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Common Risk Factors of Tokyo Stock Exchange Firms: In Finding the Mimicking Portfolios

by

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Abstract:

On the basis of the findings in Kubota and Takehara (1995) where we rejected the single risk CAPM specifications in an unconditional form for Japanese non-financial firms listed in the first section of Tokyo Stock Exchanges, in the current paper, we empirically try to find mimicking portfolios that can approximately span the locally mean-variance efficient set in the sense of Grinblatt and Titman (1987). Then, we trasform these initially estimated mimicking portfolios based on the principal component analysis. We hope that this portfolio set can generate insignifinant alpha estimates with robust corresponding multiple betas so that this portfolio set can be used as a good benchmark portfolio set.

Our original data is the monthly observations between September 1981 through June 1993 as in Kubota and Takehara (1995) and new observation will be added as a control sample. We initially use cluster analysis to form 14 portfolios from the set of 41 attribute portfolios. We, then, test whether these 14 base portfolios can approximately span the local mean-variance efficient set of the universe, where three benchmark universe is used; the mean-variance efficient sets formed by the original 41 portfolio set, the larger universe of 71 portfolios expanded from the above 41 portfolios, and 100 portfolios ranked by the size and the book to price ratios used in Kubota and Takehara (1995). For this purpose we use the test statistics generated by Gibbons, Ross and Shanken(1987) and Kandel and Stambaugh(1991).

Then, we run principal components analysis, under the non-full rank conditions as is advocated in Anderson(1958), on the sample of 776 individual securities. We rely on the

*The authors thank Professors K.C. Chan, Naifu Chen, Ravi Jagannathan, Kazuhiko Nishina, Susumu Saito, Sheridan Titman, and participants at Finance Workshop of Hong Kong University of Science and Technology for helpful discussions of the currnet paper. All remaining errors, however, belong to the authors.

result, proven by Grinblatt and Titman (1985), that the principal components analysis can get correct factor numbers and factor loadings under the approximate factor structure defined by Chamberlain and Rothchild (1983). Then, we compare these 14 base portfolios and our factor loading estimates in terms of correlation strucutre so that the initial 14 portfolios can possess the asymptotic consitency up to the deteministic linear transforms.

Based on these result we conclude that the first factor must be predominantly the market factor whose finding is in par with Fama and French (1993)and other well know results. However, because of the high pair-wise correlations between these 14 base portfolios, we re-trasform the original 41 base portfolios into 5 factor models where these portfolios are tranformed to reduce the colliniarity based on further principal component analylsis. In this final model, one of the market index, TOPIX, is substituted for the first factor, and the second factor is the return difference between the largest decile portfolio and the smallest decile portfolio. Similary, the third factor is the return difference in book to price ratio ranked portfolios, the fourth, the difference in the leverage, and the fifth, in the earnings to price ratios excluding negative earnings group. Thus derived 5 mimicking factor portfolios can represent correct factor loading estimates in a probabiity sense up to the deterministic linear transformaions, as these factors are chosen to be highly associated with factor loading from principal components analysis result.

Finally, the robustness of our five factor model is tested against the several sets of control portfolios and it is found that the alphas are insignificantly zero most of the time, and we conclude that our five factor model can be used as a good benchmark portfolios to be tested against Japanese funds where the timing information would be suppressed.

I Introduction

It has been argued empirically for sometime in the literature whether CAPM is a correct specification of the model to explain the security return behavior and the risk premium. In their cross-sectional analysis Fama and French (1992) find the beta does not have the explanatory power in correctly describing average returns of securities for US firms. This result is known to be robust for Japanese data as well as found in Kubota and Takehara (1995). Jagannathan and Wang (1994), however, take opposite view that the beta theory can be remedied when both the market portfolio inclusion problem in the sense of Roll and the beta time variations are taken care of, though their specification are also mulivarite including beta. In our current paper, based on our previous result (Kubota and Takehara (1995)) we propose the multifactor model is called for as a substitute for the beta prcing theory and try to find the correct stationary time-series multifactor return structure.

As for the time series data, however, the explanatory power of the market index, even if not as a sole factor, is predominant. Even though, Chen, Roll and Ross (1986), in their classic paper, find that the market indices, the value weighted index or the equal weighted index, are insignificant when the model is specified as the multifactor model on the set of macroeconomic variables for their cross-sectional tests, it does not exclude the possibiity that the market index is significant in explaining the time series behavior of returns[1].Besides, Fama and French (1993) and Fama, French, Booth and Sinquefield (1993) find that the market index are significant in explaining the time series behavior of

[1]The authors thank Professor Naifu Cheng in confirming this point.

security returns when the other variables are specified to be the return differences of two attribute portfolios and thus propose three factor model. In the current paper we initially form mimicking portfolios in the sense of Grinblatt and Titman (1987), and, based on the result from our principal components analysis, investigate the explanatory power of the market index against our initial mimicking portfolios.

In estimating the multifactor asset pricing models, Grinblatt and Titman (1985) prove that either the principal components analysis or the maximum likelihood factor analysis can generate the correct factors and factor loadings for the approximate factor structure defined in Chamberlain and Rothchild (1983) in the limit. Based on this point, we cross-validate our initial mimicking base portfolios with the principal components analysis applied to 776 individual securities as mentioned above, under the non-full rank conditions as is advocated in Anderson(1958). Then, we compare the above 14 base portfolios and our factor loading estimates to conclude that the first factor must be predominantly the market factor, of which finding is in par with Fama and French (1993).

Based on these observations and on further cluster analysis of the original 41 portfolios, we finaly construct 5 factor models. In this model, the market index, TOPIX, is substituted for the first factor, and the second factor is the return difference between the largest decile portfolio and the smallest decile portfolio. Similary, the third factor is the return difference in book to price ratio ranked portfolios, the fourth, the difference in the leverage, and the fifth, in the earnings to price ratios excluding negative earnings group. Thus derived 5 mimicking factor portfolios will represent correct factor loading estimates in a probabiity sense, as these factors are chosen to be associated with factor loading from principal components analysis.

Finally, this five factor model is tested against the sets of control portfolios for the insignificance of the alpha esitmates and it is concluded that our five factor model can be used as a good benchmark portfolios to test the alpha values for any Japanese funds.

Our paper outline is as follows. Section II briefly summarizes the previous result on empirical investigations of the multifactor structure of Japanese security time-series returns, and discusses the theoretical foundations in empirically finding the common factor structure and related previous empirical studies. Section III describes our data, and also the benchmark portfolio sample we use that well represent the return variation at the portfolio level to be tested aginst our mimicking portfolios. In Section IV we run principal components analysis and compare the factor loadings with the mimicking base 14 portfolios formed in Section III. Based on the results in Section IV we propose that the 5 factor model where the market index and the return differences of the attribute portfolios are used turns to be a good reliable factor model for Japanese firms and the insiginificance of alpha estimates against control sample is explored. Section V. concludes the paper.

II Previous Empirical Studies and the Theory behind Estimating the Common Factor Models

The empirical quest for finding the appropriate factor structure of security returns have been conducted thoroughly for American firms. For example, Lehman and Modest (1988) used the maximum likelihood factor analysis on daily returns and Connor and Korajyak (1988) used principal components analysis on monthly returns to estimate factor loadings.

Similar results for Japanese stocks are also reported, for example, in Elton and Gruber (1988) where the factor analysis are used for monthly returns, and four factor model is proposed. On the other hand, Sakuraba (19) proposed seven factor models. Also, the estimation of the multifactor pricing model with macroeconomic variables as their factor proxies are found in Hamao (1988).

The factor analytic methodologies are permissible as shown in Grinblatt and Titman (1985) when either the maximum likelihood factor analysis or the principal components analysis is used, as these methods can generate estimates that asymptotically approach the coefficients that are theoretically implied by the arbitrage pricing relationships in an approximate form defined in Chamberlain and Rothchild (1983).

It is also shown, with respect to the relationships between the mean variance efficiency and the arbitrage pricing theory in the limit, thus derived mimicking portfolios are locally mean-variance efficient if and only if the arbitrage pricing equation holds (Grinblatt and Titman (1987)).

