A Further Re-Examination of the Contrarian Investment Strategy: Evidence from Multivariate Tests*

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Abstract

This paper investigates the performance of the contrarian investment strategy using the CAPM and APT. The results from multivariate tests of structural changes based on the CAPM show that the systematic risks of contrarian portfolios are not stable over time. In addition, the mean-variance efficiency of two market indexes, equal-weighted and value-weighted, cannot be rejected. This confirms Chan's (1988) findings that the abnormal returns documented in previous studies can be attributed to changes in systematic risks of the contrarian stocks. Using the asymptotic principal components technique to extract the APT factors and subsequently running regressions of contrarian stock returns on those factors, we find that the APT models explain the returns of contrarian stocks very well. The empirical results suggest that the contrarian investment strategy does not outperform the market, and the CAPM and the APT work equally well in evaluating the contrarian performance.

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1 Introduction and Overview of the Literature

Most previous studies have attributed the abnormal returns of contrarian investment strategies to market overreaction or the inability of the underlying model to correctly measure the systematic risk of the contrarian portfolio [see De Bondt and Thaler (1985, 1987), Chan (1988), Ball, Kothari and Shanken (1992), and Jones (1993)]. Lo and MacKinlay (1990), on the other hand, assert that contrarian profits may not necessarily be induced by market overreaction, and they show that in theory the contrarian profits can result from the cross-autocovariance among stocks. Using weekly return data, they find that a major proportion of the contrarian abnormal returns are attributed to the cross effect, rather than market overreaction. Based on daily return data of stocks listed on the NYSE/AMEX, Jegadeesh and Titman (1993) even find that a "counter-contrarian strategy" that buys past winners and sells past losers generates positive returns over three- and twelve-month holding periods. Using the equally weighted index as the proxy for market portfolio in the Capital Asset Pricing Model (CAPM), Chan (1988) finds that the risks of losers and winners are not constant over time, and he asserts that "only small abnormal returns" are found after the changes in risks are controlled. These empirical findings appear to suggest that the performance of contrarian strategies does not persist over time, and the performance of the contrarian strategy seems to depend on the particular portfolios that are formed (i.e., based on different time-interval, different holding periods, etc).[1]

As is well known, in a "perfect world" of the CAPM, it is not possible for an investor to construct a portfolio with a significant Jensen performance measure. Significant (positive or negative) Jensen measures may be due to the inefficiency of the market index used in empirical studies or reflect the fact that there are some factors that are not absorbed by the market index. Basically, the contrarian strategy is viewed as a passive strategy in the sense that no additional information other than historical return data is required to determine the composition of the invested portfolio. Thus, it is clear that such a strategy does not possess selectivity as well as timing abilities, and should not be able to outperform the market.[2] If the contrarian strategy earns significant abnormal returns, given that the underlying market index is mean-variance efficient, it is evident that the market is not informationally efficient in the weak form.[3]

Capital market researchers and practitioners are often concerned with the risk-return tradeoff and the equilibrium risk-return relationship in capital markets. Using the standard

[1] See also Fama (1991) for a brief review.

[2] See Grinblatt and Titman (1990) for the definitions and discussion of selectivity and timing abilities.

[3] See, for example, Fama (1976) for a definition of the weak form market efficiency. Note that there are two different concepts of efficiency here. The information efficiency concerns the speed of stock prices adjusting to market information, whereas the mean-variance efficiency, implied by the CAPM, emphasizes the risk-return tradeoff under the assumption of perfect market (perfect information). However, it is well known that the market efficiency and the correctness of the underlying (equilibrium) model are empirically indistinguishable. See Fama (1991) for a discussion. In this study, we will assume that information efficiency holds so that the mean-variance efficiency of market indexes can be tested.

event study method, De Bondt and Thaler (1985) calculate the average cumulative abnormal residuals (CARs) of the contrarian portfolio over a "post-formation period," and they find that the contrarian strategy earns a substantial positive abnormal return. However, it should be noted that if there is significant changes in intercept and systematic risk, the CARs will be significant in general. More specifically, the average CAR over the observation period will be the sum of two terms:

$$CAR = \hat{\alpha}^e + \hat{\beta}^e \bar{R}_{m2}, \tag{1}$$

where $\hat{\alpha}^e$ and $\hat{\beta}^e$ are respectively the OLS estimates of changes in intercept and changes in systematic risk; $\bar{R}_{m2}$ is the average excess return of the underlying market index over the observation period [see, for example, Chou (1993) for a detailed explanation]. Thus, it is clear that if $\hat{\alpha}^e$ and/or $\hat{\beta}^e$ are significantly different from zero, the CAR will always be significant. The sign of the CAR, however, depends on the magnitude of each term in (1). In the case, the CAR is no longer an appropriate measure of abnormal return because the changes in intercept and systematic risk are ignored. Chan (1988) has investigated the systematic risks of the "extreme performers." Assuming that the equal-weighted index is mean-variance efficient, he reports that both winners and losers experience significant changes in systematic risks, and the results from regressions show that the intercepts (i.e., the Jensen's performance measure) are not significantly different from zero for most of the "test periods."[4] However, in all ranking periods these extreme performers are found to have highly significant intercepts (abnormal returns). This suggests that the market index he used may not be mean-variance efficient with respect to the contrarian stocks in the ranking periods, if the selection bias over the ranking period can be ignored.[5] Consequently, concluding that contrarian portfolios' systematic risks are not stable over time is somewhat ambiguous because the systematic risk measures may not be appropriate when the underlying market index is not mean-variance efficient. Recently, Ball, Kothari and Shanken (1992) (hereafter BKS) have provided a thorough review on the performance of this strategy, and they also address the potential bias caused by the inefficiency of the underlying market index. In addition, they argue that a major proportion of the abnormal returns are attributed to some microstructure factors that affect the measurement of contrarian portfolio returns and to the inaccurate measurement of zero-beta returns. Still, in several sub-periods of their study, the regression analysis based on the CAPM specification yields significant regression intercepts. Therefore, we are motivated to further re-examine the efficiency of different market indexes over time and the stability of contrarian stocks' systematic risks.

