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Multifactor Evaluation of Style Rotation

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Abstract

A growing literature documents that various strategies of rotating across equity styles generate significant returns. However, the conventional risk adjustment regression is problematic in evaluating the gains from style rotation. I propose a weight-based multifactor risk adjustment approach as a solution. When interpreted as a performance attribution procedure, this approach extends Sharpe's (1992) classic method by emphasizing factor loading rotation. I use a logit-based timing strategy to show that the conventional procedure produces misleading results and the new method leads to the opposite conclusion.

I. Introduction

A large body of both academic and industry research is devoted to equity style performance and fund investment style. In recent years, average return differences among styles, such as the difference between growth and value stocks, have become the focus of many investigations. For example, Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), Lakonishok, Shleifer, and Vishny (1994), and Roll (1997), among others, examine the long-term relative performances among growth, value, and small- and large-cap stocks. Meanwhile, the potential success of style rotation strategies has also attracted numerous studies (e.g., Beinstein (1995), Fan (1995), Sorensen and Lazzara (1995), Leinweber, Arnott, and Luck (1997), Kao and Shumaker (1999), Levis and Liodakis (1999), Asness, Friedman, Krial, and Liew (2000), Ahmed, Lockwood, and Nanda (2002), Lucas, Dijk, and Kloek (2002), and Teo and Woo (2002)). These studies conclude that various strategies of rotating across equity styles generate significant returns and suggest that relative performances between asset classes are time varying and predictable.[1]

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[1]Along with the growing literature on style-based investment strategies, there are many studies on investment styles of managed portfolios. For example, see Sharpe (1992), Brown and Goetzmann (1997), (2003), Daniel, Grinblatt, Titman, and Wermers (1997), Fung and Hsieh (1997), and Ibbotson and Kaplan (2000).

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In this article, I propose a weight-based return decomposition approach to multifactor evaluation of style rotation. This method is designed for risk adjustment. Alternatively, it may be viewed as a performance attribution approach that extends the method of Sharpe (1992) in evaluating dynamic investment strategies. To illustrate the methodological significance, I analyze a style timing strategy that is built on a logit model. This strategy uses the logit model to predict relative style performance, buying the predicted winner style while short selling the predicted loser style. The strategy is based on a rolling window approach, namely that at any time the logistic regressions only make use of the most recent information to make predictions. The results show that rotation based on the logit model predictions generates significant return. However, using Fama and French's (1993) three-factor model, the conventional risk adjustment method drastically fails to explain the return on the timing strategy.[2] In contrast, my approach leads to the opposite conclusion: the three-factor model can effectively account for the performance of the timing strategy. I find that most of the strategy's return can be attributed to covariances among the rotating betas and the corresponding factors.[3]

To illustrate why the conventional procedure is problematic in the presence of dynamic trading, I provide a simple example using the relative strength strategy of Lo and MacKinlay (1990) to show that in a factor model without any mispricing the conventional procedure in general produces a non-zero regression intercept. In this model, the betas of basis assets (i.e., the underlying styles) are constant over time, but the strategy's beta varies over time due to the time-varying portfolio weights. I show that, in this example, the strategy's beta is correlated with the conditional factor risk premium, giving rise to a non-zero value of Jensen's alpha, even though the factor model completely captures the basis asset returns. Moreover, I use the Sharpe-Lintner capital asset pricing model (CAPM) to explain intuitively why the covariance between the beta and the factor is part of the risk premium.

The key feature of my solution is to explicitly incorporate the time-varying portfolio weights, whose impact on fund performance evaluation has been discussed in several studies. Dybvig and Ross (1985), for instance, show that linear factor models fail to properly rank fund managers when they change their asset weights over time. Grinblatt and Titman (1993) propose a weight-based measure to avoid problems posed by time variation in asset weights. Brown and Goetzmann (1997) emphasize the importance of time-varying portfolio weights in manager style classification. More recently, extending the benchmark-free measure of Grinblatt and Titman (1993), Ferson and Khang (2002) propose a weight-based measure with conditioning information.