Recently, Grinblatt and Titman (1994) constructed the mimicking portfolios, using attributes of individual securities like the size and the dividend yield, and found that these portfolios, which they call P8 Portfolio, constitute the set of good benchmark mimicking portfolios in the sense that these base portfolios can measure correctly the performance of mutual funds; that is, being able to generate the correct alpha estimates for funds without timing information. As these P8 portfolios are expected to be correlated each other to some degree, it may be mistakenly interpreted that their model does not satisfy the usual assumptions imposed on the arbitrage pricing theory; the scaled factors that are uncorrelated[2]. However, it is always possible to find the linear transformation matrix of K by K to diagonalize these portfolios , where the number of the factors are assumed to be K and the number of the observed assets are assumed to be N(¿K), and this is not a restriction. Zero mean and unit variance diagonal factors are assumed only for simplicity in most of the theoretical discussion. More serious problem is that they are highly correlated each other as we discuss when we estimate the similar 14 base mimicking portfolio.

Another line of attempt to find the multifactor model, using the portfolios classified by the attributes of individual securities are conducted by Fama and French (1993). They suggest the three factor model, composed of the market factor, the return differences between the high book-to-price portfolios and the low porfolos, and the similar differences between the large and the small size portfolios, can well explain the time-series variations of security returns. Their model can be classified as somewhat between the factor analytic approaches and Grinblatt and Titman's P8 portfolio. It is similar to the former in the sense that the correlations between these three factor portfolios are minimized by taking the differences of the last two attribute portfolios. It is similar to the latter in the sense that these two attribute portfolios, the book to price ranked portfolios and the size ranked portfolios are used.

In the current study, on the basis of the findings in Kubota and Takehara (1995) where the cross-section returns were regressed on financial attributes of classified portfolios, we

[2]The orthogonality of factors are normally stated (Grinblatt and Titman (1985,p.1368) to describe Ross (1976)'s arbitrage pricing theory or assumed for simplicity(Huberman, Kandel, and Stambaugh (1987,p.1). Also, factor analysis generates orthogonal estimates as their computing mechanisms. However, Ross(1976, P.347) clearly states ,"the δ_i need not be jointly independent, or even independent of ϵ_is, they need not possess variances, and none of the random variables need be normally distributed."

initially try to form mimicking portfolios based on the attributes that well explain the cross sectional behavior of security returns. We use cluster analysis to reduce the number of factor from 41 into 14. These portfolios have the property that these can span the locally mean-variance efficient frontier in the limit in the sense of Chamberlain and Rothchild (1983) and Grinblatt and Titman (1987).

However, in view of the high correlations between those 14 portfolios, we further transform the original mimicking portfolios so that the correlations between 14 portfolios are reduced and more reliable beta estimates can be obtained. Also, based on the theoretical foundations in using the principal components analysis to find the correct loadings for the approximate factor structure proven by Chamberlain (1983) and Grinblatt and Titman (1985), we compare the associations between the transformed mimicking portfolios and the principal components factor loadings to guarantee the probabilistic resemblance between our mimicking portfolios and the factors.

III Data and the Benchmark Portfolio

We use monthly return series for Japanese manufacturing and non-manufacturing firms listed on the Tokyo Stock Exchange First Section between the months starting from September 1981 through June 1993. The number of the sample is 792 in 1981 and increasing up to 1023 in 1993. We also use observations since September 1993 to date as the control sample. These monthly return series were collected also another preceding three years to compute the necessary beta estimates and the average of past returns which we call Momentum variable. Based on the previous study to explain cross-sectional returns in Kubota and Takehara (1994), we choose 4 attributes, size, leverage, book to price ratios, and earnings to price ratio for portfolios formation, and we rank each security based on these attributes to form 10 portfolios based on the ranking of the former three attributes. We form 11 portfolios based on earnings to price ratio where the negative earnings groups are classified separately. Thus made 41 portfolios become the initial base candidate portfolios to form our mimicking base portfolios in order to span the local mean variance efficient frontier (see the diamond dots in Figure 3). In the following section we further reduce the number of the mimicking portfolios into smaller 14 portfolios.

Each portfolio formation month is the beginning of September each year when all firm-specific accounting variables become publicly available to the most institutional investors in a machine readable form as is provided by Nikkei Data Services. As most of the Japanese companies have March 31st as their fiscal year end, we classify each security into the ranked portfolios based on both the accounting variables computed as of each previous fiscal year end and the corresponding stock prices as of the beginning of September. For example, book to price ratios are computed from the end of March book value and the beginning of September price for every March fiscal year company at the beginning of the first portfolio formation month. When we refer to the earnings figures we exclusively use "current earnings" which we believe are less subject to accounting manipulations than the net profits and also are known to be more widely used by Japanese financial analysts. As for the current earnings numbers, Nikkei Data Services provides forecast numbers updated monthly in recent years, and these are the current earnings figures we use, instead of the realized numbers. It is implicitly known that the most analysts use these forecast numbers when they conduct financial analysis, and because of this reason we use these numbers as the pertinent earnings numbers which contrasts our study from Chan, Hamao and Lakonishok (1991) where they used the realized earnings from previous fiscal year and found that earnings to price ratios are not significant in their cross-sectional tests. Each portfolio is formed on every September 1st and is equal-weighted[3]. Thus constructed portfolios will be regrouped every year on September 1st, and in this way the continuous monthly observations of portfolios ranked by the financial attributes of our interest are constructed while the composition and the number of firms of each portfolios are different every year.

We also construct 71 portfolios and 100 portfolios as our benchmark portfolios as our larger universe portfolio set to produce our control sample. As for the former 71 portfolios, in addition to the above 41 portfolios, we add portfolios ranked by dividend yield, the beta computed from the previous 36 months, and the past returns also computed from past 36 months. The pre-beta would be the typical instrument variable to classify securities for a typical Fama-MacBeth studies. The momentum variable is purported to signify some kind of mean reversion phenomenon, if there is any.

The 100 portfolios set is based on Kubota and Takehara (1995) where it was found that portfolios ranked by size and book-to-price ratios can represent good wide variations of asset returns. The ranking procedure is based on two steps as follows. Initially we rank each security according to the size in the natural log of the total market value of each firm and form 10 portfolios by their deciles. We then further rank these size-ranked 10 portfolios into another 10 sub-portfolios by deciles based on the rankings of book to price ratios within each 10 portfolios, and thus construct 100 portfolios as of the beginning of September each year as before. These constructed portfolios will be also regrouped every year and thus compositions of each portfolio are again different every year. This portfolio set will give us the sample size large enough to be used as the benchmark portfolios representing the universe of asset mean variance combinations at somewhat more aggregated level (see Figure 1).

IV Forming the Base Mimicking Portfolios

Figure 2 shows the result from the cluster analysis applied to each attribute portfolio where the group with lower pair-wise Euclidean distance are arranged next to each other and thus a tree is constructed which shows the closeness (vertical axis measures the distance between the groups).

Based on these cluster trees for attribute portfolios we decide to form 14 portfolios in the following way. For example, for the size we choose, among decile portfolios, the largest and the smallest which we denote MV10 and MV1, respectively. Then. we aggregate from MV2 through MV6 portfolios into S1 portfolio(small aggregated group) and do the same from MV7 through MV9 to form S2 portfolio(large aggregated group). Similarly, among book to price ratio attribute group , we choose the smallest and the largest to form BP1 and BP10 portfolio and aggregate decile portfolios from BP2 through BP4 to form smaller book to price ratio group BPL and from BP5 through BP9 to form the larger group BPH. For the leverage we split decile portfolios into 3 by aggregating from LEV1 through LEV3 into LEVL, from LEV4 through LEV7 into LEVM, and from LEV8 through LEV10 into

[3] Note that Grinblatt and Titman(1985)'s proof applies only to the equal weighte portfolios.