[4]Chan (1988) studies the period from 1926 to 1989. He divides the sample into eighteen 6-year sub-periods; each sub-period is then divided into two periods: the first three years being the ranking period and the remaining the test period.

[5]The reason is that the CAPM asserts that in equilibrium the expected excess returns of *all* stocks and that of the market index should have a linear relationship with no intercept term, given that the underlying market index is mean-variance efficient. Here an implicit assumption behind the assertion is that the "information efficiency" also holds. See also a brief discussion in footnote 3.

Another issue addressed in the literature is the potential bias of the CAPM systematic risk measure if the underlying true model is multifactor [see Jones (1993)]. Somewhat surprisingly, the contrarian strategy performance has not been examined using the APT.[6] We thus examine whether the abnormal performance disappears when the APT is used as the underlying pricing model. Equivalently, we intend to examine whether those stocks that comprise the contrarian investment strategy are properly priced by the APT.

The purpose of this paper is twofold: first, we re-examine the stability of contrarian stocks' risks and the efficiency of the market indexes based on the CAPM; and second, using the APT as an alternative model, we examine if the contrarian stocks are properly priced by the APT. The first model is essentially a model of structural changes, and is the same as Chan's (1988). However, our tests differ from Chan (1988) in that our tests are based on a multivariate framework so that we can test whether the Jensen measures (intercepts) for all contrarian stocks equal zero simultaneously (i.e., $H_0: \ \alpha_i = 0 \ \forall \ i$, a joint hypothesis), rather than test that the summation of individual Jensen measures equals zero (i.e., $H_0: \ \sum \alpha_i = 0$), as in Chan (1988). It is possible that the former is rejected, while the latter cannot be rejected. Roughly, one may say that our test has a higher "power," given the underlying null hypothesis being $H_0: \ \alpha_i = 0 \ \forall \ i$. Testing the zero-intercept hypothesis is equivalent to examining a necessary condition for a market index to be *ex ante* mean-variance efficient [see, e.g., Gibbons, Ross and Shanken (1989)(hereafter GRS)]. If we cannot reject the efficiency of the market index, it then is more meaningful to look at the stability of the systematic risk measures. Otherwise, looking at the stability of betas is ambiguous.

The second model based on the APT follows Connor and Korajczyk (hereafter CK) (1986, 1988, 1990), in which they use asymptotic principal components technique to extract the APT factors. We apply this method to see if the APT can explain the performance of the contrarian investment strategy.

It should be noted that our purpose in this paper is not to investigate the factors that can be attributed to the behavior of systematic risk or factor loadings. Instead, we intend to see which model, the CAPM or the APT, provides a better account of the contrarian returns based on a multivariate statistical framework.

Similar to most previous studies [e.g., BKS (1992) and Chan (1988)], our study uses monthly return data. We investigate the performance of the contrarian strategy for the period from 1940 to 1989, which is divided equally into 10 5-year sub-periods. Following BKS (1992) closely, we identify 50 winner and 50 loser stocks based on the average returns during the first 30 months of each sub-period; then, their performance during the following 30 months is evaluated.

Similar to Chan (1988), our empirical results also show that the contrarian portfolio stocks have experienced significant changes in systematic risks. Besides, the zero-intercept

[6] Jegadeesh and Titman (1993) use a one-factor model in their study. Their emphasis, however, is on the decomposition and identification of sources of excess returns on the trading strategies employed in their study, rather than on the "correctness" of asset pricing theories.

hypotheses cannot be rejected for almost all sub-periods studied, using both the equal-weighted and the value-weighted indexes. This result suggests that these two indexes are indeed mean-variance efficient with respect to the contrarian stocks, and the hypothesis that all contrarian stocks earn no abnormal return over the testing period therefore cannot be rejected.

Moreover, as the result based on the CAPM, in most sub-periods under study, we find that using the APT models the joint hypothesis that intercepts equal zero for all contrarian stocks cannot be rejected. Thus, we conclude that the contrarian investment strategy overall earns no abnormal returns.

The remainder of the paper is organized as follows: Section 2 describes the data, and section 3 contains the methodology and empirical procedures. The results are presented in section 4, while the last section contains the conclusions.

2 The Data

We use stock returns from the monthly CRSP (Center for Research in Security Prices) data base. The data for riskfree rates are from the Fama tape. We study the period from 1940 to 1989. This 40-year period is divided into ten 5-year sub-periods. All stocks listed on NYSE/AMEX which do not have missing data during each sub-period are included in the sample. Thus, each sub-period contains 60 monthly observations for all stocks.[7] We then divide each sub-period equally into two intervals: the first 30 months are used as the ranking period and the remaining 30 months as the testing period. The ranking period is used to identify winners and losers. Specifically, all stocks are ranked in ascending order according to their (average) returns during the ranking period. The best (worst) 50 performing stocks are identified as winners (losers). Table 1 presents the average returns of losers, winners, and the contrarian portfolio that holds a long position on losers and a short position on winners. The results indicate that the contrarian strategy earns positive average returns for seven of the ten subperiods (see the last column in Table 1). It appears that on average the performance of this particular strategy earns a positive return. In all subperiods, loser (winner) portfolio has better (worse) performance in the testing period than in ranking period (i.e., the second column in Table 1 is less than the fourth and the third is greater than the first). This conforms to the "price reversal" phenomenon documented in the literature. The result also appears to support Lo and Mackinlay's finding (1990) that individual stocks' monthly returns are (weakly) negatively autocorrelated.