It is interesting to note the relative strengths of my approach and the approach of Ferson and Khang (2002). Ferson and Khang's conditional weight measure is

[2]Largely due to Jensen's (1968) influential study on mutual funds, it has become a widely applied portfolio evaluation procedure to run a time-series regression of the portfolio's excess return on the factor(s) and interpret the regression intercept, the so-called Jensen's alpha, as the risk-adjusted return for the portfolio. Throughout the paper, this approach is referred to as the *conventional* procedure.

[3]The logit-based timing strategy involves buying the predicted winner style and short selling the predicted loser style. To denote the performance of such a zero-cost portfolio (e.g., the return difference between the predicted winner and loser), I simply use the term "strategy's return" throughout the paper.

a benchmark-free measure aimed at testing whether fund managers have private information. This is a general approach that does not require a factor model, but instead relies on a set of pre-specified variables that represent public information. Ferson and Khang's measure is well suited for detecting superior performance of fund managers whose information set is unknown to researchers and whose investment strategies may not be consistent over time. In contrast, my approach is a factor-based method to decompose returns on dynamic strategies. This method is well suited for evaluation of clearly specified dynamic strategies that do not use private information.[4] Examples of trading strategies without private information include all the style rotation strategies proposed in the literature and technical trading rules such as those studied by Brock, Lakonishok, and LeBaron (1992) and Sullivan, Timmermann, and White (1999).

In fact, the analysis of style rotation is comparable in spirit to many studies on technical trading rules. Technical analysis has received considerable attention in recent years (e.g., Brock, Lakonishok, and LeBaron (1992), Jegadeesh and Titman (1993), Brown, Goetzmann, and Kumar (1998), Conrad and Kaul (1998), Allen and Karjalainen (1999), Sullivan, Timmermann, and White (1999), Lo, Mamaysky, and Wang (2000), and Grundy and Martin (2001)). One of the most important issues in evaluation of the trading rules is how to account for risk. Brown, Goetzmann, and Kumar (1998), for example, demonstrate that risk adjustment is critical in evaluation of the Dow theory. Similarly, I aim at risk adjustment for the style timing strategy. Over various sample periods, the logit timing strategy has not only high raw return but also a large alpha from the conventional risk adjustment regression. Although its raw return is as impressive as many of the documented trading rules, my goal in this paper is not to promote the logit-based style rotation. The strategy serves as an example to demonstrate the problem of the conventional risk adjustment procedure and the significance of my solution.

In the empirical study, I focus on the Fama and French (1993) three-factor model.[5] The model is applied to evaluate the style-based dynamic strategy. To highlight the effects of beta rotation, I analyze the case of constant multifactor betas for the underlying styles. A conditional evaluation analysis is also performed, using a model with betas that vary over time in response to economic circumstances. This is an approach adopted by numerous studies, such as Ferson and Schadt (1996), Ferson and Harvey (1999), and Wu (2002). Without explicitly incorporating portfolio weights, this popular conditional evaluation approach is still unable to account for the strategy's performance.

The article is organized as follows. Section II provides a simple example to illustrate the problem of the conventional risk adjustment regression with dynamic trading. I discuss the economic intuition and then propose my solution. Section III presents the empirical analysis. The first two subsections describe the data and

[4]Substantial estimation risk may be associated with construction of many dynamic strategies such as the logit-based rotation strategy of this paper. The estimation noise is accounted for in my testing approach.

[5]There are competing explanations for the empirical success of the Fama-French size and book-to-market factors. For example, see Fama and French (1996) and Liew and Vassalou (2000) for a risk-based explanation; see MacKinlay (1995) and Barberis and Shleifer (2003) for a behavioral-based explanation. For my purpose, I simply take the three-factor model as the default risk model.

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the logit-based style timing. Then, I report and discuss empirical results from the unconditional and conditional multifactor evaluation. Section IV concludes.

