。
關鍵字：三因子模型、兩階段估計、誤差變項模型

Abstract: In this paper, a few common approaches to implementing the two-stage test on the Fama-French three-factor models are examined for Taiwan's stock

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market. Much of the evidence favors the *MKT* factor, while the support for the *HML* factor is weak. The significance of the risk premium is deeply dependent on the grouping and rolling procedure. Adjustments for errors-in-variable or non-synchronous trading do not affect the results very much.
Keywords: Three Factor Model; Two-stage estimation; Errors in Variables

1. Introduction

Based on empirical observations, Fama and French (1993) propose a three-factor model to explain the cross-sectional behavior of stock returns in the U.S. market. Although the model is not derived from an equilibrium theory, its predictions have been widely used as a benchmark for asset returns (Carhart, 1997; Mitchell and Stafford, 2000).

In this work, we study the estimation of the three-factor model under the traditional two-stage test. Compared to the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model is subject to similar estimation problems. The two major problems are, first, the factor loadings (or betas) and the expected risk premium are not observable, and second, the returns, even after accounting for the effects of betas, are cross-sectionally correlated. Fama and MacBeth (1973) proposed a two-stage test to solve the second problem. In the first stage, they estimate the time-series regressions betas. In the second stage, they run cross-sectional regressions to obtain monthly risk premium, and use the average to perform t-tests. By doing this, they hope to avoid the downward bias of the error terms of the cross-sectional regressions. To lessen the problem of unobservable betas, Fama and MacBeth group the securities into portfolios in the time-series regressions to estimate the betas, so that measurement errors of the betas may be reduced.

The two-stage procedure has become very common, not only because it is equivalent to tests that are based on a solid econometric theory, for example, the maximum likelihood method (Shanken, 1992), but also because it produces statistics with economic interpretations. Of course, there is room for researchers to improve the implementation of the two-stage tests. For example, to answer such questions as how to form the portfolios? How to estimate the betas in the first stage? How to further reduce the measurement errors? In the literature, complicated procedures have been proposed for improvements; see, for example, Fama and French (1992).

In this paper, we compare and contrast a few commonly employed techniques that improve the testing procedure. Some of the methods are derived from econometric theories; some of them come from judgments and observations. We would like to know how they work empirically. The methodology will be detailed in Section 2.

Specifically, most of the proposed methods are aimed at improving the estimations of the betas. The use of first-stage betas as independent variables in the second stage is typical of the errors-in-variable (EIV) problem. Shanken (1992) derives the asymptotic distribution of the t-values in the second stage after the EIV adjustment. We compare the t-values obtained with and without the Shanken's adjustments. Secondly, non-synchronous trading among securities may cause problems in estimating market betas; using Dimson's (1979) method to account for the effect has become a common practice. We will examine the performance of market betas obtained with and without the adjustment.

Thirdly, we examine the betas estimated from portfolios versus those estimated from individual returns. Although estimating portfolio betas is a well-established practice, it is worth comparing the performance of betas estimated from both individual securities and portfolios. Fourthly, we compare the estimation of a single (unconditional) beta and time-varying (conditional) betas. The former benefits from the use of all the available information from the data, but loses the flexibility, while the latter maintains stability by being estimated on a series of sub-samples. Finally, we compare the use of portfolios versus individual security returns in the second stage, including the replacing of individual betas with portfolio betas proposed by Fama and French (1992).

We use data from Taiwan stock returns to examine the above issues, as reported in Section 3. A few researchers have discussed the behavior of cross-sectional returns in Taiwan, for example, Huang (1997), Chui and Wei (1998), Fang and Yau (1998), Sheu, Wu, and Ku (1998), Hung and Lei (2002), Huang et al. (2003), and Huang (2005). However, they have mainly focused on characteristic-based models and have paid less attention to factor models. Among the recent papers, only Chou and Liu (2000) and Chen (2002) have been concerned with the three-factor model. The latter does not employ the two-stage approach. The results from the former are consistent with ours.

Our conclusions surely depend on the data we use, and one must be careful in applying the results obtained to other sets of data. However, the same principle holds for applying the results obtained from the other markets to Taiwan. For example, non-synchronous trading adjustment may be essential to some, say, the U.S. market. In Taiwan's market, the turnovers of most of the stocks are very high, so we do not find it necessary to adjust for non-synchronous trading. Moreover, in our sample, the standard errors of the factor returns are close to those of the risk premium obtained in the second stage, meaning that econometric adjustment for the EIV has virtually no effect on the inferences.

On the other hand, the portfolio grouping greatly reduces the standard errors of the first-stage regressions, especially for unconditional estimations. However, it may not be sufficient to dismiss the betas obtained from the other methods, because they do possess some nice properties. Issues regarding the selection of the estimation method are discussed in Section 4, and Second 5 provides some concluding remarks.

2. Methodology

2.1 The Basic Model

The central prediction of a multi-factor model is that

$$E(r_i) = \mathbb{B}_i'\Gamma, \quad i = 1, 2, \ldots, N,$$

where $E(r_i)$ is the expected excess return of the asset or portfolio i, B_i is a $(K\times 1)$ vector of the factor loadings (betas) of *i*, and Γ is a $(K\times 1)$ vector of the expected risk premiums. As none of the expected returns, factor loadings, or expected risk premiums are observable, the two-stage procedure proposed by Fama and MacBeth (1973) is often employed to test the model. The first stage is to obtain the factor loadings by regressing time-series returns on the factor returns

$$r_{i,t} = \beta_{0,i} + \sum_{k=1}^{K} \beta_{k,i} F_{k,t} + \varepsilon_{i,t}, \quad t = 1, 2, \ldots, T, \tag{1}$$

where $r_{i,t}$ represents excess returns for asset i at time t and $F_{k,t}$ represents returns for factor k.

The estimated $\hat{\beta}$'s from the first stage are used to run the cross-sectional regressions in the second stage

$$r_{i,t} = \gamma_{0,t} + \sum_{k=1}^{K} \gamma_{k,t} \hat{\beta}_{k,i} + \eta_{i,t}, \quad \mathrm{i} = 1, 2, \ldots, \mathrm{N}. \tag{2}$$

$\hat{\gamma}_{k,t}$ is the estimated risk premium of factor k at time t. Next, t-tests are performed on the average $\hat{\gamma}_{k,t}$'s; this step is also called the third stage.If the t-value of $\hat{\gamma}$ is significant, then this factor explains the expected returns well.