To form the portfolios used in our study, we again rank these extreme stocks in ascending order based on their average return during the ranking period. Then, the 50 losers

[7] Choosing 5-year time interval as study period is somewhat arbitrary. Basically, the rationale for choosing 5-year data is that several studies have suggested that systematic risks remain stable in a 5 year time interval. See, for example, the discussions in MacKinlay (1987) and GRS (1989).

Table 1: The Average Monthly Returns of Loser and Winner Portfolios in Each Subperiod

The average monthly returns of loser and winner portfolios are the sample averages on raw return data. Each number in the cell below is the average of 50 stocks over a 30-month period (ranking or testing period).

	Ranking Period		Testing Period		Contrarian
Subperiod	Loser	Winner	Loser	Winner	(Loser-Winner)
40-44	-1.2278%	8.3067%	1.3241%	-0.0583%	1.3824%
45-49	-1.1552%	0.8276%	3.9045%	0.6508%	3.2537%
50-54	-0.5920%	1.4705%	4.6697%	1.9714%	2.6983%
55-59	-1.5812%	2.4165%	3.8790%	1.2202%	2.6588%
60-64	-2.7116%	2.1566%	2.6401%	1.3054%	1.3347%
65-69	-2.6424%	5.5634%	2.6078%	3.9617%	-1.3539%
70-74	-3.4524%	5.2680%	-2.7479%	-3.9317%	1.1838%
75-79	-0.6226%	8.3997%	1.9615%	1.8318%	0.1297%
80-84	-3.1638%	5.3486%	1.9425%	2.3344%	-0.3919%
85-89	-2.1162%	6.4755%	-0.3921%	-0.0182%	-0.3739%

(winners) are divided evenly into 5 loser (winner) portfolios. That is, the first loser portfolio contains the first ten worst stocks, the second loser portfolio contains the subsequent ten stocks, and so on. In the same manner, the first ten of the bottom 50 stocks are grouped as the sixth portfolio, then the following ten stocks comprise the seventh portfolio, etc. The tenth portfolio contains the ten stocks that have the best performance among all stocks during the ranking period. Thus, in total we have 10 portfolios: 5 winners and 5 losers. In the following, we will call these portfolios extreme portfolios or contrarian portfolios interchangeably. Next, their performance over the testing period is tested by the two models which we present in the next section.

3 The Models and Empirical Procedures

This section summarizes the two models used in this study. The first model is from Chou (1993). Some testable hypotheses with exact testing statistics are derived there. The second model is proposed by CK (1988).

3.1 Model 1: A Model of Structural Changes Based on The CAPM

This model extends GRS's model (1989) to the case in which systematic risks of portfolios or individual assets are allowed to change over two different periods. Therefore, the model can be viewed as a model for testing structural changes.

Assume that the returns of each portfolio follow the linear relationship below:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \alpha_i^e \delta_t + \beta_i^e R_{mt} \delta_t + \varepsilon_{it} \qquad i = 1, ..., N; t = 1, ..., T_1 + T_2 \tag{2}$$

where

R_{it}	=	excess return on portfolio i in period t,
R_{mt}	=	excess return on the market index m in period t,
δ_t	=	a dummy variable, which equals 1 when $t > T_1$, and zero otherwise.
ε_{it}	=	a normally distributed random disturbance term with zero mean, conditional on R_{mt};
α_i, β_i	:	parameters for portfolio i,
α_i^e, β_i^e	:	parameters measuring the effect captured by the dummy variable.

Let $T \equiv T_1 + T_2$, where T_1 is the length of the ranking period and T_2 the length of the testing period. Here, $T_1 = T_2 = 30$, and N=10 (10 contrarian portfolios). Also, assume that the covariance matrix is stationary over time, and the returns of all securities are only contemporaneously correlated. More specifically, we assume that

$$cov(\varepsilon_{is}, \varepsilon_{jt}) = \begin{cases} \sigma_{ij} & \text{if } s = t \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

We can rewrite (1) and (2) in a more compact form as follows:

$$\boldsymbol{R} = \boldsymbol{XB} + \boldsymbol{E}, \qquad \text{where } \boldsymbol{E} \sim N(0, I_T \otimes \Sigma) \tag{4}$$

where

$$\boldsymbol{R} = \begin{pmatrix} \boldsymbol{R_1} \\ \boldsymbol{R_2} \end{pmatrix} \quad \boldsymbol{E} = \begin{pmatrix} \boldsymbol{E_1} \\ \boldsymbol{E_2} \end{pmatrix}$$

$$\boldsymbol{X} = \begin{pmatrix} \boldsymbol{X_1} & \boldsymbol{0} \\ \boldsymbol{X_2} & \boldsymbol{X_2} \end{pmatrix}$$

$$\boldsymbol{B} = \begin{pmatrix} \alpha_1 & \dots & \alpha_N \\ \beta_1 & \dots & \beta_N \\ \alpha_1^e & \dots & \alpha_N^e \\ \beta_1^e & \dots & \beta_N^e \end{pmatrix}$$

and

$$\boldsymbol{R_1} = \begin{pmatrix} R_{11} & R_{12} & \dots & R_{1N} \\ \vdots & \vdots & \ddots & \vdots \\ R_{T_1 1} & R_{T_1 2} & \dots & R_{T_1 N} \end{pmatrix} \qquad \boldsymbol{X_1} = \begin{pmatrix} 1 & R_{1p} \\ \vdots & \vdots \\ 1 & R_{T_1 p} \end{pmatrix}$$

$$\boldsymbol{E_1} = \begin{pmatrix} \varepsilon_{11} & \varepsilon_{12} & \dots & \varepsilon_{1N} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{T_1 1} & \varepsilon_{T_1 2} & \dots & \varepsilon_{T_1 N} \end{pmatrix}$$

R_2, X_2, and E_2 are defined in the same manner.