II. Risk Adjustment

A. Conventional Procedure and Dynamic Trading

Factor-based asset pricing models are the most widely applied tool for risk adjustment. However, the conventional procedure can be problematic with dynamic trading strategies. This subsection presents a simple analytical example to illustrate the issue.

I consider a relative strength strategy of Lo and MacKinlay (1990) that has the following portfolio weights,

$$w_{it-1} = \frac{1}{n}\left(r_{it-1} - \bar{r}_{t-1}\right), \tag{1}$$

for $i = 1, \ldots, n$, where r_{it-1} is the excess return of style i and $\bar{r}_{t-1}$ is the excess return on the equal-weighted portfolio.[6] The relative strength strategy is analytically convenient since the weights are linear in the returns. Conrad and Kaul (1998), for example, utilize the linear structure of the weights to derive a decomposition of the strategy's return. However, there is no analytical result on the conventionally risk-adjusted return or Jensen's alpha of the relative strength strategy.

To ease exposition and highlight the key issue, I use a single-factor model without any pricing errors. In this simple case, the excess returns on all the styles are assumed to be perfectly captured by a constant single beta model, $r_{it} = \beta_i f_t$, where β_i is the beta of style i, for $i = 1, \ldots, n$, and f_t is the risk factor, or more precisely, the time-t excess return on the factor mimicking portfolio. The risk factor f_t is normally distributed with mean μ and variance σ^2. The factor risk premium is time varying, $E_{t-1}(f_t) = c_0 + c_1 z_{t-1}$, where z_{t-1} is a conditioning variable and $c_1 \neq 0$. If f_{t-1} and z_{t-1} are correlated, the factor f_t is autocorrelated. Let ρ denote the first autocorrelation.[7]

Given the weights in (1), the performance of the relative strength strategy is determined by $r_{pt} = \beta_{pt-1} f_t$, where $r_{pt} = \sum_{i=1}^{n} w_{it-1} r_{it}$ and $\beta_{pt-1} = \sum_{i=1}^{n} w_{it-1} \beta_i$. One should note that the beta β_{pt-1} of the strategy is not constant over time, even though the excess return r_{it} is determined by the constant beta model.

It is a standard procedure to run an ordinary least squares regression of r_{pt} on f_t and then take the regression intercept as the risk-adjusted return of the relative strength strategy. The regression estimates of the intercept and the slope converge to a_p and b_p, which minimize the expected value of the squared error,

$$E\left|r_{pt} - a_p - b_p f_t\right|^2. \tag{2}$$

[6] Note that the weights sum up to 0, and hence for this zero-cost portfolio, the risk-adjusted return should be equal to 0 if the n style portfolios (i.e., the basis assets in this case) are correctly priced.

[7] Consistent with perfectly efficient markets, autocorrelation in a common risk factor may arise from time variation in the factor risk premium (e.g., Fama and French (1989) and Ferson and Harvey (1991)). However, autocorrelation in the return of a factor mimicking portfolio may be contaminated by proxy errors (i.e., Roll's critique) and non-synchronous trading (e.g., Lo and MacKinlay (1990)). In practice, for the Fama-French three-factor model and others, it is difficult to disentangle empirically among the causes of autocorrelation in the factors.

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In Appendix A, I show that

$$a_p = \operatorname{cov}(\beta_{pt-1}, f_t)\left(1 - \frac{\mu^2}{\sigma^2}\right), \tag{3}$$

$$b_p = (1+\rho)E(\beta_{pt-1}), \quad \text{and} \tag{4}$$

$$\begin{aligned}\operatorname{cov}(\beta_{pt-1}, f_t) &= \frac{1}{n}\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}\right)^2 c_1 \operatorname{cov}(z_{t-1}, f_{t-1}) \\ &= \frac{1}{n}\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}\right)^2 \sigma^2 \rho.\end{aligned} \tag{5}$$

As the portfolio weights vary over time, the strategy's beta β_{pt-1} changes over time, which can be correlated with f_t. Equation (3) shows that the correlation between the strategy's beta and the factor gives rise to a non-zero regression intercept.[8] Furthermore, result (5) shows that as long as f_t is autocorrelated, or equivalently, f_{t-1} is correlated with the conditioning variable z_{t-1}, and there is cross-sectional dispersion in betas, the covariance between the strategy's beta β_{pt-1} and the factor f_t will differ from 0. Note that $(1/n)\sum_{i=1}^{n}(\beta_i - \bar{\beta})^2$ may be viewed as the variance of cross-sectional variation in style betas. This cross-sectional variance is not equal to 0 unless all the style betas are of the same value.