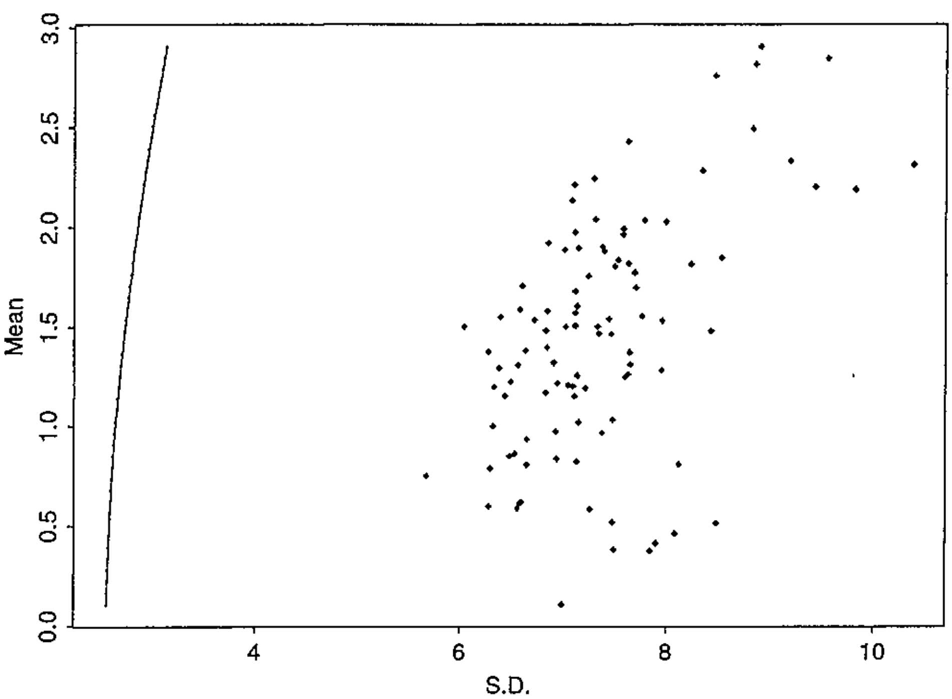

Figure 1: Mean Standard Deviation Plot of Size-BPR ranked 100 Portfolios

LEVH group. Finally, for the EPR decile portfolios and a separate negative earnings group portfolio, we separate the negative earning group and then aggregate from EP1 through EP6 into EPL group and from EP7 through EP10 into EPH group. These aggregation steps are taken to reduce the number of factors while minimizing the risk of aggregating the portfolios with different return variation characteristics.

The approach is somewhat similar in spirit to Grinblatt and Titman's P8 portfolio construction, though they test the significance of alphas in the regression equaions as their purpose is in finding the model used in the fund performance measurement. So, they derive the model by paying attention to whether alpha coefficients can generate zero values on average for their testing sample, using t and F test on the alpha estimates.

By the same sense that Grinblatt and Titman claim their P8 portfolios form the mimicking base in the locally efficient set, our 14 portfolios are also expected to form the mimicking base. We can casually find the degree of this apploximation by looking at whether the mean variance efficient set formed from these 14 portfolios are close enough to the mean variance efficient set generated from this original 41 portfolios and the similar set generated from the larger set, for which purpose we haven chosen to use the above mentioned 71 portfolios and 100 portfolios. We can test the siginificance of whether our sets are siginifincantly different from the benchmark set is available, for example, in Kandel and Stamabough(1991) and will be added in our later research. Momentarirly, we resort to this casual method. Also, from the viewpoint of alphs insignificance test, as we do not have the sample of mutual fund or control sample Grinblatt and Titman (1994) could use,

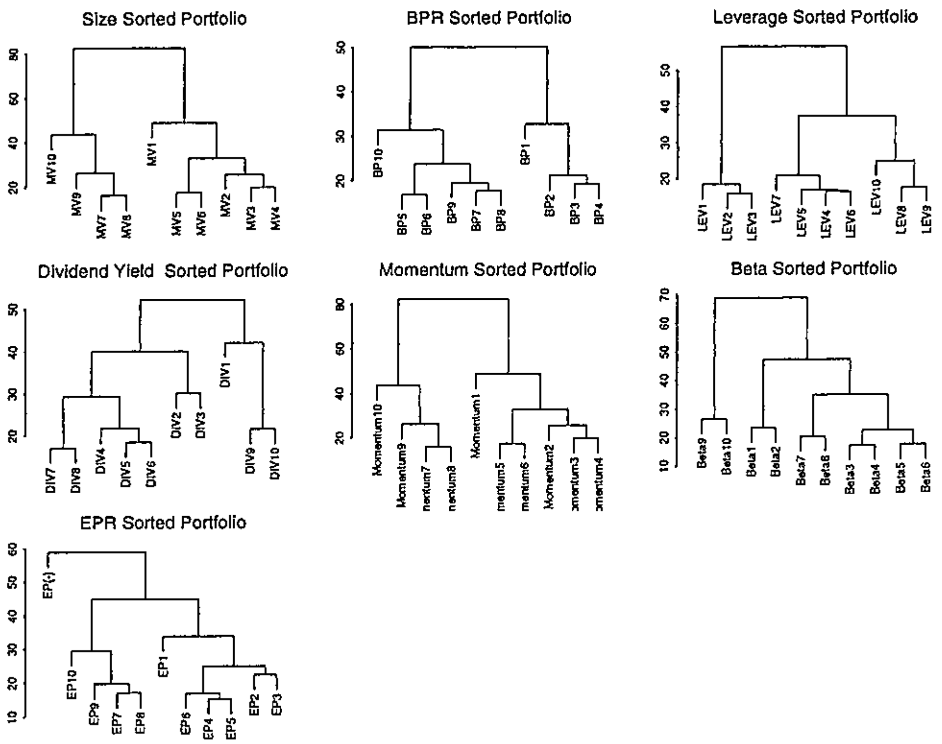

Figure 2: Cluster Analysis of 71 Portfolios

for this purpose, not only we use the above benchmark portfolios agains our final, we also use our new observations after September 1993 and will test the alpha coefficients in our later version of this paper.

Figure 3 shows the plots 41 portfolios on the mean and standard deviation plane and the mean variance efficient sets formed by 41 portfolios (smaller standard deviation) and by the 14 mimcking portfolios. The next Figure 4 shows the plot of our 14 portfolios. Our original total equal weighted sample has the mean of 1.453% and the standard deviation of 6.281% per month, which gives us the variance estimate of 39.45%. At the same level of the mean return, the standard deviation of the 14 portfolio M-V efficient set and the one of the 41 portfolios are 4.489% and 3.854%, respectively. Thus, in case of the 41 portfolios 62.4% of the total risk variations are diversified away and the rest of the 37.6% in the systematic risk components remain. Similarly, in case of our 14 portfolios 51.1% of the total risk are diversified away and the rest is 48.9%. The simple variance difference of these two figures, ignoring the corresponding covariance terms, will be 11.3% of the total variance of the whole sample and this will be a rough measure of the approximateness of our 14 mimicking portfolios to the original universe of 41 portfolios. The approximation error relative to the universe will cause underpricing in arbitrage pricing in general as is pointed out in Grinblatt and Titman (1983). However, the accurate computations involve the measurement in the risk aversion coefficients and we do not further elaborate on this point. As a comparison we also have the mean-standard deviation frontier of the benchmark universe 100 size-book to price ratio ranked portfolios. As shown in Figure 1