The model can be estimated by ordinary least square, i.e., $\hat{B} = (X'X)^{-1}X'R$, and the covariance matrix can be estimated as:

$$\hat{\Sigma} = \frac{1}{T-4}(R - X\hat{B})'(R - X\hat{B}) \tag{5}$$

Some testable hypotheses of interest are summarized in Table 2. As is well known, the CAPM asserts that if a portfolio, say p, is mean-variance efficient, then the expected excess returns of individual assets, $E(R_i)$, and that of the portfolio, $E(R_p)$, will have the following relationship:

$$E(R_i) = \beta_{ip}E(R_p) \qquad \forall\ i,$$

which is referred to as the *security market line* (SML) in the literature. This implies that if we regress the excess returns of individual securities on those of an efficient portfolio, the resulting intercepts should be indistinguishable from zero. Thus, it is clear that hypotheses 1 and 2 can be used to test the *necessary condition* for a given portfolio, in this study the equal-weighted or value-weighted index, to be mean variance efficient over the ranking period and testing period, respectively. The hypotheses can be tested based on a statistic derived by GRS (1989). Specifically, by exploiting Hotelling T^2 statistic, they derive that the following statistic has a central F distribution under the null hypothesis:

$$GRS = \frac{T_j(T_j - N - 1)}{N(T_j - 2)} \frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1 + \bar{r}_{mj}^2/S_{mj}^2} \tag{6}$$

where $\bar{r}_{mj}$ and S_{mj}^2 are the average return and sample variance of the market index over period j, respectively. Note that all statistics in Table 2 are very similar to the statistic in (6). In addition, hypothesis 3 is designed to examine the changes in intercepts, while hypothesis 4 examines the changes in systematic risks. It should be noted that only under the condition that the underlying market index is efficient over time does it make sense to test the stability of the systematic risk measure, provided that all underlying assumptions are fulfilled.

It is also worth mentioning that in effect we are testing if the market index significantly deviates from the *ex post* efficient frontier, spanned by different linear combinations of

Table 2: Summary of Hypotheses Underlying Model 1

Hypothesis	Statistics*	Distribution**
$H_1 : \alpha = 0$	$\frac{T-N-3}{N(T-4)} m_{11}^{-1} \hat{\alpha}' \hat{\Sigma}^{-1} \hat{\alpha}$	$F_{N,T-N-3}$
$H_2 : \alpha + \alpha^e = 0$	$\frac{T-N-3}{N(T-4)} (m_{11} + 2m_{31} + m_{33})^{-1} (\hat{\alpha} + \hat{\alpha}^e)' \hat{\Sigma}^{-1} (\hat{\alpha} + \hat{\alpha}^e)$	$F_{N,T-N-3}$
$H_3 : \alpha^e = 0$	$\frac{T-N-3}{N(T-4)} m_{33}^{-1} \hat{\alpha}^{e\prime} \hat{\Sigma}^{-1} \hat{\alpha}^e$	$F_{N,T-N-3}$
$H_4 : \beta^e = 0$	$\frac{T-N-3}{N(T-4)} m_{44}^{-1} \hat{\beta}^{e\prime} \hat{\Sigma}^{-1} \hat{\beta}^e$	$F_{N,T-N-3}$

* m_{ij} in each statistic is the (i, j)th element of $(X'X)^{-1}$. Solving it explicitly, we have the following:
$m_{11} = T_1^{-1}(1 + \bar{R}_{m1}^2 / S_{m1}^2)$
$m_{22} = T_1^{-1} S_{m1}^{-2}$
$m_{33} = m_{11} + T_2^{-1}(1 + \bar{R}_{m2}^2 / S_{m2}^2)$
$m_{44} = m_{22} + T_2^{-1} S_{m2}^{-2}$
$m_{11} + 2m_{31} + m_{33} = T_2^{-1}(1 + \bar{R}_{m2}^2 / S_{m2}^2)$
Here $T_1 = T_2 = 30$. Subscript 1 denotes the ranking period, and subscript 2 denotes the test period. $\bar{R}_{mt}$ and S_{mt}^2 $(t = 1, 2)$ are the average and sample variance of the excess return on the market index m over the period i, respectively.

all sampled portfolios and the underlying market index [see GRS(1989) for detail]. Thus, it is possible that the compositions of the "true" market portfolio has changed, while the constant-weight market index still maintains its efficiency (i.e., H_4 is accepted and H_3 is rejected).

A Comparison to Chan's (1988) Hypotheses

The model specification (2) is essentially the same as Chan (1988). However, we have a different design on the tests of the contrarian profits. Using the CAPM as the underlying model, Chan (1988) chooses the equal-weighted index as the proxy for the market portfolio. Assuming that the equal-weighted index is efficient and using the same model as equation (2), Chan (1988) tests the following three kinds of hypotheses for abnormal returns:

$$
\begin{aligned}
H_w : \sum_{winners} \alpha_i &= 0 \\
H_l : \sum_{losers} \alpha_i &= 0 \\
H_c : \sum_{losers} \alpha_i - \sum_{winners} \alpha_i &= 0
\end{aligned}
$$

What Chan tests is a hypothesis that the sum of the individual stocks' intercepts equals zero. However, as we have explained previously, the CAPM asserts that *all* stocks should