Apparently, without taking into account the time-varying portfolio weights, the conventional risk adjustment regression is misspecified such that it generates a biased intercept estimate. Even though the factor model completely captures the n style returns in this case of dynamic trading, the conventional risk-adjusted return or the intercept of the conventional regression is generally non-zero.

B. Risk Premium

The example above is oriented to the econometrics of the issue. I now use the CAPM to highlight the economic intuition. Suppose that there are n basis assets that are correctly priced by the CAPM. The assets satisfy

$$r_{it} = \beta_i r_{mt} + \varepsilon_{it}, \quad i = 1, \ldots, n, \tag{6}$$

where r_{it} is the excess return on the ith asset, r_{mt} is the excess return on the market, β_i is the CAPM beta of the asset, and $E_{t-1}(\varepsilon_{it}) = 0$.

To demonstrate why time-varying portfolio weights make a difference, I start with the case of constant weights. Let portfolio p have constant weights such that the market beta of the portfolio is equal to 0, $\beta_p \equiv \sum_{i=1}^{n} w_i\beta_i = 0$ and $\sum_{i=1}^{n} w_i = 1$. Clearly, according to the CAPM, the expected excess return on the portfolio is equal to 0. Next, suppose that I let the weights of the portfolio p change over time such that the expected value of the portfolio beta is equal to 0, that is, $E(\beta_{pt-1}) = 0$, where $\beta_{pt-1} \equiv \sum_{i=1}^{n} w_{it-1}\beta_i$ and $\sum_{i=1}^{n} w_{it-1} = 1$. Is the expected excess return on the portfolio p still equal to 0? It is straightforward to show that even if the beta

[8] Typically, $\mu^2/\sigma^2 \neq 1$. For example, as one can verify in Table 1, μ^2 is small relative to σ^2 for any of the three Fama-French factors.

of the portfolio is expected to be equal to 0 on average, the time-varying portfolio weights can give rise to a non-zero expected excess return on the portfolio. By (6), the portfolio's excess return may be expressed as $r_{pt} = \beta_{pt-1} r_{mt} + \varepsilon_{pt}$, where $r_{pt} = \sum_{i=1}^{n} w_{it-1} r_{it}$, $\beta_{pt-1} = \sum_{i=1}^{n} w_{it-1} \beta_i$, and $\varepsilon_{pt} = \sum_{i=1}^{n} w_{it-1} \varepsilon_{it}$. Thus,

$$
\begin{aligned}
(7) \qquad E(r_{pt}) &= E(\beta_{pt-1} r_{mt}) \\
&= E(\beta_{pt-1}) E(r_{mt}) + \operatorname{cov}(\beta_{pt-1}, r_{mt}) \\
&= \operatorname{cov}(\beta_{pt-1}, r_{mt}).
\end{aligned}
$$

That is, the expected excess return is equal to the covariance between the time-varying beta and the market factor, which may not be equal to 0.

To understand the intuition of (7), assume that the market return is predictable and let the following predictive regression for the market return hold,

$$
(8) \qquad r_{mt} = a + b(\mathrm{DIV}_{t-1}) + e_t,
$$

where $b > 0$, and DIV_{t-1} is the dividend yield.[9] Consider a trading strategy that builds on the predictive regression (8). At time $t-1$, if the dividend yield DIV_{t-1} is high (low), one rebalances the portfolio to increase (decrease) the beta β_{pt-1}. The strategy should have a positive average payoff, even if the average value of the strategy's beta is equal to 0. This is simply because when the market return is expected to be high, buying high beta stocks, which tend to be highly correlated with the market, will generate a positive average return. However, this positive average return is compensation for risk. In the rational framework, the expected value of the market return goes up when investors expect times of high risk. The high expected excess market return is just compensation for the high risk state of the economy. Thus, it is a risky strategy to buy high beta stocks when the expected value of the market rises. As a result, even with an average beta of 0, the strategy should earn a positive expected excess return as a reward for bearing risk.