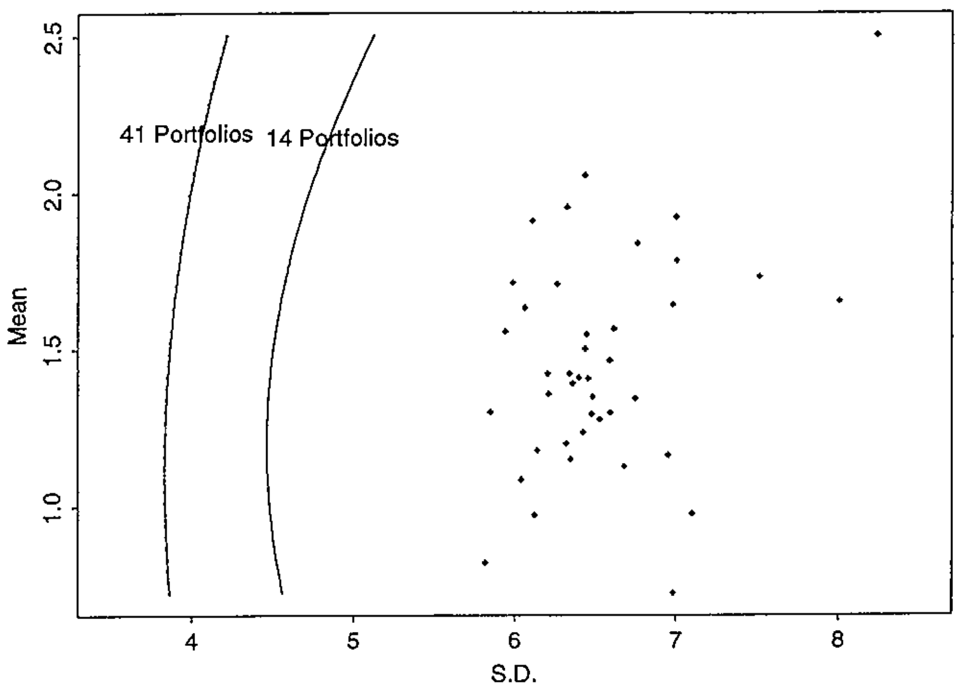

Figure 3: 41 Portfolios on Mean Standard Deviation Plane

the 100 portfolios are good universe and we use this 100 portfolios as one of the benchmark universe in section VI.

As a final remark of this section, we reluctantly have to report the rather high correlations between those 14 portfolios(Table 1) in spite of the cluster analytic procedure that possibly could have reduced the pair-wise correlations at least. Although some of the correlations were successfully reduced to less than 0.90, in general the level is too high to run any meaningful time series regressions for individual securities to obtain beta reliable beta estimates for each attribute mimicking portfolio. We infer that the correlations of P8 portfolios in Grinblatt and Titman (1994) are also not so low, as attribute portfolios are derived from rankings of dividend yield and the size for the first seven mimicking portfolios and the momentum portfolio is added as the eighth one, but their approach is justified as they want to measure correctly only the alpha coefficients, not beta coefficients[4]. As we are primarily interested in finding both the risk factors and the beta coefficients in addition to the alpha estimates, this high level of correlations are definitely not allowed, and we try to reduce these correlations by transforming these base portfolios fhrther in the Section VI. In the next section V we run principal components analysis as a preparation for this purpose, and will get more insight into the return variation structure of Tokyo Stock Exchange Firms and finalize our mimicking factor model.

[4]Authors thank Professor Sheridan Titman for discussing their method of forming their mimicking portfolios. Authors also thank Professor Naifu Chen for discussing this point.

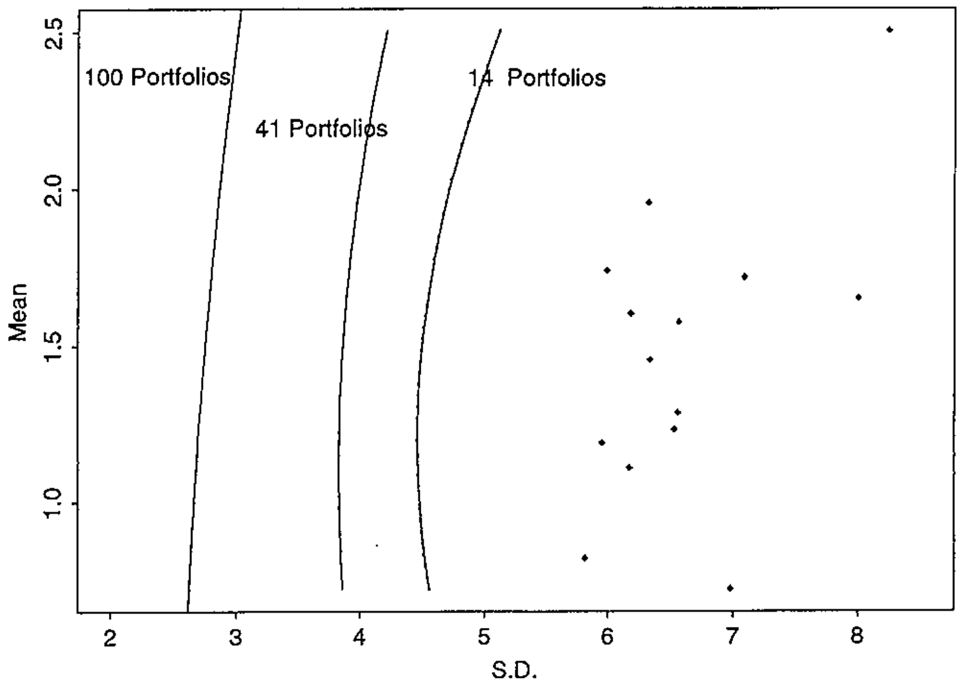

Figure 4: 14 portfolios on Mean Standard Deviation Plane

V Cross-validation by the Principal Components Analysis

We ran principal components analysis on 776 individual manufacturing and non-manufacturing Tokyo Stock Exchange First Section firms during the same observation period. As these samples have to have data observations for the total observation periods in our study between September 1981 through June 1993, the number of the sample is greatly reduced. As the data have to include the observations from the most recent month, this sample test would possess serious forward looking bias as well as the survivorship bias. On the other hand, in Section II we pointed out that the principal components analysis guarantee the nice property of being able to generate the correct factor loadings. So, these pros and cons

	MV1	S1	S2	MV10	BP1	BPL	BPH	BP10	LEVL	LEVM	LEVH	EP(-)	EPL	EPH
MV1	1.00	0.94	0.82	0.59	0.87	0.90	0.92	0.91	0.83	0.92	0.93	0.91	0.91	0.89
S1	0.94	1.00	0.93	0.71	0.93	0.97	0.98	0.94	0.93	0.99	0.96	0.89	0.98	0.97
S2	0.82	0.93	1.00	0.88	0.91	0.97	0.97	0.89	0.94	0.97	0.92	0.78	0.97	0.96
MV10	0.59	0.71	0.88	1.00	0.76	0.82	0.79	0.69	0.78	0.80	0.76	0.57	0.81	0.79
BP1	0.87	0.93	0.91	0.76	1.00	0.95	0.91	0.82	0.90	0.93	0.91	0.86	0.95	0.89
BPL	0.90	0.97	0.97	0.82	0.95	1.00	0.97	0.89	0.93	0.99	0.96	0.85	0.99	0.96
BPH	0.92	0.98	0.97	0.79	0.91	0.97	1.00	0.95	0.94	0.99	0.96	0.86	0.98	0.99
BP10	0.91	0.94	0.89	0.69	0.82	0.89	0.95	1.00	0.89	0.94	0.91	0.84	0.92	0.95
LEVL	0.83	0.93	0.94	0.78	0.90	0.93	0.94	0.89	1.00	0.94	0.84	0.78	0.95	0.94
LEVM	0.92	0.99	0.97	0.80	0.93	0.99	0.99	0.94	0.94	1.00	0.96	0.86	0.99	0.98
LEVH	0.93	0.96	0.92	0.76	0.91	0.96	0.96	0.91	0.84	0.96	1.00	0.89	0.96	0.94
EP(-)	0.91	0.89	0.78	0.57	0.86	0.85	0.86	0.84	0.78	0.86	0.89	1.00	0.87	0.82
EPL	0.91	0.98	0.97	0.81	0.95	0.99	0.98	0.92	0.95	0.99	0.96	0.87	1.00	0.96
EPH	0.89	0.97	0.96	0.79	0.89	0.96	0.99	0.95	0.94	0.98	0.94	0.82	0.96	1.00

Table 1: Correlation Matrix of 14 Portfolios

must be weighed carefully.