In this work, the focus is testing Fama-French (1993) three-factor model. The three factors are the market factor *(MKT)*, the small-minus-big-size factor *(SMB)*, and the high-minus-low-value factor *(HML)*. Equation (1) may therefore be rewritten as

$$r_{i,t} = \beta_{0,i} + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t}, \tag{3}$$

and (2) may be written as

$$r_{i,t} = \gamma_{0,t} + \sum_{k=1}^{3} \gamma_{k,t} \hat{\beta}_{k,i} + \eta_{i,t}. \tag{4}$$

Finally, to test the null hypothesis that the risk premium are non-zero, the time-series $\hat{\gamma}$'s are averaged

$$t(\gamma_k) \equiv \frac{\frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_{k,t}}{se(\hat{\gamma}_{k,t})} = 0, \quad k = 1, 2, 3, \tag{5}$$

where se($\hat{\gamma}_{k,t}$) is the estimate of the standard error of $\hat{\gamma}_{k,t}$

2.2 Estimation Issues

The main problem encountered in testing the validity of the factor models arises from the fact that the betas are not observable. In the Fama-MacBeth procedure, the betas used in Equation (4) have to be estimated from (3). This is a typical errors-in-variable (EIV) problem. The econometric treatment of the EIV problem will be discussed later. In addition to implementing the proper econometric procedure, the literature has developed sophisticated procedures to reduce the potential damage of the EIV problem. The procedures include grouping, rolling, and replacing.

2.2.1 Grouping

Although a valid factor model must hold for both individual assets and portfolios, the Fama-MacBeth procedure is often performed on portfolios alone. In terms of reducing the EIV problem, the idiosyncratic risk of portfolios is smaller than that of individual assets, meaning that the estimation of factor loading is presumably more precise. In other words, portfolio betas are less subject to the EIV problem. There are other benefits to using portfolios. For example, it is easier to interpret the results obtained from the less numerous portfolios (usually dozens), while it is tedious if not meaningless to report the results from the hundreds or even thousands of individual assets.

Specifically, if N assets are grouped into G portfolios with returns $r_{g,t}$ at time t, where $g = 1, 2, \ldots, G$, then the first-stage equation (3) has to be rewritten as

$$r_{g,t} = \beta_{0,g} + \beta_{1,g} MKT_t + \beta_{2,g} SMB_t + \beta_{3,g} HML_t + \varepsilon_{g,t}, \quad (6)$$

and (4) should be rewritten as

$$r_{g,t} = \gamma_{0,t} + \sum_{k=1}^{3} \gamma_{k,t} \hat{\beta}_{k,g} + \eta_{i,t}. \quad (7)$$

However, portfolio estimation does have side effects. Some of the cross-sectional variation of individual stocks is lost during portfolio construction. If the returns used in the second stage are the same as in the first stage, as in Fama and MacBeth (1973), then the sample size can be greatly reduced and the power of estimation is much less. In this work, we compare and contrast the performance of the three-factor model using both group and individual returns in the second stage.

2.2.2 Rolling

Are factor loadings for an asset constant over time? It is possible that factor loadings for assets or portfolios will vary over time, but the changes in the factor loadings may not be very volatile. Consequently, Fama and MacBeth (1973) assume that betas would change every year. They estimate the beta using the past four years of data. Later researchers such as Chen, Roll, and Ross (1986) also follow this approach, except that five years of data are used. As in Chou and Liu (2000), the betas estimated following this procedure are called "conditional" betas.

We adhere to Fama and French's 1992 convention to rebalance the factor portfolios, to rebalance the return portfolios, and to estimate the conditional betas at the beginning of each July. In other words, each July (month t) we estimate the betas using data from the past five years

$$r_{i,t-\tau} = \beta_{0,i,t} + \beta_{1,i,t} MKT_{t-\tau} + \beta_{2,i,t} SMB_{t-\tau} + \beta_{3,i,t} HML_{t-\tau} + \varepsilon_{i,t-\tau}, \tag{8}$$

where $\tau = 1, 2, \ldots, 60$. The estimated $\hat{\beta}_{k,i,t}$ are used for the next twelve months, that is, between month t and month $t + 11$. The group betas $\hat{\beta}_{k,g,t}$ can be estimated using a similar approach

$$r_{g,t-\tau} = \beta_{0,g,t} + \beta_{1,g,t} MKT_{t-\tau} + \beta_{2,g,t} SMB_{t-\tau} + \beta_{3,g,t} HML_{t-\tau} + \varepsilon_{g,t-\tau}, \tag{9}$$

In contrast, "unconditional" betas are those which are estimated using the full sample, that is, the individual betas in (3) or the group betas in (6).

2.2.3 Replacing

The conditional method is not without drawbacks. The estimation period is much shorter than the sample period. If the factor loadings vary considerably, then the conditional method may produce better estimates. If they do not, then Chan and Chen (1988) argue that it is better to use whole-period data. Fama and French (1992) propose another way to solve the problem. Recognizing the possibility of time-varying betas for individual stocks, they use Equation (6) to estimate the unconditional group betas. In the second stage of regression (4), individual betas $\hat{\beta}_{k,i}$ are replaced with the group betas $\hat{\beta}_{k,g(i)}$ from (6), provided asset i is grouped in portfolio g at time t. That is, they estimate

$$r_{i,t} = \gamma_{0,t} + \sum_{k=1}^{3} \gamma_{k,t} \hat{\beta}_{k,g(i)} + \eta_{i,t}, \quad i = 1, 2, \ldots, N. \tag{10}$$

The conditional group beta $\hat{\beta}_{k,g,t}$ can be used to replace an individual beta in a similar way. We call the replacement procedure the "group beta to individual return" approach, or "g2i" for short. The other procedures include "allocating portfolio betas to portfolio returns" ("g2g") and "allocating asset betas to asset returns" ("i2i"). The three different procedures are examined in the next section.

2.2.4 Errors-in-Variables

Shanken (1992) proves that the average of $\hat{\gamma}_{k,t}$ from the second stage Fama-MacBeth procedure yields consistent estimators of the risk premium, and more importantly, he provides the asymptotic distribution of the average $\hat{\gamma}_{k,t}$. The adjustment can be implemented on either the "g2g" or the "i2i" procedure. Taking the "i2i" procedure as an example, we denote $\overline{\Gamma}$ the vector of risk premium estimated from the cross-sectional regression in Black, Jensen, and Scholes (1972):

$$\bar{r}_i = \gamma_0 + \sum_{k=1}^{3} \gamma_k \hat{\beta}_{k,i} + \eta_i,$$

where $\bar{r}_i$ is the average of $r_{i,t}$, $t = 1, 2, \ldots T$ and $\hat{\beta}_{k,i}$ is estimated from (3).