Figure 1: An Example

have zero intercepts, if the market index is efficient. It is possible that in fact some stocks have significant intercepts, but the sum of the intercepts are not significantly different from zero. To see this, we draw a graph demonstrating the test in Chan (1988). Figure 1 draws the joint parameter space for the intercept of loser portfolio and the negative intercept of winner portfolio. The 45 degree dashed line represents Chan's null hypothesis on the zero abnormal return of the contrarian portfolio: $H : \alpha_c = \alpha_l + (-\alpha_w) = 0$, where α_c refers to the Jensen's measure for the contrarian portfolio, and α_l and α_w are the Jensen's measures for the loser and winner portfolios respectively. For both possible estimates in Figure 1, one will not be able to reject Chan's hypothesis because both the confidence intervals contain part of the 45 degree line. However, here one will reject the null hypothesis that both winner and loser portfolios have zero intercepts because none of the confidence intervals contain the origin, which represents the joint hypothesis. From this demonstration, one may say, roughly, that our test has a higher "power" than Chan's, given the underlying null being the joint hypothesis specified in our model.

In Chan's (1988) study, he finds that abnormal returns obtained by the contrarian investment strategy are due to the changes in systematic risk of winner and loser portfolios. His empirical results also show that the regression intercepts are significant in the ranking periods. This suggests that the equal-weighted index may not be mean-variance efficient with respect to the contrarian stocks.[8] If it is so, the systematic risk measure obtained by using the excess returns of the inefficient index is somehow inaccurate.[9]

However, since in each sub-period the contrarian stocks are chosen based on their realized average returns over the ranking period which is also included in our model here, the estimation of α's and β's over the ranking period may be biased due to a selection bias. In particular, in this case it is possible that the covariance matrices are different between ranking and testing periods. Therefore, we also use the standard GRS test (6) to test the zero-intercept hypothesis using the data over the testing periods only. The results can be used to see if the empirical results of our model is "robust." Note that in this case the GRS statistic will have F a distribution with degrees of freedom 10 and 19, rather than 10 and 47. We use equal-weighted and value-weighted indexes as proxies for the market portfolio.

[8] Alternatively, if one adopts Chan's assumption on the ex ante efficiency of the underlying index, the resulting intercepts (Jensen's performance measures) can be viewed as abnormal returns adjusted for risks. In this sense, then, contrarian portfolios are considered to have abnormal performance. The sign of the abnormal return for the contrarian strategy depends on the magnitude of the resulting intercepts for the loser and winner portfolios.

[9] See, for example, the arguments in Roll (1977). Of course, if we know the correlation between the market index and the true market portfolio, then the resulting risk measure can still be an indication of riskiness. However, this requires imposing a strong assumption on the characteristics of missing assets and therefore is considered implausible [see, e.g., Dybvig and Ross (1985).]

3.2 Model 2: A Model Based on the APT

This section summarizes the equilibrium APT and the asymptotic principal components method proposed by CK (1988). The empirical procedure implementing the test is also presented. Readers familiar with their studies may skip this section.

3.2.1 The Equilibrium APT

CK (1988) assume that there are an *infinite* number of risky assets whose returns are generated by the linear relationship below:

$$\tilde{r}_t = E(\tilde{r}_t) + B\tilde{f}_t + \tilde{\varepsilon}_t \qquad t = T_1 + 1, ..., T_1 + T_2; \tag{7}$$

where

$$E(\tilde{\varepsilon}|\tilde{f}_t) = 0, E(\tilde{f}_t) = 0, E(\tilde{\varepsilon}_t\tilde{\varepsilon}_t') = V. \tag{8}$$

Here, $\tilde{r}_t$ is the $(\infty \times 1)$ vector of asset returns, B is the $(\infty \times k)$ factor loading matrix, $\tilde{f}_t$ is a $(k \times 1)$ vector of unobserved factors, and the number of factors, k, is assumed known. The equilibrium APT implies:

$$E(\tilde{r}_t) = r_{Ft}\ e + B\gamma_t, \qquad t = T_1 + 1, ..., T_1 + T_2, \tag{9}$$

where e is a column vector of ones, and r_{Ft} is the riskfree rate at time t. Combining (7) and (9), we have:

$$\tilde{r}_t - r_{Ft} = B(\gamma_t + \tilde{f}_t) + \tilde{\varepsilon}_t \qquad t = T_1 + 1, ..., T_1 + T_2; \tag{10}$$

With a finite sample of n assets, (10) can be written as:

$$R^n = B^n F + \varepsilon^n, \tag{11}$$

where R^n is an $(n \times T_2)$ vector of excess returns, B^n is the corresponding $(n \times k)$ submatrix of B, and $F \equiv (F_1, ..., F_t, ..., F_{T_2})$, with $F_t \equiv \gamma_t + \tilde{f}_t$. Equation (11) implies that performing regressions of R^n on F (and on a constant term) should yield insignificant intercepts, if F is known. Since the factors are not observable, CK (1988) propose an asymptotic principal components method, suggested by Chamberlain and Rothschild (1983), to find a linear transformation of the factors. The method extracts the factors from the time series of all stock returns, which a priori cannot be identified or related to any known factors such as GNP or inflation. We summarize the method in the following.