This is another reason why we use our attribute ranked portfolio approach as our main sample where we can have less survivorship and forward looking bias, as at every September portfolio formation beginning month all firms listed are included in the sample.

In the previous section we formed the base portfolios from attribute portfolio. In fact, Grinblatt and Titman (1985) point out that securities regressed on any base portfolios can possibly generate good proxies for the mean variance efficient portfolios in the limit as long as they are equal weighted. But, we believe it is also worthwhile to use larger number of individual firm data on the principal components analysis and compare those result. In this way we can get clues on how to transform our original 41 portfolios to get more reliable estimates than our initial 14 portfolio base.

When we apply principal components analysis to our individual data, first factor counts 31.06% of the total return variations, and 5.68%, 3.13%, 2.08%, 1.92%, and 1.83%, respectively for the consecutive next five factors. The same result for 41 portfolios are 92.26%, 2.55%, 1.22%, 1.0%, 0.45% and 0.31%, respectively. (See also Table 3 first row for standard deviations.) Also, in Table 2A. we have the correlation matrix (14 by 10) of the computed correlations between our fourteen base portfolios and the first ten factors from the individual securities principal components analysis. One can see the first factor has predominantly extremely high correlations for all portfolios except for the largest decile portfolio MV10 at 0.79 and the negative earnings group of earnings to price ranked portfolio EP(−) at 0.88.

Similar results are listed for all decile 71 portfolios in the following Tables 2(B) and 2(C) for the same ten principal components. Again, the correlations between the first factor and all decile portfolios are extremely high. The correlation is higher than 0.90 for all portfolios except for the small leverage group (LEV1) and the highest momentum group (MMT10) at 0.89, in addition to the previous 0.79 for the largest group and 0.88 for minus earnings to price ratio group. However, the results for the next factors are rather mixed between each decile portfolios and show the wide variation in the way these attribute decile portfolios are related to each factor. Table 3 show the result for the principal components analysis applied to 41 portfolios, and denote factor loadings for the first ten factors. Again, we note that the factor loading to the first factor possesses the very similar number between all the decile portfolios unanimously.

Based on these observations and also on the property of the principal components analysis that can correctly and uniquely identify the true approximate factor structure (Chamberlain (1983)) mentioed before, we try to reduce the number of factors, starting once again from our original 41 portfolio set in the next section in a trasformed way different from the approach in Section IV.

VI Five Factor Portfolios as the Mimicking Base Portfolios for Japanese Stocks

A Constructing the Mimicking Five Factor Portfolio

In view of the analysis in the previous section we decide that the final factor model should include the market factor to incorporate the strong first factor contributions as our all decile portfolios were highly correlated with the first factor. Even though our sample includes only manufacturing and non-manufacturing firms and excludes financial firms, we adopt TOPIX as the first factor as it is a well known and well used market index. We include TOPIX as if it is an exogenous factor variable and try to generate the rest of the factors from our 41 portfolios. By analyzing cluster trees for 41 portfolios (Figure 5) as well as the distibution of factor loadings on these dcile portfolios(Table 3), we chose to use the return spread between the highest decile and the smallest decile of four attributes, as, in general, the mid-ranking decile portfolios are very clustered together relative to the extreme end decile portfolios. However, we did not use the negative group of the earning to price ranked portfolio for two reasons: one is that this group shows the strong mean reversion in 12 months returns as was found in Kubota and Takehara (1995) and we did not want this factor to get in as we wanted the model to be stationary and we are not sure of the consequence of this mean reverting variable, and the second reason is that this group had extremely high correlations with the smallest firm decile group and this latter variable was already chosen.

Table 4 denotes the correlation matrix of our 5 factor model and it shows the suceess of our new approach in reducing the pair-wise correlations. The highest correlation is 0.58 between the spread of book to price ratio ranked portfolios and the spread of earning to price ratio ranked portfolios where each spread is the return difference between the highest decile and the lowest decile. In this way the correlation between the market index, TOPIX, and other base portfolios are kept rather low between 0.25 and 0.016, and thus could avoid the possibility for pair-wise multicollinearity, which plagued our initial 14 mimicking portfolios. It shoud be emphasized that we want to rely on the beta estimates of each factor in the individual time series regression for individual securities as seen below and reducing the correlations are imperative not like the case in Grinblatt and Titman(1994). As we pointed out in Section III, if the purpose of our constructing common factor model is in applying to fund performance measurement in computing the fair alpha, our original 14 portfolios or its smaller subset might have done the job well enough. However, as we wanted to construct the robust model that can generate the reliable risk factor sensitivities on individual securities as weak as any constructed portfolios, we have chosen this five factor model to be our final model to be tested aginst our control sampmle further.

On Table 5 we have the summary statistics of time series regressions using the above

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
MV1	0.93	-0.0162	-0.2913	-0.040	0.08123	-0.0102	-0.0879	0.03059	-0.0054	0.01857
S1	0.99	0.0642	-0.1185	-0.024	0.00017	0.0350	-0.0044	0.02196	0.0024	0.01316
S2	0.97	0.0513	0.2185	-0.048	0.00417	-0.0189	0.0401	-0.04267	-0.0159	-0.01071
MV10	0.79	-0.0412	0.5203	-0.124	-0.07218	-0.1527	-0.0318	-0.06218	0.0251	-0.01715
BP1	0.94	0.1296	-0.0337	0.045	0.01142	-0.1143	0.0183	0.00842	0.0093	0.04552
BPL	0.99	0.0330	0.0319	-0.044	-0.02020	-0.0300	0.0100	-0.00811	-0.0140	-0.00444
BPH	0.99	0.0307	0.0190	-0.062	0.00669	0.0166	-0.0042	0.00014	0.0061	0.00844
BP10	0.94	0.0276	-0.0405	-0.040	0.07134	0.1146	-0.0813	-0.01183	-0.0140	-0.03268
LEVL	0.93	0.3172	0.0911	-0.100	0.03744	0.0299	0.0179	-0.04136	-0.0222	-0.01936
LEVM	0.99	0.0276	0.0069	-0.068	-0.01239	-0.0044	-0.0205	0.01386	-0.0126	0.01446
LEVH	0.98	-0.1753	-0.0515	0.037	-0.00111	-0.0278	-0.0055	0.01040	0.0287	0.01245
EP(-)	0.88	-0.0018	-0.2563	0.084	0.02845	-0.1049	-0.1151	-0.03103	0.0763	0.00088
EPL	0.99	0.0672	0.0141	-0.026	-0.02276	-0.0457	-0.0015	0.01200	0.0104	0.01521
EPH	0.98	0.0266	0.0638	-0.102	0.03979	0.0938	-0.0133	-0.02488	-0.0185	0.00342

Table 2: (A) Correlation Matrix between First 10 Principal Components and 14 Portfolios