Furthermore, let $\hat{\Sigma}_F$ be the variance of the factor returns and $\hat{\Sigma}_F^*$ is defined as $\hat{\Sigma}_F$ bordered with zeros in the top row and the top column. The unconditional EIV-adjusted variance-covariance matrix of in (4) is now given by

$$\hat{\Sigma}_{\hat{\gamma}} = \frac{1}{T}[(1+c)(\hat{W} - \hat{\Sigma}_F^*) + \hat{\Sigma}_F^*], \qquad (11)$$

where c is $\hat{c} = \bar{\Gamma}'\hat{\Sigma}_F^{-1}\bar{\Gamma}$, and $\hat{W}$ is the sample variance-covariance matrix of the time series of $\hat{\gamma}_{k,t}$. The square roots of the diagonal elements of $\hat{\Sigma}_{\hat{\gamma}}$ are the standard errors of $\hat{\gamma}_k$ and are substituted for se($\hat{\gamma}_{k,t}$) in (5) to perform the t-tests.

The EIV-adjustment coefficient c has to be modified for the conditional betas. In our sample, sixty monthly-return observations are used to estimate the annual beta; the procedure is performed for fifteen years. According to Shanken, in (11), $(1 + (1 - 1.6/15)c)$ should be used instead of $(1 + c)$ to adjust the standard errors of gammas.

2.2.5 Non-synchronous trading

The return of the market portfolio is central to the CAPM as well as the Fama-French three-factor model. In practice, an index return is often used as a proxy for the market return. An index is computed from the prices of a basket of assets, some of which may be infrequently traded. As a result, an asset return may not be closely related to the market return simply because the sampling times of the two are not perfectly matched. To overcome this problem, Dimson (1979) proposes to regress the asset returns on current and past index returns, which has been adopted by Fama and French (1992). Although Fama and French (1993) do not include the lag term in their three-factor model, Chou and Liu (2000) have made such an adjustment for Taiwanese stock market estimations. To see how the estimation is sensitive to the adjustment, we estimate the factor loading by

$$r_{i,t} = \beta_{0,i} + \beta_{1,i}MKT_t + \beta_{-1,i}MKT_{t-1} + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \varepsilon_{i,t}, \quad (12)$$

and use the sum of $\hat{\beta}_{1,i}$ and $\hat{\beta}_{-1,i}$ in the second stage to estimate the market risk premium:

$$r_{i,t} = \gamma_{0,t} + \gamma_{1,t}(\hat{\beta}_{1,i} + \hat{\beta}_{-1,i}) + \gamma_{2,t}\hat{\beta}_{2,i} + \gamma_{3,t}\hat{\beta}_{3,i} + \eta_{i,t}. \quad (13)$$

3. Empirical Results

3.1 Data

We collect the Taiwan Stock Exchange Corporation (TSEC) stock data from Taiwan Economic Journal (TEJ) database. Few stocks were listed in the early years, so we only use the data between December 1981 and June 2002. Firms must have been listed for at least two years before their data can be included into the sample.

To construct the factors, we follow Fama and French (1993). The *MKT* factor $(r_m - r_f)$ is the market return, r_m, minus the risk free rate, r_f. The one-month TSE index (TAIEX) return is the proxy of r_m, which is value-weighted, ex-dividend, and includes almost all of the listed stocks. Since the liquidity of the treasury bill rate in Taiwan is notoriously low, we use the average one-month domestic bank deposit rate obtained from the web site of the Central Bank of China as the risk free rate.

The next step is to compute the firm sizes (ME) and the book-to-market values (BE/ME). We use a firm's book and market equity at the end of December for the year $n - 1$ to compute its BE/ME in year n, and its market equity for June to measure its ME. The market values provided by the TEJ are rounded off to millions of NT dollars, which causes some problems in grouping the stocks. Therefore, we re-compute ME by multiplying common shares outstanding (rounded off to thousand shares) by the stock price, then divide by ten. The book value of equity (BE) is defined as the TEJ book value of the stockholders' equity, plus the balance sheet deferred taxes and investment tax credit, minus the book value of the preferred stock. Thus, the book-to-market equity (BE/ME) is BE divided by ME for the fiscal year ending in calendar year $n - 1$.

At the end of June in each year n, stocks on the TSE with positive BEs are allocated to three book-to-market equity groups based on breakpoints of the bottom 30 % *(L)*, middle 40 % *(M)*, and top 30 % *(H)* of the values of BE/ME. These stocks are also allocated to either the small *(S)* or the big *(B)* group based on whether their June market equity is below or above the median ME. The six size-BE/ME portfolios, *S/L, S/M, S/H, B/L, B/M* and *B/H,* are the intersections of the two ME and the three BE/ME groups. The returns for the six portfolios are used to compute the factor returns. The returns for the "small-minus-big" factor *(SMB)* are the monthly difference between the average returns for the three small-stock portfolios *(S/L, S/M, S/H),* and the average returns for the three big-stock portfolios *(B/L, B/M, B/H)*. The returns for the "high-minus-low" factor *(HML)*, are the monthly difference between the average returns for the two high-BE/ME portfolios *(S/H* and B/H) and the average returns for the two low-BE/ME portfolios *(S/L* and *B/L).*

In Figure 1, the accumulated wealth of investing one dollar in each of the three factor portfolios in July 1982 and rebalancing them each July is plotted. The *MKT* portfolio yields the highest return with the biggest variation. The *HML* portfolio performs poorly, with a loss of about 18.5% at the end of June 2002. The returns for the *SMB* portfolio increase slightly with the smallest variation. Apparently, the factor returns are not correlated. The correlation coefficient are -0.01 between *MKT* and *SMB*, 0.003 between *MKT* and *HML*, and 0.13 between the *SMB* and the *HML.*