3.2.2 The Asymptotic Principal Components for Extracting the APT Factors

Define $\Omega \equiv (1/n)R^{n\prime}R^{n}$. Let G_k denote the orthonormal ($k \times T_2$) matrix consisting of the first k eigenvectors of Ω . CK (1988) prove that G_k is a linear transformation of the factors. Specifically, they prove that

$$G_k = L^n F + \phi^n$$

where L^n is a nonsingular matrix for all n and $plim_{n\to\infty}\phi^n = 0$. Therefore, as n, the number of assets, approaches infinity, G_k will be a linear transformation of the true factors F. We may estimate the factor loadings of individual stocks by running time-series regressions of their excess returns on G_k and a constant term. The (equilibrium) APT implies that the resulting intercepts should not be significantly different from zero. Also, since a linear transformation of the factors, the design matrix in a regression, will not affect R^2 and the significance of regression coefficients, using G_k yields the same result as using the original factors. Assuming that the regression errors are jointly normally distributed, the joint hypothesis that the intercepts are zero for all sampled stocks can be tested based upon the Hotelling T^2 statistic, which is distributed as an F variate if the hypothesis is true.[10]

3.2.3 The Empirical Procedure

The empirical procedure is:[11]

1. Estimate $\hat{\Omega}$ using all stock returns over the testing-period data ($T_2 = 30$).

2. Calculate the first k ($k = 1, 5, 10$) eigenvectors. These k vectors are used to construct the orthonormal matrix, G_k .[12]

3. Run a regression of each winner (and loser) portfolio on a vector of ones, e, and G_k'. Then, check the significance of the resulting intercepts.

We explain step three and derive the statistics for testing the zero-intercepts hypothesis in the appendix.

[10]Theoretically, the APT does not require the assumption of normality. If the normality assumption is not imposed, the resulting statistic will have a χ^2 distribution asymptotically. However, CK (1988) still use F instead of χ^2 to test the joint hypotheses because the F test is more conservative, while using χ^2 tends to reject the null hypotheses too often. See footnote 6 of CK (1988) for a discussion on this issue.

[11]All empirical tests are carried out using SAS. The asymptotic principal components and most testing statistics are calculated using SAS/IML procedure.

[12]CK (1988) propose an iterative procedure to extract the factors. However, they also point out that there is no need to iterate the estimation because a large sample will result in a good estimate of G_k in the first estimation. Here, we follow their procedure.

4 Empirical Results

4.1 Empirical Results of the CAPM

Table 3 presents the empirical results of the first model. It shows that almost all hypotheses for all subperiods are rejected at the 1% significance level. Recall that rejection of hypotheses 1 and 2 implies that the underlying market index, equal-weighted (EWI) or value-weighted (VWI), is not mean-variance efficient with respect to the contrarian stocks. Thus, the rejection of hypothesis 1 indicates that both indexes are not mean-variance efficient with respect to the contrarian stocks over all ranking periods. This conforms to Chan's empirical results that both winner and loser portfolios have significant intercepts (i.e., "abnormal returns") for all ranking periods. However, as we have mentioned in section 2, there is a potential problem of selection bias.

The results of testing hypothesis 2 in Table 3 overall quite support Chan's findings. Chan (1988) reports that both winner and loser portfolios have insignificant intercepts for most of the testing periods. His result seems to suggest that the equal-weighted index may be efficient with respect to these extreme portfolios over the testing periods. Our empirical results also show that the efficiency of both indexes cannot be rejected for almost all of the sub-periods.

In addition, the empirical results of hypothesis 3: $\alpha^e = 0$ show that there are also significant changes in intercepts. In fact, OLS regressions show that in the ranking periods losers have negative intercepts, whereas the winners have positive intercepts. This suggests that winners (losers) earn positive (negative) "abnormal returns" even after adjusting for the systematic risks, provided that the assumption of efficiency of the market indexes is imposed. In the testing periods, we find that there is a "reversal" effect; the sign of changes in intercept, α^e, is positive for losers and negative for winners.[13]

In addition, the results of testing hypothesis 4 indicate that there are very significant changes in systematic risks for the contrarian stocks over the ranking and testing periods, which confirm Chan's (1988) findings.

Thus, the results suggest that abnormal returns of the contrarian stocks are eliminated through changes in intercepts and systematic risks. There is "market reaction," but no "overreaction." The results seem to indicate that there is a tendency for the indexes to reduce their "inefficiency" with respect to the contrarian stocks. Or alternatively, one may consider that the market reacts in a way such that these extreme performers' abnormal returns are eliminated.

In Table 4 we reports the empirical results of the standard GRS tests using the testing period data only. Again, we cannot reject the zero-intercept hypothesis for all subperiods for both indexes at 5% significance level, except that the hypothesis for the equal-weighted index at the last sub-period is marginally rejected (p-value 0.04953). However, the resulting

[13] We do not report all the regression results here. They are, of course, available from the author upon request.

Table 3: Empirical Results of Model 1

This table presents the results of the four hypothesis tests based on model 1, presented in Table 1. Both equal-weighted and value-weighted indexes are used. The first statistic in each cell is calculated based on the formula in Table 1, and the second statistic in parenthesis is the corresponding p value. All p values are calculated based on an F distribution with degrees of freedom 10 and 47.

Value Weighted Index

Period	$H_1 : \alpha = 0$	$H_2 : \alpha + \alpha^e = 0$	$H_3 : \alpha^e = 0$	$H_4 : \beta^e = 0$
40-44	6.32566	0.61225	1.84292	18.0487
	(4.6208E-6)	(0.7955443)	(0.0786876)	(6.316E-13)
45-49	7.0790	0.88029	3.8180	7.31245
	(1.1614E-6)	(0.5576855)	(0.000806)	(7.6798E-7)
50-54	6.46711	0.52015	3.73872	2.87372
	(3.5455E-6)	(0.8672496)	(0.0009629)	(0.0070372)
55-59	3.39708	1.49541	2.61861	6.76788
	(0.0020914)	(0.1711112)	(0.0128125)	(2.0363E-6)
60-64	9.37220	1.06316	4.95490	5.27711
	(2.606E-8)	(0.4086332)	(0.0000694)	(0.0000358)
65-69	8.28417	1.34421	5.71062	2.08789
	(1.4707E-7)	(0.2357903)	(0.0000151)	(0.0446233)
70-74	11.6232	1.34376	8.53072	8.28837
	(1.0247E-9)	(0.2360081)	(9.8309E-8)	(1.4605E-7)
75-79	4.55101	0.87117	3.35329	8.76498
	(0.0001623)	(0.5656874)	(0.0023124)	(6.7446E-8)
80-84	8.54719	1.11660	4.35369	7.14574
	(9.5721E-8)	(0.3702058)	(0.000248)	(1.0311E-6)
85-89	11.7041	1.30890	6.39829	3.58735
	(9.192E-10)	(0.2535866)	(4.0318E-6)	(0.0013553)