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
MV1	0.93	-0.01621	-0.2913	-0.03957	0.08123	-0.01015	-0.08792	0.03059	-0.00536	0.01857
MV2	0.95	0.01497	-0.2299	-0.07292	0.03864	0.02371	-0.04356	0.03651	0.03800	0.00391
MV3	0.96	0.10419	-0.1964	-0.01919	-0.04958	0.02867	-0.01222	0.02131	0.01851	-0.00594
MV4	0.97	0.08348	-0.1294	-0.01964	-0.01543	0.01820	-0.02119	0.02043	-0.01002	0.02417
MV5	0.98	0.06152	-0.0624	0.01298	0.02215	0.06553	0.02648	0.02309	-0.00998	0.03239
MV6	0.98	0.05289	0.0458	-0.01700	0.00428	0.03711	0.03209	0.00564	-0.02740	0.01150
MV7	0.98	0.03836	0.1076	-0.03434	0.01915	-0.00039	0.02973	-0.00533	-0.01964	-0.00844
MV8	0.96	0.02526	0.2033	-0.03269	0.00062	0.00152	0.02850	-0.03536	-0.02680	-0.02795
MV9	0.91	0.08940	0.3399	-0.07456	-0.00787	-0.05826	0.06101	-0.08711	-0.00011	0.00521
MV10	0.79	-0.04115	0.5203	-0.12358	-0.07218	-0.15267	-0.03177	-0.06218	0.02511	-0.01715
BP1	0.94	0.12963	-0.0337	0.04476	0.01142	-0.11432	0.01835	0.00842	0.00928	0.04552
BP2	0.97	0.06008	0.0382	-0.04648	0.00042	-0.03740	-0.00275	0.00037	-0.01191	-0.01146
BP3	0.98	0.02690	-0.0109	-0.04773	-0.07403	-0.03616	0.01994	-0.01495	-0.01929	0.00957
BP4	0.98	0.00880	0.0676	-0.03554	0.01297	-0.01468	0.01331	-0.01009	-0.01036	-0.01097
BP5	0.98	0.03716	0.0401	-0.03422	0.00486	-0.00872	0.02260	-0.00289	-0.00649	0.01843
BP6	0.98	0.06232	0.0426	-0.04118	-0.03032	0.00964	0.02118	-0.01901	-0.00336	0.02685
BP7	0.98	0.03172	-0.0036	-0.06744	0.02600	0.00934	-0.02422	-0.02620	0.00892	0.00048
BP8	0.97	0.01316	0.0066	-0.08657	0.01061	0.00674	-0.01351	0.03929	0.00886	-0.00514
BP9	0.97	0.00644	0.0083	-0.07786	0.02132	0.06659	-0.02682	0.01035	0.02267	0.00111
BP10	0.94	0.02761	-0.0405	-0.04021	0.07134	0.11462	-0.08134	-0.01183	-0.01401	-0.03268
LEV1	0.89	0.37411	0.1117	-0.08524	0.06890	0.04490	0.00675	-0.05875	-0.00353	-0.02990
LEV2	0.92	0.30888	0.0956	-0.11928	0.03691	0.03181	0.01329	-0.04600	-0.04220	-0.00994
LEV3	0.95	0.25696	0.0622	-0.09169	0.00391	0.01123	0.03376	-0.01715	-0.02041	-0.01747
LEV4	0.98	0.07453	0.0166	-0.08102	-0.01510	0.00903	-0.01932	0.03731	-0.03490	0.02983
LEV5	0.98	0.05228	0.0110	-0.08203	-0.03571	0.00602	0.00147	-0.00016	0.00138	-0.01232
LEV6	0.99	0.04578	-0.0223	-0.04121	-0.00814	-0.00255	0.00142	0.02007	0.00341	0.00920
LEV7	0.98	-0.05914	0.0219	-0.06503	0.00899	-0.02876	-0.06336	-0.00133	-0.02012	0.03027
LEV8	0.97	-0.17000	-0.0194	0.02310	-0.03884	-0.02457	-0.01849	-0.00048	0.01069	0.02250
LEV9	0.97	-0.19998	-0.0521	0.00366	0.01205	-0.02642	0.00671	-0.00125	0.01900	-0.00181
LEV10	0.96	-0.15175	-0.0792	0.08001	0.02170	-0.03122	-0.00462	0.03106	0.05351	0.01601
EP(-)	0.88	-0.00178	-0.2563	0.08370	0.02845	-0.10490	-0.11513	-0.03103	0.07626	0.00088
EP1	0.97	-0.00753	-0.1187	0.05163	-0.00237	-0.07983	-0.03943	0.01106	0.03788	0.04953
EP2	0.98	0.01870	-0.0412	-0.05589	-0.06647	-0.06155	0.03299	0.02306	-0.00951	0.03661
EP3	0.97	0.07807	0.0641	-0.01671	-0.00173	-0.06561	-0.00268	0.02430	0.02546	-0.01548
EP4	0.98	0.10338	0.0616	-0.00165	-0.02890	-0.04095	-0.01049	0.00499	0.00823	0.00623
EP5	0.98	0.08510	0.0671	-0.07449	-0.01451	-0.03793	0.00969	0.01272	0.01335	0.01649
EP6	0.97	0.12779	0.0643	-0.06386	-0.02095	0.02167	0.00305	-0.00630	-0.01623	-0.00712
EP7	0.97	0.07578	0.0710	-0.10288	-0.01037	0.06343	0.02866	-0.04156	-0.00815	-0.02264
EP8	0.98	0.03944	0.0727	-0.06475	0.01810	0.02680	-0.03187	-0.01023	-0.00231	0.00175
EP9	0.96	0.04311	0.0418	-0.13518	0.04961	0.10351	0.01130	-0.00797	-0.03525	-0.00278
EP10	0.93	-0.04882	0.0649	-0.09842	0.09510	0.16875	-0.05745	-0.03666	-0.02648	0.03503

Table 2: (B) Correlation Matrix Between First 10 Principal Components and 41 Portfolios

	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
DIV1	0.89	0.03136	-0.1608	-0.11967	0.10810	0.00367	0.03106	-0.07633	-0.02258	0.00202
DIV2	0.94	-0.02485	-0.0902	-0.11298	0.07530	0.07595	-0.01018	-0.01521	0.01589	0.03160
DIV3	0.96	-0.06383	-0.0333	-0.10927	0.06496	0.04541	0.01991	-0.01817	-0.01804	-0.02130
DIV4	0.97	0.01620	-0.0762	-0.09491	0.05326	0.02198	0.01656	0.00643	-0.01457	-0.00533
DIV5	0.98	0.01244	-0.0514	-0.04290	0.00487	0.00241	0.00581	0.04411	0.02151	-0.05095
DIV6	0.98	0.02747	-0.0291	-0.05429	0.01288	-0.01053	0.01577	0.03521	-0.02048	-0.01010
DIV7	0.98	0.03764	0.0388	-0.03409	-0.00478	-0.01257	-0.02229	0.01587	-0.02603	0.02703
DIV8	0.97	0.08838	0.0821	0.01401	-0.04056	-0.00823	0.00881	0.00027	-0.00030	0.00975
DIV9	0.94	0.14669	0.1379	0.02232	-0.09955	-0.04055	-0.02583	-0.01062	0.01014	0.03971
DIV10	0.88	0.11076	0.2248	0.08133	-0.08703	-0.08370	-0.07136	-0.00976	0.03025	0.01335
Beta1	0.94	-0.04943	-0.1940	0.06680	0.04299	-0.07948	0.00241	0.06065	0.01360	0.03218
Beta2	0.93	0.19313	-0.0515	-0.01430	0.03993	-0.09141	0.00198	-0.06450	-0.04540	-0.01298
Beta3	0.92	0.22142	0.1387	-0.10220	0.00663	-0.03204	-0.00562	-0.04308	-0.01195	0.01696
Beta4	0.96	0.14060	0.0644	-0.10126	0.02126	-0.00191	-0.00437	-0.01450	-0.00906	0.03160
Beta5	0.97	0.10664	0.0507	-0.08147	0.01029	-0.01321	0.01943	-0.00291	-0.01578	0.00394
Beta6	0.98	0.05418	0.0315	-0.05965	-0.05291	0.04636	0.02219	0.00501	-0.02084	0.01478
Beta7	0.98	0.03347	0.0472	-0.00045	-0.01518	0.02391	-0.01508	-0.00987	-0.00717	-0.00670
Beta8	0.99	-0.01114	-0.0087	-0.00975	-0.03780	0.03035	0.00532	-0.00546	0.02909	-0.00443
Beta9	0.97	-0.11094	0.0018	-0.04642	-0.00440	0.03885	-0.01417	0.00929	0.01669	-0.01614
Beta10	0.93	-0.15974	0.0572	-0.08694	0.03902	0.06352	-0.06417	0.03269	0.03178	-0.01902
MMT1	0.91	0.17051	-0.0807	-0.02760	0.05946	0.00724	-0.04800	-0.02553	0.00255	-0.01665
MMT2	0.96	0.04443	-0.0280	-0.06685	0.02854	0.01457	-0.00296	0.01649	0.03326	-0.01090
MMT3	0.97	0.03519	-0.0030	-0.03833	0.02385	0.00147	0.04084	0.03464	-0.01745	-0.01677
MMT4	0.98	0.00266	-0.0164	-0.01275	0.03774	0.01631	0.01076	-0.01958	0.02458	-0.00885
MMT5	0.98	0.02998	-0.0310	-0.01450	-0.00465	0.00450	0.02316	0.00017	-0.00591	0.01792
MMT6	0.98	-0.04367	-0.0357	-0.05803	-0.05733	0.01375	0.02885	-0.00023	0.00522	0.01709
MMT7	0.98	-0.03242	0.0392	-0.06343	0.00172	-0.01000	0.00257	0.00234	-0.00393	0.01304
MMT8	0.98	-0.00085	0.0362	-0.05207	-0.00905	-0.00654	-0.03842	-0.01053	-0.02149	0.02714
MMT9	0.96	0.05920	0.0951	-0.03878	-0.01140	-0.01569	-0.00099	-0.01718	-0.02731	-0.02159
MMT10	0.89	0.14543	0.1324	-0.04720	-0.01676	-0.04935	-0.05986	-0.00372	-0.00459	0.04051