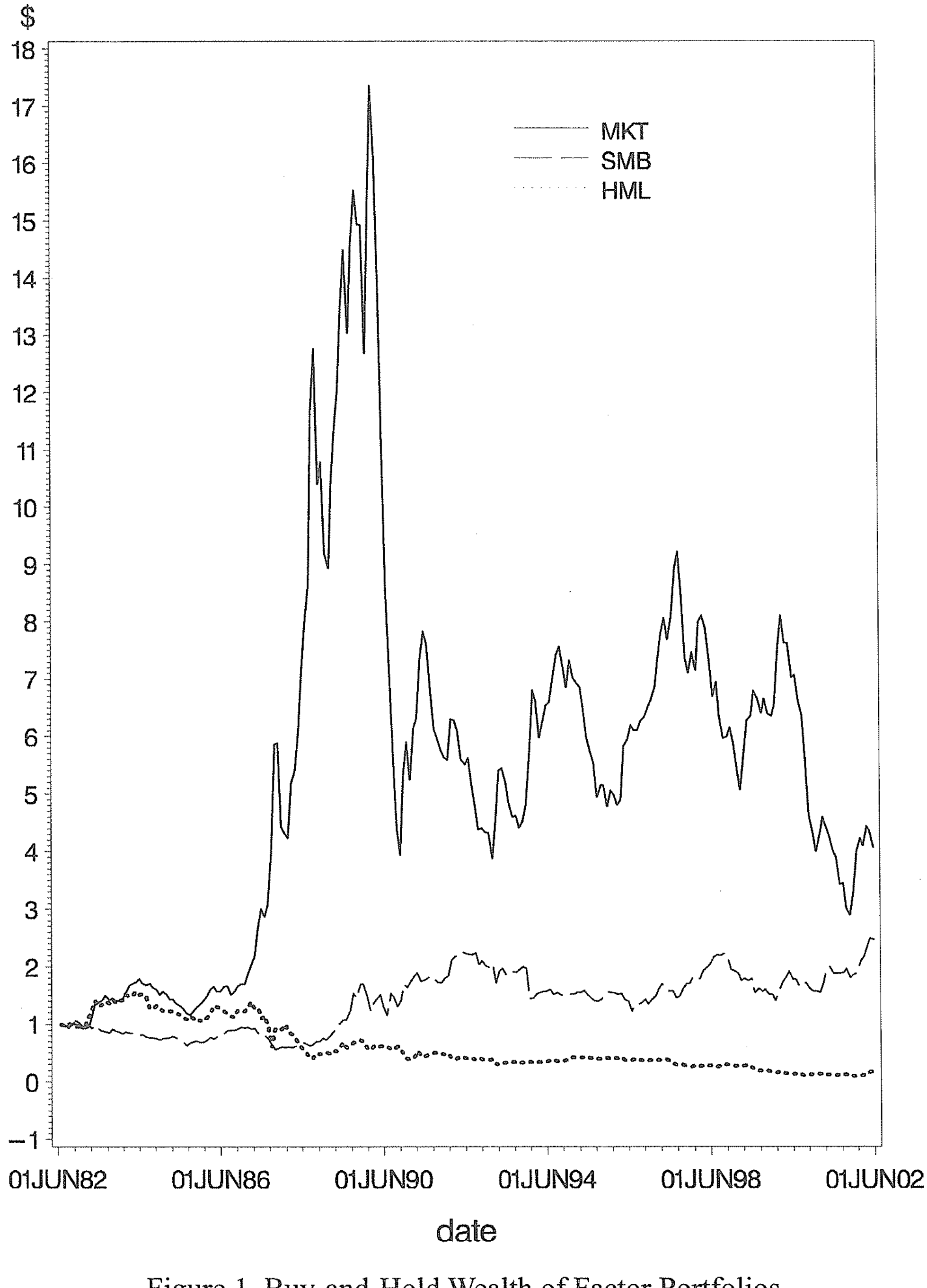

Figure 1. Buy-and-Hold Wealth of Factor Portfolios

In this figure the accumulated wealth for investing one dollar in the three factor portfolios (*MKT*, *SMB*, and *HML*) at the beginning of July 1982 and re-balancing the portfolios annually is plotted.

3.2 Returns

The data set consists of 57,456 monthly stock returns from 590 firms. Following Chou and Liu (2000), we group the stocks by year into twenty-five portfolios. Beginning into July of year n, we first classify the stocks into five portfolios based on their ME in June of n; then we further divide each portfolio into five according to the BE/ME at the end of year $n-1$. This procedure differs from the independent sort procedure used by Fama and French (1993), as their

Table 1: Summary of the Statistics

Twelve months of stock returns beginning in July each year are included in the sample provided (a) the stock had been listed on the TSEC for two years, (b) the June market value is available for that year, and (c) the book-to-market ratio (BE/ME) at the end of the previous year is positive. The stock returns are further grouped into twenty-five portfolios according to the stocks' market values and BE/ME ratios. Panel A reports the total number of firms in the sample in the selected year and the average number of firms forming the portfolios. Panel B reports the time-series average returns for each size-BE/ME portfolio.

Panel A: Number of Firms

Year	1982	1987	1992	1997	2002
Total Number of Firms	74	105	201	382	537
Firms Per Group	3.0	4.2	8.0	15.3	21.5

Panel B: Mean Group Returns

	Book-to-Market Quintile									
Size	low	2	3	4	high	low	2	3	4	high
quintile	Mean Returns					Standard Deviations				
small	3.45	3.27	2.76	2.18	2.36	15.37	15.51	13.64	13.60	15.06
2	3.42	2.12	2.14	1.85	2.00	15.63	12.74	13.70	12.01	13.88
3	3.04	2.22	2.08	1.45	2.22	15.08	13.63	12.61	10.97	13.65
4	3.56	2.02	2.12	1.33	1.90	15.66	14.56	13.87	12.00	11.99
big	3.84	2.21	2.49	1.99	1.71	18.49	16.07	15.58	13.95	13.73

approach would create empty portfolios for some of the years in our sample. The group returns are the value-weighted averages of the individual returns, and the grouping lasts for twelve months.

Table 1 summarizes the data. Panel A shows the statistics of the firms included in the sample. During the last quarter of a century, the number of firms listed in the TSEC has grown, and therefore, the sample increases from 74 firms in 1982 to 537 in 2002. Each size-BE/ME group is allocated with roughly equal number of firms each year, increasing from 3.0 in 1982 to 21.5 in 2002.