Equally Weighted Index

Period	$H_1 : \alpha = 0$	$H_2 : \alpha + \alpha^e = 0$	$H_3 : \alpha^e = 0$	$H_4 : \beta^e = 0$
40-44	6.04124	0.80315	1.48152	13.84195
	(7.9349E-6)	(0.6263996)	(0.1763221)	(6.127E-11)
45-49	7.18540	0.72344	3.58216	8.06797
	(9.6103E-7)	(0.6984365)	(0.0013714)	(2.1049E-7)
50-54	7.42860	0.66284	3.83489	4.61534
	(6.2671E-7)	(0.7522942)	(0.0007762)	(0.0001416)
55-59	3.27871	1.40800	2.50397	9.53297
	(0.0027452)	(0.206304)	(0.0167847)	(2.0381E-8)
60-64	9.28927	1.45177	5.17698	7.37692
	(2.9611E-8)	(0.187958)	(0.0000439)	(6.859E-7)
65-69	6.86939	1.41183	5.48995	5.21942
	(1.6931E-6)	(0.2046374)	(0.0000234)	(0.0000403)
70-74	11.3164	1.31677	8.14813	12.0858
	(1.5544E-9)	(0.2495249)	(1.8418E-7)	(5.54E-10)
75-79	4.75099	0.86238	3.17310	20.90000
	(0.0001063)	(0.5734431)	(0.0035037)	(4.385E-14)
80-84	9.03391	2.0848	4.82438	9.49186
	(4.4066E-8)	(0.044946)	(0.0000911)	(2.1698E-8)
85-89	11.6357	1.25257	5.97680	5.08336
	(1.0077E-9)	(0.2842456)	(8.9825E-6)	(0.0000532)

Table 4: Empirical Results of GRS test

This table presents the results based on the GRS test [Gibbons, Ross, and Shanken (1989)]. The p-values are calculated based on an F distribution with degrees of freedom 10 and 19.

	VWI		EWI	
Period	Statistic	(p-value)	Statistic	(p-value)
40-44	1.43389	(0.23922)	1.64292	(0.16879)
45-49	0.79859	(0.63200)	0.79860	(0.63200)
50-54	1.46508	(0.22716)	1.24246	(0.32721)
55-59	1.61232	(0.17766)	1.56834	(0.19123)
60-64	1.85914	(0.11749)	1.56544	(0.19216)
65-69	1.37796	(0.26238)	1.52854	(0.20440)
70-74	1.99083	(0.09433)	2.05127	(0.08532)
75-79	0.99515	(0.48043)	1.08226	(0.42120)
80-84	1.29556	(0.30026)	1.32323	(0.28702)
85-89	2.13933	(0.07378)	2.38383	(0.04953)

statistics are different from Table 3, which may be due to changes in the covariance matrix. However, since the degrees of freedom here are different, there is not much we can say about the nonstationarity of the covariance matrix. The GRS test results, though, suggest that our model is "robust" here.

4.2 Empirical Results of APT Model

After deleting stocks that have missing data during each subperiod, the remaining stock return data are used to extract the APT factors. The number of stocks used for each of the ten sub-periods is, respectively, 716, 803, 945, 938, 931, 1507, 1872, 1723, 1724, and 1509. Note that in each subperiod under study only the data over the testing period are used to extract the APT factors. The empirical results are summarized in Table 5.

Table 5 shows that none of the zero-intercept hypothesis can be rejected at 1% significance level for all subperiods in the 1-, 2- and 5-factor APT models. At 5% significance The 1-factor APT model rejects the zero-intercept hypothesis only for one sub-period, while four sub-periods have significant intercepts at 10% significance level.

The 2-factor APT seems to explain the contrarian performance very well. The hypothesis is rejected only in one sub-period at 10% significance level, while none of the statistics have p-value smaller than 5%.

The empirical results of the 5-factor APT model are very similar to those of the 2-factor APT model. As in the 2-factor model, the result shows that the zero-hypothesis for the

Table 5: Empirical Results of the APT

This table presents the testing results of the APT models. The first statistic in each cell is calculated based on the formula derived on section 3.2, and the second statistic in parenthesis is the corresponding p value. In this case, the p values for 1-factor model are calculated based on an F distribution with degrees of freedom 10 and 19. The p values for 2 factor model is based on F distribution with degrees of freedom 10 and 18, and for 5-factor model degrees of freedom are 10 and 15.