Table 2: (C) Correlation Matrix Between First 10 Principal Components and Dividend, Beta and Momentum Ranked Portfolios

	1st	2nd	3rd	4th	5th	6th	7th	8th
S.D.	40.37	6.71	4.63	4.20	2.85	2.35	1.97	1.82
MV1	-0.19	0.3849	0.0966	-0.01696	0.07382	0.5675	0.1250	0.0155
MV2	-0.17	0.2301	0.1350	-0.01434	0.11228	0.2769	0.0401	0.0332
MV3	-0.16	0.1511	0.1628	-0.13132	0.15591	-0.0846	-0.1410	-0.0818
MV4	-0.16	0.0989	0.1105	-0.08341	0.12061	-0.2230	-0.1923	-0.0597
MV5	-0.16	0.0490	0.1125	0.00247	0.09365	-0.2827	0.0174	-0.0204
MV6	-0.16	-0.0623	0.0135	0.00069	0.09990	-0.2467	0.1154	-0.0705
MV7	-0.15	-0.1043	-0.0258	0.05321	-0.00544	-0.1592	0.0701	0.1263
MV8	-0.15	-0.1853	-0.0787	0.07754	-0.05165	-0.1739	0.1758	0.0859
MV9	-0.14	-0.3178	-0.1223	0.02803	-0.18265	0.0115	0.0019	-0.0498
MV10	-0.11	-0.3961	-0.3730	0.15148	-0.33078	0.3425	-0.2012	-0.0624
BP1	-0.16	0.0101	-0.2298	-0.40894	-0.00482	-0.0351	0.3481	-0.4154
BP2	-0.17	-0.0740	-0.1548	-0.16042	0.15005	0.1871	0.2700	0.0845
BP3	-0.16	-0.0143	-0.1295	-0.11202	0.13114	-0.0352	0.0733	0.2832
BP4	-0.16	-0.0585	-0.0897	0.02350	0.07366	0.0114	0.0752	0.2038
BP5	-0.15	-0.0467	-0.0023	0.05287	0.09216	-0.1332	-0.0542	0.0995
BP6	-0.15	-0.0526	0.0485	0.06253	0.03266	-0.1410	-0.1960	-0.0863
BP7	-0.16	-0.0032	0.0726	0.07091	-0.00037	0.0716	0.0111	0.0403
BP8	-0.15	0.0120	0.0932	0.12061	-0.06625	0.0844	-0.1140	0.0217
BP9	-0.15	0.0096	0.1532	0.19005	-0.05849	0.0112	-0.2819	-0.0339
BP10	-0.15	0.0749	0.2802	0.23292	-0.26247	0.0093	-0.1279	-0.2883
LEV1	-0.14	-0.1995	0.2985	-0.28936	-0.22816	-0.0219	0.1331	-0.0613
LEV2	-0.14	-0.1883	0.2480	-0.22034	-0.09501	0.0906	-0.0202	0.0096
LEV3	-0.14	-0.1357	0.1769	-0.17533	-0.00240	0.0092	0.0253	-0.0141
LEV4	-0.15	-0.0414	0.0603	-0.01470	0.09415	0.0397	-0.0849	0.0138
LEV5	-0.16	-0.0299	0.0177	-0.01949	0.02147	0.0997	-0.0697	0.0427
LEV6	-0.16	0.0152	0.0250	0.00034	0.06271	-0.0524	-0.1147	0.0669
LEV7	-0.16	0.0027	-0.0780	0.13213	0.03625	0.1334	-0.0472	-0.0608
LEV8	-0.17	0.0987	-0.2320	0.21978	0.07844	-0.1001	-0.0410	0.1146
LEV9	-0.17	0.1362	-0.2112	0.27369	0.10182	-0.0451	0.0027	0.0394
LEV10	-0.18	0.2038	-0.2760	0.16544	0.02278	-0.1235	0.2273	-0.2390
EP(-)	-0.17	0.4371	-0.1353	-0.23444	-0.68699	-0.1815	-0.0336	0.3748
EP1	-0.17	0.1629	-0.1597	-0.09785	-0.02086	-0.0406	-0.2444	-0.4305
EP2	-0.16	0.0226	-0.1132	-0.08101	0.13802	-0.0109	-0.1219	0.0668
EP3	-0.16	-0.0741	-0.1179	-0.14288	0.00252	0.0881	-0.1660	-0.1734
EP4	-0.16	-0.0879	-0.0544	-0.11951	0.11015	-0.0060	-0.1491	0.0359
EP5	-0.16	-0.0890	-0.0198	-0.06044	0.05283	0.0757	-0.0928	0.0725
EP6	-0.16	-0.1142	0.0839	-0.05994	0.09938	-0.0022	-0.0709	0.1815
EP7	-0.15	-0.0973	0.1000	0.06397	0.04256	-0.0535	0.0428	0.0728
EP8	-0.14	-0.0721	0.0285	0.05865	0.05101	-0.0045	0.1017	0.1309
EP9	-0.14	-0.0562	0.1854	0.15094	-0.02279	0.1318	0.2128	0.1006
EP10	-0.15	-0.0195	0.2162	0.38079	-0.18318	-0.0792	0.4295	-0.1724

Table 3: Factor Loadings

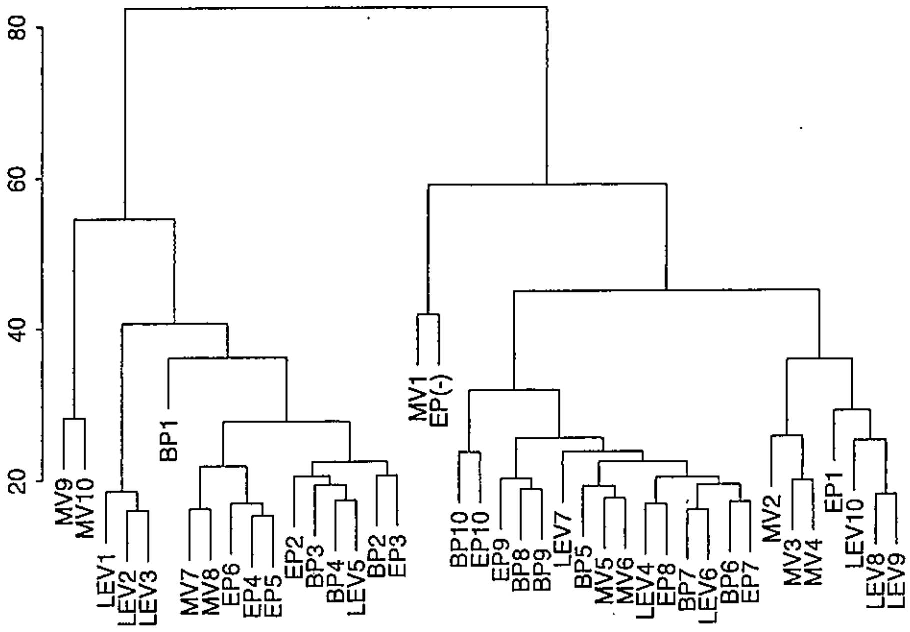

Figure 5: Cluster Analysis of 41 Portfolios

five factor model[5]. The result is rather comforting as we could obtain rather high R-square average of 0.398 for individual serurity regressions. In general, by looking at the average t values, we find the market factor naturally as well as the size return spreads are strongly significant. As for the spread between the book to price ratio portfolio, leverage portfolio, and earnings to price ratio, at the individual level they also seem to be significant, especially by looking at the absolute value of t averages as the loadings of factor portfolios can be either positive or negative for any security. Although not stated in the table, on average we reject the null hypothesis that all slope coefficients are zero(Average F Value was for this time series regressions).