The mean returns for each portfolio are reported in Panel B. Similar to Chou and Liu (2000), there is no monotonic relationship with the size or book-to-market sort, but small stocks and low BE/ME stocks tend to have higher returns. The lowest returns tend to occur in the second biggest size group or the second highest BE/ME group, when the other characteristic is controlled. On the other hand, the highest returns tend to take place with the smallest ME or the lowest BE/ME group, which is different from Chou and Liu (2000).

3.3 Betas

Table 2 presents the statistics of the coefficients estimated from the first stage regressions. $\hat{\beta}_0$ is the estimated intercept and $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ are, respectively, the estimated coefficients for the returns of *MKT*, *SMB*, and *HML*. Panel A shows the betas estimated from the individual return regression models (3) and (8); the betas in Panel B are estimated from the group return models (6) and (9). In each panel both the unconditional betas and conditional betas and the R-squares from the regressions are presented.

The unconditional estimation yields slightly bigger mean betas estimates than does the conditional estimation in both panels. This is also true of the medians in general, except that the individual $\hat{\beta}_2$ of the unconditional estimation is smaller. Neither estimation yields universally bigger standard deviations or ranges in individual betas, while the standard deviations and the ranges of the group

Table 2: Beta Statistics

Panel A shows unconditional and conditional betas estimated from individual returns by regression models (3) and (8), respectively; the betas in Panel B are estimated from group return models (6) and (9). Apart from the maximum (Max), mean, median, minimum (Min), and standard deviation (Std) of the cross-sectional betas, the table also reports the $\overline{se(\beta)}$, the average standard errors of the betas, "Frac 0", the proportion of insignificant betas on the 0.1 level, *Wk*, the Wald statistics under the null hypothesis that all betas are jointly zero, *Df(W)*, the degrees of freedom of W_k in the Chi-square tests, and p*(W)*, the p-values of the tests. For the conditional betas, the time-series average of $W_{k,t}$ and the average degrees of freedom are reported.

Panel A: Individual Betas

	Unconditional Betas					Conditional Betas				
	$\hat{\beta}_{0,i}$	$\hat{\beta}_{1,i}$	$\hat{\beta}_{2,i}$	$\hat{\beta}_{3,i}$	R^2	$\hat{\beta}_{0,i}$	$\hat{\beta}_{1,i}$	$\hat{\beta}_{2,i}$	$\hat{\beta}_{3,i}$	R^2
Max	17.61	3.97	6.41	1.95	0.9970	18.61	3.47	3.25	2.99	0.8570
Mean	0.98	1.03	0.26	0.16	0.3774	0.24	0.86	0.26	0.14	0.3760
Median	0.50	0.94	0.20	0.21	0.3672	0.16	0.83	0.22	0.20	0.3736
Min	-6.58	-1.71	-2.44	-2.52	0.0098	-8.69	-0.30	-2.27	-3.16	0.0032
Std	2.25	0.52	0.67	0.54	0.1485	1.71	0.36	0.63	0.56	0.1490
$\overline{se(\beta)}$		0.23	0.37	0.21			0.23	0.31	0.29	
Frac 0		0.06	0.62	0.38			0.18	0.54	0.58	
W_k		22730	4006	4749			4623	1420	1010	
Df*(W)*		590	590	590			233.5	233.5	233.5	
p*(W)*		<0.0001	<0.0001	<0.0001			<0.0001	<0.0001	<0.0001	

Panel B: Group Betas

	Unconditional Betas					Conditional Betas				
	$\hat{\beta}_{0,g}$	$\hat{\beta}_{1,g}$	$\hat{\beta}_{2,g}$	$\hat{\beta}_{3,g}$	R^2	$\hat{\beta}_{0,g}$	$\hat{\beta}_{1,g}$	$\hat{\beta}_{2,g}$	$\hat{\beta}_{3,g}$	R^2
Max	2.29	1.08	1.12	0.63	0.6198	3.25	1.17	1.78	0.99	0.8192
Mean	1.26	0.91	0.42	0.11	0.5286	1.07	0.88	0.31	0.06	0.5433

Median	1.19	0.91	0.47	0.13	0.5257	0.98	0.88	0.32	0.12	0.5442
Min	0.49	0.72	-0.43	-0.63	0.4425	-0.85	0.33	-1.15	-1.07	0.2964
Std	0.45	0.08	0.50	0.35	0.0515	0.76	0.13	0.59	0.40	0.0968
$\overline{se(\beta)}$		0.06	0.10	0.07			0.13	0.20	0.16	
Frac 0		0.00	0.04	0.24			0.00	0.38	0.43	
W_k		5102	992	605			1169	319	159	
Df(W)		25	25	25			25	25	25	
p(W)		<0.0001	<0.0001	<0.0001			<0.0001	<0.0001	<0.0001	

betas from unconditional estimation are smaller than those from the conditional estimation. There is not much difference between the mean or median R-squares provided by the two estimation methods. However, all of the R-squares are smaller than those in Fama and French (1993) (between 0.83 and 0.97) and Chou and Liu (2000) (between 0.81 and 0.93).

The difference between the individual and group betas is pronounced. Although the mean and the median of $\hat{\beta}_1$ are similar for the two sets of returns, those of individual $\hat{\beta}_2$ ($\hat{\beta}_3$) are lower (higher) than those of group betas under both estimation methods. Moreover, the betas from the individual returns exhibit bigger ranges and standard deviations. The R-squares of individual return regressions are in general smaller than those of group return regressions.

Fama and French (1992) argue the precision of the unconditional group betas outweighs the fact that individual betas in the portfolio are not the same. The average standard errors of the betas from our sample, $\overline{se(\beta)}$, support their claim. The standard errors of the group betas are smaller than those of the individual betas. The standard errors of the group betas under the unconditional estimation method are about a half of those under the conditional estimation method. The two estimation methods result in similar standard errors for the individual betas.