Period	1-factor	2-factor	5-factor
42/7-44	0.9759	0.8405	0.6304
	(0.4943)	(0.5985)	(0.7671)
47/7-49	0.6350	0.8608	1.0315
	(0.7668)	(0.5825)	(0.4635)
52/7-54	0.75992	0.4723	0.5376
	(0.76680)	(0.8868)	(0.8378)
57/7-59	1.7364	1.5095	1.8347
	(0.1443)	(0.2147)	(0.1396)
62/7-64	2.3015	1.9652	1.9028
	(0.0566)	(0.1019)	(0.1261)
67/7-69	2.2387	1.6101	2.0143
	(0.0627)	(0.1821)	(0.1068)
72/7-74	1.9238	1.8423	1.5613
	(0.1055)	(0.1245)	(0.2109)
77/7-79	2.7144	2.2697	3.6082
	(0.0293)	(0.0625)	(0.0126)
82/7-84	2.3015	1.9652	1.9028
	(0.0566)	(0.1019)	(0.1261)
87/7-89	1.8053	1.2849	1.5451
	(0.1286)	(0.3087)	(0.2162)

Significance level	1-factor	2-factor	5-factor
1%	0	0	0
5%	1	0	1
10%	4	1	1

eighth sub-period (7/77-79) is rejected (p-value 0.01262). The empirical results somehow confirm some findings in the APT literature that the number of the APT factors is between 2 and 6.[14]

5 Conclusions

In this study, we have reexamined the performance of the contrarian investment strategy by introducing a model of structural changes based on the CAPM and a model based on the APT. Our study differs from previous studies mainly in two aspects. First, our test is based on a multivariate framework. This allows us to test some joint hypotheses by further considering the correlation among the contrarian stocks. First, we have found that for all sub-periods in our study, the winner and loser stocks have experienced significant changes in intercepts and systematic risks. Since the zero-intercept hypothesis cannot be rejected for almost all sub-periods, the abnormal returns documented in previous studies can be attributed to changes in systematic risks and intercepts of contrarian stocks. Second, we use the APT as the alternative pricing model, which so far has not been done by other studies. We found that overall the APT models have explained the contrarian performance very well. The empirical results based on the 2-factor APT is especially satisfactory.

To conclude, we found that overall the contrarian investment strategy does not earn no abnormal returns, and the CAPM and the APT models have explained its performance equally well.

[14]We have also examined if the January effect can account for the performance of the contrarian stocks. The results are similar to the APT without including the January effect. Also, overall we found no significant January effect for the contrarian stocks. However, since each subperiod only contains 30 months, this means that the dummy variable that represents the January observations only takes value on for two observations. This may cause a problem in estimating the regression coefficient and its standard deviation. Thus, we do not report the results here. They are available from the authors.

Appendix A

This appendix derives the statistic for testing the zero-intercept hypothesis described in section 3.2. The statistic we derive below is actually very similar to the statistics described in section 7 of GRS (1989), but differs in that here we are using “principal components” rather than a set of “efficient portfolios.” Let R_c be the $(10 \times T_2)$ matrix of excess returns of the 10 contrarian portfolios (5 winners and 5 losers) over the testing period. Thus, in step three we run the following regression:

$$R_c = \alpha_c e_{T_2}' + B_c G_k + \varepsilon_c \tag{12}$$

where

$$\begin{aligned} \alpha_c &= (\alpha_1, ..., \alpha_{10})' \\ e_{T_2} &= (1, ..., 1)' \end{aligned}$$

and B_c is the corresponding $(10 \times k)$ factor-loading matrix.[16] Therefore, equation (10) implies a testable hypothesis: $\alpha_c = 0$, analogous to the zero-intercept hypothesis in the CAPM test. This hypothesis can be viewed, roughly, as a joint hypothesis of the validity of the APT and zero abnormal returns of the contrarian portfolios. If the hypothesis is rejected, it may suggest that the APT is not an appropriate pricing model, in spite of the fact that the APT *does not* assure that *all* assets will be correctly priced. However, if we fail to reject this hypothesis, it then suggests that the contrarian strategies do not earn abnormal returns. This hypothesis can also be tested based on a statistic similar to the GRS test. We now derive the statistic for testing this hypothesis. Equation (12) can be written as the following:

$$\boldsymbol{R}_c' = \boldsymbol{X} + \boldsymbol{\varepsilon}_c', \tag{13}$$

where

$$\begin{aligned} X &= [e_{T_2} : \ G_k']_{T_2 \times (k+1)} \\ \Gamma &= [\alpha_c : \ B_c]_{(k+1) \times 10} \end{aligned}$$

Thus, based on the assumptions above, we have the unbiased estimators: $\hat{\Gamma} = (X'X)^{-1}X'R_c'$. Note here that using the OLS yields the estimators with desirable small-sample properties, since in the case where explanatory variables are identical across equations GLS method (or SUR method) yields the same results as OLS. Thus, we have

$$\hat{\Gamma} \sim N(\Gamma, (X'X)^{-1} \otimes \Sigma) \tag{14}$$

[16]Here B_c actually is the true factor-loading matrix multiplied by a nonsingular matrix (i.e., $B_c \times L^{n-1}$).

where Σ is the variance-covariance matrix of the residuals. From (14), we have $\hat{\alpha}_c \sim N(\alpha_c, a_{11}\Sigma)$, where a_{11} is the (1,1) element of $(X'X)^{-1}$. In addition, the covariance matrix can be estimated as:

$$\hat{\Omega} = \frac{1}{T_2 - k - 1}(R_c' - X\hat{\Gamma})'(R_c' - X\hat{\Gamma}) \tag{15}$$

$(T_2 - k - 1)\hat{\Omega}$ has a Wishart distribution, denoted as $W_{10}(T_2 - k - 1, \Sigma)$.[15] It can be shown that $\hat{\alpha}_c$ and $\hat{\Omega}$ are independent. Then, by a theorem from Muirhead (1982, p.211), we have the following statistic a standard Hotelling T^2, which has a central F distribution under the null hypothesis:

$$J \equiv \frac{T_2 - k - 10}{10 a_{11} T_2} \hat{\alpha}_c' \hat{\Omega}^{-1} \hat{\alpha}_c \sim F(10, T_2 - k - 10) \tag{16}$$

Note that the statistic J has a very similar form as the GRS.

[15]For an introduction of the Wishart distribution and its properties, see, for example, Anderson (1984) and Muirhead (1982).

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