Another important point in this regressions is that the alpha estimates are very low and it suggests the possibility that we can use this mimicking set as the suitable benchmark portfolio for performance measurement of mutual fund and other portfolios. In the next section we use the control sample to test this assertion.

Finally, we list the correlation matrix between the first ten principal components and our five factor mimicking base portfolios (Table 6) and conjecture that the size is related to third factor, book to price ratio related to sixth and seventh factors, leverage to second

[5]The regression equation we used here is :

$$\begin{aligned}(r_i)_j - (r_f)_j = \;& \alpha + \beta_1(MARKET_j - (r_f)_j) + \beta_2 SPR(Size)_j + \beta_3 SPR(BPR)_j \\ & + \beta_4 SPR(LEV.)_j + \beta_5 SPR(EPR)_j + \varepsilon_j, \quad j = 1, \ldots, 142\end{aligned}$$

where r_i and r_f denote a return series of ith security and risk free interest rate where we use call rate.

	Market (TOPIX)	Spread			
		Size	BPR	Leverage	EPR
Market	1.0000	-0.0165	0.2587	-0.2523	0.1445
SPR(size)	-0.0165	1.0000	-0.1009	-0.3840	0.2725
SPR(BPR)	0.2587	-0.1009	1.0000	-0.0898	0.5823
SPR(Lev.)	-0.2523	-0.3840	-0.0898	1.0000	-0.3225
SPR(EPR)	0.1436	0.2725	0.5823	-0.3225	1.0000

Table 4: Correlation matrix of Five Factor Portfolios

Regression Coefficients						
Var.	Intercept	Market (TOPIX)	Spread			
			Size	BPR	Leverage	EPR
Average	-0.077	0.942	0.426	-0.055	0.088	0.049
Maximum	3.511	1.804	1.405	1.115	1.801	1.341
Minimum	-2.299	0.079	-0.616	-1.250	-1.299	-1.559
Median	-0.083	0.950	0.470	-0.051	-0.104	0.066
t value						
Var.	Intercept	Market (TOPIX)	Spread			
			Size	BPR	Leverage	EPR
Average	-0.141	7.260	3.133	-0.288	0.482	0.128
Ave. $\|t\|$	0.651	7.260	3.650	1.039	2.600	1.189
Maximum	2.393	14.255	10.008	3.948	10.100	4.605
Minimum	-2.866	0.356	-6.569	-5.471	-7.780	-5.668
Median	-0.103	7.367	3.661	-0.200	0.482	0.246

(Average Adjusted $R^2 = 0.398$, Average DW statistics $= 2.167$)

Table 5: Summary of Time Series Individual Regressions

	Market	SPR(size)	SPR(BPR)	SPR(Lev.)	SPR(EPR)
1st	0.829	0.451	0.1542	-0.364	0.251
2nd	-0.102	0.016	0.1812	0.726	0.072
3rd	0.398	-0.807	0.0053	0.271	-0.349
4th	-0.103	0.059	0.1406	-0.238	0.277
5th	-0.044	0.162	-0.0922	0.055	-0.174
6th	-0.117	0.120	-0.3779	0.108	-0.458
7th	-0.020	-0.080	0.1594	0.016	0.025
8th	-0.074	0.091	0.0332	-0.126	0.087
9th	-0.032	-0.028	0.0381	-0.090	0.122
10th	-0.019	0.038	0.1301	-0.064	0.035

Table 6: Correlation between First 10 Factors (Principal Components) and Five Factor Portfolios

factor and finally earning to price related to fourth and fifth factors. As the correlation between the TOPIX and the first factor is at the level of 0.82 and smaller than the case for the most of decile portfolios in Table 2, it would give more room for other factor variations to explain individual security return variations, and in this way, we can span the mean variance space with reliable mimicking portfolio set with market index included.

B Testing the Fairness of Alpha Estimates on Control Sample.

Table lists the similar time series regressions on 30 portfolios. These 30 portfolios are the rest of the 71 portfolios ranked by beta, dividend yield and the momoentum. Although it came from the same sample and thus results in the reduction of the degrees of freedom, these return groups are generated with different ranking criteria and could be used as the independent fund sample to be tested on the siginificance of the alpha estimates. We find average ts are -0.4682 and larger in absolute value than -0.077 for individual security case in Table 5, though not significant overall. By looking at each portfolio, we find , for example, the small momentum portfolios .

In the case of the similar test for 100 benchmark portfolios the results, which is shown in Table 8, are similar with higher average R^2 values. Again, alpha estimates are insiginificant.

Moreover, the test for these control sample, though not independent sample, reveals the model itself with the absolute t values considered stand very robust, even if the model is applied to different portfolios.

Regression Coefficients						
Var.	Intercept	Market	Spread			
		(TOPIX)	Size	BPR	Leverage	EPR
Average	-0.096	0.928	0.449	-0.047	0.125	0.034
Maximum	0.276	1.070	0.593	0.531	0.402	0.374
Minimum	-0.446	0.757	0.250	-0.483	-0.125	-0.170
Median	-0.104	0.928	0.450	-0.048	0.126	0.021
t value						
Var.	Intercept	Market	Spread			
		(TOPIX)	Size	BPR	Leverage	EPR
Average	-0.468	25.473	13.068	-0.718	2.512	0.371
Ave. $\|t\|$	0.650	25.473	13.068	2.736	2.953	0.955
Maximum	0.957	29.600	16.740	7.945	8.732	4.095
Minimum	-1.868	18.600	5.090	-7.374	-2.451	-2.205
Median	-0.466	25.850	13.195	-0.741	2.534	0.283

(Average Adjusted $R^2 = 0.870$, Average DW statistics = 2.003)

Table 7: Summary of Time Series Regressions on 30 Ranked Portfolios

Regression Coefficients						
Var.	Intercept	Market	Spread			
		(TOPIX)	Size	BPR	Leverage	EPR
Average	-0.098	0.927	0.448	-0.055	0.125	0.033
Maximum	0.683	1.143	0.999	0.607	0.375	0.326
Minimum	-0.776	0.736	-0.204	-0.675	-0.172	-0.305
Median	-0.095	0.921	0.504	-0.051	0.140	0.029
t value						
Var.	Intercept	Market	Spread			
		(TOPIX)	Size	BPR	Leverage	EPR
Average	-0.299	16.237	7.875	-0.584	1.640	0.250
Ave. $\|t\|$	0.757	16.237	8.410	2.035	1.800	0.814
Maximum	1.917	23.770	17.970	5.401	5.758	2.726
Minimum	-2.225	8.030	-3.820	-6.015	-2.222	-2.746
Median	-0.267	15.990	9.185	-0.529	1.661	0.238

(Average Adjusted $R^2 = 0.740$, Average DW statistics = 2.089)

Table 8: Summary of Time Series Regressions on Size-BPR sorted 100 Portfolios

VII Conclusion

We initially formed 14 base mimicking portfolio from 41 portfolios, derived from four attributes, size, book to price ratio, earnings to price ratio and the leverage, that can well span the return variations of Japanese manufacturing and non-manufacturing firms between the period of 1981 and 1983. Then, based on the result from the principal components analysis applied to individual firm sample, we further transform this 41 portfolios and derive the five factor model where we use TOPIX as the first factor and the return spread of attribute portfolios for the remaining four factors. Our five factor model can characterizes the risk structure of Japanese stock well for our time series individual firm sample and for our control sample, andcan illuminates the way return and the risk are related for Japanese firms with reliable multifactor models.

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