The next row in each panel shows the fractions of betas that do not reject the hypothesis that they equal to zero. The significant level is 0.1. Kan and Zhang (1999) argue that a factor may not be useful if all of its betas are not different from zero. The individual $\hat{\beta}_2$ and $\hat{\beta}_3$ fractions are quite large compared with those of $\hat{\beta}_1$. The bottom rows present the Wald statistics, its degrees of freedom and p-values under the null hypothesis that all betas are jointly zero,

$$W_k = \hat{\boldsymbol{\beta}}_k' Var(\hat{\boldsymbol{\beta}}_k)^{-1} \hat{\boldsymbol{\beta}}_k \sim \chi^2_{df},$$

where $\hat{\boldsymbol{\beta}}_k' = (\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3)$ is the vector of the estimated cross-sectional betas, with the variance-covariance matrix $Var(\hat{\boldsymbol{\beta}}_k)$. Assuming that $\hat{\beta}_{k,i}$ ($\hat{\beta}_{k,g}$) is uncorrelated, the variance-covariance matrix is one with $Var(\hat{\boldsymbol{\beta}}_{k,i})$ ($Var(\hat{\boldsymbol{\beta}}_{k,g})$) on the diagonal, and zero elsewhere. The $W_{k,t}$ of the conditional beta can be calculated in a similar way for $\hat{\beta}_{k,i,t}$ ($\hat{\beta}_{k,g,t}$) in year t

$$W_{k,t} = \hat{\boldsymbol{\beta}}_{k,t}' Var(\hat{\boldsymbol{\beta}}_{k,t})^{-1} \hat{\boldsymbol{\beta}}_{k,t} \sim \chi^2_{df},$$

The table reports the time-series average $W_{k,t}$ for the conditional betas. The Wald statistics follow a Chi-square distribution with degrees of freedom equal to the number of betas being tested. In other words, for the group betas, the degrees of freedom are 25, and for the individual betas, the (average) degrees of freedom are 590 and 233.5, for unconditional and conditional betas, respectively. All of the Wald statistics are very large; the p-values are all smaller than 0.0001, which indicates that all three factors are potentially useful in explaining the expected returns.

3.4 Risk premium

Table 3 presents the risk premiums (gammas) from the second-stage regressions. Panel A shows the results obtained from individual returns with individual betas (the "i2i" procedure), Panel B shows the results from individual returns with group betas (the "g2i" procedure), and Panel C shows the results for group returns with group betas (the "g2g" procedure). The risk premium in each panel may be estimated by either unconditional or conditional betas. $\hat{\gamma}_1$, $\hat{\gamma}_2$, and $\hat{\gamma}_3$ are, respectively, the estimated risk premiums for $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$.

Table 3: Gamma Statistics

This table presents the maximum (Max), third quartile (Q3), mean, median, first quartile (Q1), minimum (Min) and the standard deviation (Std) of the the risk premium($\hat{\gamma}$'s) from the second-stage regressions and the regression R2s. Panel A shows the results obtained from individual returns with individual betas (the "i2i" procedure), Panel B shows the results from individual returns with group betas (the "g2i" procedure), and Panel C shows the results from group returns with group betas (the "g2g" procedure).

Panel A: Individual Betas to Individual Returns (i2i)										
	Unconditional					Conditional				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2
Max	30.66	54.90	35.40	54.29	0.6212	51.37	36.17	31.07	18.02	0.5906
Q3	5.35	6.21	2.04	3.12	0.2232	6.15	3.57	2.07	2.28	0.1403
Mean	0.46	1.48	-0.13	-1.09	0.1588	1.18	0.36	0.37	-0.07	0.1062
Median	-0.30	0.05	-0.50	-0.77	0.1245	0.05	-0.26	-0.03	-0.01	0.0806
Q1	-4.99	-5.62	-3.57	-5.27	0.0606	-5.98	-3.64	-2.34	-3.02	0.0368
Min	-35.19	-24.88	-27.55	-48.07	0.0032	-30.96	-26.02	-22.10	-25.57	0.0006
Std	8.94	10.83	6.67	9.69	0.1277	11.98	8.23	5.56	6.48	0.0987

Panel B: Group Betas to Individual Returns (g2i)										
	Unconditional					Conditional				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2

Max	55.37	70.98	34.83	37.23	0.5370	63.19	40.96	32.51	33.49	0.5154
Q3	7.60	11.55	2.52	3.78	0.1447	7.67	7.12	2.94	3.13	0.1145
Mean	-1.56	3.24	0.46	-0.49	0.1081	-0.75	2.27	0.87	-0.51	0.0916
Median	-1.38	1.04	0.06	-0.40	0.0748	-0.54	1.06	0.48	-0.27	0.0631
Q1	-10.63	-9.00	-2.52	-4.60	0.0339	-10.03	-3.75	-2.13	-4.42	0.0262
Min	-58.12	-51.95	-22.96	-25.68	0.0020	-43.77	-33.14	-20.31	-20.59	0.0015
Std	16.56	19.26	6.37	8.27	0.1038	14.91	11.94	6.65	7.74	0.0904

Panel C: Group Betas to Group Returns (g2g)

	Unconditional					Conditional				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2
Max	57.31	96.77	37.08	47.45	0.8784	75.09	53.45	34.67	43.39	0.8254
Q3	8.05	14.10	3.52	3.72	0.5513	8.25	8.30	3.63	2.61	0.5421
Mean	-1.98	3.97	0.87	-0.58	0.3881	0.13	1.80	1.30	-0.66	0.3811
Median	-1.87	1.91	0.42	-0.47	0.3794	0.33	0.09	1.01	-0.31	0.3859
Q1	-10.85	-10.30	-2.50	-4.68	0.2087	-9.98	-5.42	-2.29	-4.44	0.2345
Min	-71.49	-54.62	-25.51	-33.00	0.0083	-47.47	-48.68	-23.06	-25.60	0.0074
Std	17.70	21.73	6.90	9.03	0.2190	16.15	14.68	7.25	8.50	0.2014

A comparison of the means and medians of the unconditional-beta estimation and the conditional-beta estimation shows a seemingly small difference in the betas, as in Table 2, turns out to create a big difference in the gammas. In general, $\hat{\gamma}_1$ is bigger under unconditional than under conditional estimations. The only exception occurs in the medians in panel B, where the unconditional $\hat{\gamma}_1$ is smaller than the conditional counterpart by 0.02. By contrast, the $\hat{\gamma}_2$ of the unconditional estimation is smaller than under the conditional estimation; neither estimation method universally yields a higher $\hat{\gamma}_3$. Variations in the standard deviation, the range and the inter-quartile range of the gammas are bigger under the unconditional estimation method. The R-squares of the models for unconditional betas are also slightly bigger.

A comparison of the mean and median gammas produced by individual and group returns shows that the magnitudes of the means and medians of the "i2i" gammas are often the smallest except for a $\hat{\gamma}_3$ under conditional estimation, which is the biggest. The "g2i" $\hat{\gamma}_3$ under an unconditional estimation and $\hat{\gamma}_1$ under an conditional estimation are the biggest. The "g2g" $\hat{\gamma}_1$ under and unconditional estimation and the $\hat{\gamma}_2$ under both types of estimation are the biggest.

The variations in the standard deviation, the range and the inter-quartile range of the "g2g" gammas are always greater than the corresponding "g2i" gammas, and are also often greater than the "i2i" gammas. The variation between "i2i" and "g2i" is similar. Furthermore, the R-squares of the "g2g" regressions are the biggest; those of the "g2i" are the smallest.

3.5 The tests

Table 4 lists the t-values of the mean gammas. Both the simple and the EIV-adjusted t-values for the "i2i" and "g2g" gammas are reported. Shanken's (1992) EIV-adjustment method requires that the returns used in the first and the second pass regressions be the same, meaning that it cannot be applied to the "g2i" gammas. However, the adjustments do not change the results very much. The biggest adjustment takes place to the t-values of "g2g" $\hat{\gamma}_i$; these fall by nearly 7% under unconditional and conditional estimations. The other adjustments change the rest of the "g2g" t-values by less than 0.4; the "i2i" t-values are almost unchanged after the adjustments.

Table 4: Gamma Tests

This table presents the mean, the t-value, and the Shanken's (1992) EIV-adjusted t-value of the time-series risk premium $\hat{\gamma}_i$. Panel A shows the results obtained from individual returns with individual betas (the "i2i" procedure), Panel B shows the results from individual returns with group betas (the "g2i" procedure), and Panel C shows the results from group returns with group betas (the "g2g" procedure). One, two, and three asterisks (*) indicates that the t-values are significant at the 0.1, 0.05, and 0.01 level, respectively.

Panel A: Individual Betas to Individual Returns (i2i)								
	Unconditional				Conditional			
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$
Mean	0.46	1.48	-0.13	-1.09	1.18	0.36	0.37	-0.07
t-value	0.80	2.12**	-0.30	-1.75*	1.32	0.59	0.90	-0.15
t-EIV	0.79	2.12**	-0.30	-1.75*	1.31	0.59	0.90	-0.15
Panel B: Group Betas to Individual Returns (b2i)								
	Unconditional				Conditional			
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$
Mean	-1.56	3.24	0.46	-0.49	-0.75	2.27	0.87	-0.51
t-value	-1.46	2.61***	1.11	-0.92	-0.67	2.55**	1.75*	-0.88
Panel C: Group Betas to Group Returns (g2g)								
	Unconditional				Conditional			
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$
Mean	-1.98	3.97	0.87	-0.58	0.13	1.80	1.30	-0.66
t-value	-1.73*	2.83***	1.96*	-1.00	0.11	1.64	2.40**	-1.05
t-EIV	-1.58	2.64***	1.93*	-0.99	0.10	1.54	2.38**	-1.09

Chou and Liu (2000) perform an unconditional estimation of the "g2i" procedure. They find that $\hat{\gamma}_1$ is significant, whereas $\hat{\gamma}_2$ and $\hat{\gamma}_3$ are not. We obtain the same result using the same approach, but the result will be different if the estimation method changes. The significance of the gammas depends on the dependent variables (individual or group returns), on the estimation method (unconditional or conditional), and by definition, on the level of significance. If we choose 0.01 as the significance level, then only the "g2i" and "g2g" $\hat{\gamma}_1$ are significant under unconditional estimation. If we choose 0.1 as the significance level, then the other four gammas are significant. Of the six sets of gammas, four $\hat{\gamma}_1$, three $\hat{\gamma}_2$, and one $\hat{\gamma}_3$ are significant when the level is 0.10. However, the signs of the coefficients are quite consistent. All of the $\hat{\gamma}_1$ are positive, all but one $\hat{\gamma}_2$ is positive, and all the $\hat{\gamma}_3$ are negative.

We now summarize the conclusions that may be drawn from our sample:

- Do not accept any factor: set the significance level to 0.01; use either the "i2i" procedure or conditional betas.
- Accept only the *MKT* factor: use the unconditional betas and set the significance level to no greater than 0.05.
- Accept only the *SMB* factor: use the conditional group betas and set the significance level to no smaller than 0.05.
- Accept only the *HML* factor: such a conclusion is not supported with our sample.
- Accept only the *MKT* and *SMB* factors: use the "g2g" procedure on the unconditional betas or the "g2i" procedure on the conditional betas; set the significance level to 0.1.
- Accept only the *MKT* and *HML* factors: use the "i2i" procedure on the unconditional betas and set the significance level to 0.1.
- Accept only the *SMB* and *HML* factors: such a conclusion is not supported by our sample.
- Accept all three factors: such a conclusion is not supported with our sample.

3.6 Non-Synchronous Trading Adjustments

Table 5 shows the test statistics for gammas after adjustments for non-synchronous trading, that is, (12) and (13) respectively, are used for the first and the second pass regressions. The adjustment, however, does not much affect the estimation, because $\hat{\beta}_{1,i}$ and ($\hat{\beta}_{1,i}+\hat{\beta}_{-1,i}$) are highly correlated. The lowest correlation coefficient ranges from 0.8340 for conditional group betas to 0.9129 for unconditional group betas. Compared with Table 4, the biggest difference occurs for unconditional estimation of "i2i" $\hat{\gamma}_1$ and $\hat{\gamma}_3$. The t-values respectively shrink by 0.72 and 0.84 respectively, and become insignificant. The means and t-values for the rest of the gammas are not very different from those in Table 4. Table 5 also reports the mean, median, and standard deviations of the R-squares from the second stage regression. A comparison with Table 3 shows that the mean and median R-squares, with and without adjustments, are very similar. Thus, the adjustment for non-synchronous trading does not materially change the second-stage estimation.

Table 5: Gamma Statistics Adjusted for Non-Synchronized Trading

This table presents the mean, median, standard deviation (Std), and the t-value of the risk premium ($\hat{\gamma}_i$'s) from the second-stage regressions and the regression R-squares, where the betas are computed by Dimson's (1979) method to adjust for non-synchronous trading. Panel A shows the results obtained from individual returns with individual betas (the "i2i" procedure), Panel B shows the results from individual returns with group betas (the "g2i" procedure), and Panel C shows the results from group returns with group betas (the "g2g" procedure). One, two, and three asterisks (*) indicates that the t-values are significant at the 0.1, 0.05, and 0.01 level, respectively.

Panel A: Individual Betas to Individual Returns (i2i)										
	Unconditional					Conditional				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2

Mean	1.10	0.94	-0.05	-0.99	0.1547	1.33	0.17	0.39	-0.07	0.1048
Median	0.85	0.20	-0.29	-0.91	0.1177	0.19	-0.55	0.00	-0.10	0.0698
Std	10.27	10.41	6.76	9.47	0.1257	12.54	7.63	5.77	6.37	0.1005
t-value	1.66*	1.40	-0.12	-1.63		1.42	0.31	0.91	-0.16	
Panel B: Group Betas to Individual Returns (g2i)										
	Unconditional					Conditional				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2
Mean	-1.17	3.51	0.47	-0.54	0.1084	-0.20	2.08	0.90	-0.49	0.0907
Median	-1.48	1.98	-0.08	-0.45	0.0756	-0.81	2.44	0.50	-0.40	0.0604
Std	15.95	21.08	6.38	8.32	0.1021	13.99	10.32	6.70	7.76	0.0907
t-value	-1.14	2.58**	1.14	-1.01		-0.19	2.71**	1.79*	-0.84	
Panel C: Group Betas to Group Returns (g2g)										
	Unconditional					Conditional				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$	R^2
Mean	-1.75	4.64	0.87	-0.67	0.3923	0.37	1.96	1.33	-0.64	0.3806
Median	-1.60	2.57	0.47	-0.24	0.3891	0.07	1.25	1.09	-0.47	0.3961
Std	16.92	23.87	6.90	9.06	0.2168	14.78	13.52	7.29	8.57	0.2048
t-value	-1.60	3.01***	1.96*	-1.14		0.34	1.94*	2.45**	-1.01	

4. Discussion

In the previous section we examine the three-factor model in different ways. Regardless of the significance of the t-values, the coefficients for the estimates of the risk premium from the second pass regressions are almost the same. Specifically, $\bar{\hat{\gamma}}_1$ is always positive, $\bar{\hat{\gamma}}_2$ is always positive except for the "i2i" under unconditional estimation, and $\bar{\hat{\gamma}}_3$ is always negative. Different ways of estimating and testing the model may change the level of significance of the coefficients, but the signs remain virtually unchanged. The Shanken's EIV adjustment turns out to have too little effect on the t-values to alter any conclusions. The t-values of the "i2i" procedure are almost unchanged. To see the effects of the EIV adjustment we rewrite (11)

$$\hat{\Sigma}_{\hat{\gamma}} = \frac{1}{T}[\hat{W} + c(\hat{W} - \hat{\Sigma}_F^*)].$$

If the EIV adjustment does not change the t-values very much, then either c is small or $\hat{W}$ is close to $\hat{\Sigma}_F^*$. In fact, for our sample both are true. The diagonal elements of $\hat{W}$ consist of the variance of $\hat{\gamma}_i$, and those of $\hat{\Sigma}_F^*$ consist of the variance of the factor returns. The differences between the first two elements (corresponding to $\hat{\gamma}_0$ and $\hat{\gamma}_1$) are around a few hundreds, but the differences between the last two elements (corresponding to $\hat{\gamma}_2$ and $\hat{\gamma}_3$) are often less than ten. Divided by the sample size T, the differences contribute little to the EIV adjustment. Furthermore, the adjustment coefficient c is 0.3 for group returns and 0.01 for individual returns, which offers little help in adjusting the variance of the "i2i" gammas.

The purpose of non-synchronized trading adjustment is to obtain betas that more closely represent the risk-return relationship. In our sample, however, the effect of the adjustment is small. None of the signs of the gammas change after the adjustment, and only one gamma becomes insignificant. In Section 3.6 we attribute the result to the highly correlated $\hat{\beta}_{1,i}$ and $(\hat{\beta}_{1,i} + \hat{\beta}_{-1,i})$. In fact, $\hat{\beta}_{-1,i}$ is often small relative to $\hat{\beta}_{1,i}$. We believe the reason is the turnover in TSEC is so high that the problem of non-synchronized trading is very small.

The above discussion focuses on the consistency of the findings. The main difference is in relation to the statistical significance of the gammas. Different estimation methods yield different results. The bottom line is that the evidence never supports a complete three-factor model, and that one cannot allow *HML* to be a factor without allowing *MKT*. However, note that both the factor returns and the average risk premium of *HML* are always negative in our sample, which is in sharp contrast to those in the U.S. data. Therefore, even if *HML* serves as a factor in Taiwan, its economic implications might be very different from that in other markets.

What should the reader believe? If we resort to the precision of the betas, as shown in Table 2, then the unconditional group betas are the best in terms of fitness (R-squares) and precision ($\overline{se(\beta)}$). Therefore, the results obtained from an unconditional estimation of the "g2g' or "g2i" gammas may be more reliable. However, there is a serious problem with the group beta for the market factor, which is that it does not vary very much. Its standard deviations are 0.08 for the unconditional and 0.13 for the conditional betas. It is doubtful whether conclusions can be drawn from the regression of such an invariant independent variable. Therefore, we are not comfortable with the assertion that only *MKT* is a useful factor.

The conditional versus unconditional betas are partly consistent with the predictions of Chou and Liu (2000), that is, that the choice affects the model inference. Specifically, the use of conditional betas increases the t-values of $\hat{\gamma}_1$, lowers those of $\hat{\gamma}_2$, and has no ambiguous effects on $\hat{\gamma}_3$. However, it is difficult to conclude which method yields better estimates. For example, although the unconditional group betas enjoy better fitness and precision than the conditional group betas, these properties are not seen with individual betas.

5. Conclusions

We have examined several common approaches for implementing the two-stage test on the Fama-French three-factor models using Taiwan stock market data. While the signs of the coefficients of the risk premium are almost the same by these approaches, their significance levels often depend on which approach is used. Overall, much of the evidence supports the *MKT* factor, while the support for the *HML* factor is weak. The adjustments for errors-in-variable or non-synchronous trading do not affect the results very much.

Our findings are consistent with Chou and Liu (2000), who find that the market factor explains the cross-sectional returns. However, this result is not consistent with some of the characteristic-based studies, for example, Huang et al. (2003), even though they use the same unconditional "g2i" approach. This inconsistency may rest on the sample selection or portfolio grouping, which are interesting issues and worthy of future research work.

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