In other words, the risk premium of the dynamic portfolio in the CAPM setting may be attributed partly to the level of the portfolio's beta and partly to time variation of the beta. The second part of the risk premium will not be equal to 0 if the beta is correlated with the factor risk premium. As long as time variation in the factor risk premium is rational, the payoff to this strategy is completely rational and should not be attributed to mispricing of the basis assets. However, the example in Section II.A shows that, without taking into account the time-varying portfolio weights, the conventional procedure does not correctly separate the abnormal return from the risk premium. Even without any mispricing of the basis assets, Jensen's alpha from the conventional regression differs from 0 when the second part of the risk premium is not equal to 0.

[9] Using the dividend yield is for the ease of illustration, as this variable is the most widely used stock market predictor. As long as the predictability of the market return is genuine, all of the discussion will remain valid if I replace the dividend yield with any predictive variables.

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C. A Solution

I propose a simple but generally applicable solution to the problem of the conventional method. I consider a multifactor structure for the excess returns on n style portfolios,

$$r_{it} = \alpha_i + \beta_i f_t + \varepsilon_{it}, \tag{9}$$

where r_{it} is the excess return on the ith style portfolio, β_i is a $1 \times k$ vector of betas for $i = 1, \ldots, n$, and f_t is a $k \times 1$ vector of common risk factors. The factors are based on mimicking portfolios and they are measured either in terms of return in excess of the risk-free rate or the return difference between two portfolios. For the Fama-French (1993) three-factor model, for example, f_t is a 3×1 vector: $f_t = (\mathrm{MKT}_t \ \mathrm{SMB}_t \ \mathrm{HML}_t)'$, where MKT_t is the market factor (market return in excess of the risk-free rate), SMB_t is the size factor (constructed as the return difference between a small- and a large-cap portfolio), and HML_t is the book-to-market factor (constructed as the return difference between two portfolios of stocks with high and low book-to-market ratios, respectively).[10] Note that (9) is a general set-up that allows for the existence of mispricing of the basis assets. The intercepts α_is may differ from 0. The regression residuals ε_{it}s satisfy $E(\varepsilon_{it}|f_t) = 0$, but they are not required to satisfy $E_{t-1}(\varepsilon_{it}) = 0$. As I explain below, both the intercepts and the residuals can contribute to the abnormal return of a trading strategy.

Given the regression equations in (9), one can decompose the return of any dynamic style strategy. For example, suppose that an investor uses a model to forecast relative style performance and purchases the predicted winner. As the forecast varies over time, the investor rotates among the styles. More specifically, the portfolio weights are

$$w_{it-1} = \begin{cases} 1 & \text{if style } i \text{ is the predicted winner at time } t-1, \\ 0 & \text{otherwise,} \end{cases}$$

for $i = 1, \ldots, n$. The excess return on this style rotation strategy (and others in general) can be written as $r_{pt} = \alpha_{pt-1} + \beta_{pt-1} f_t + \varepsilon_{pt}$, where r_{pt} is the excess return on the strategy, such that $r_{pt} = \sum_{i=1}^{n} w_{it-1} r_{it}$, $\alpha_{pt-1} = \sum_{i=1}^{n} w_{it-1} \alpha_i$, $\beta_{pt-1} = \sum_{i=1}^{n} w_{it-1} \beta_i$, and $\varepsilon_{pt} = \sum_{i=1}^{n} w_{it-1} \varepsilon_{it}$. The average excess return can be expressed as

$$\bar{r}_p = \overline{\alpha_{pt-1} + \beta_{pt-1} f_t + \varepsilon_{pt}} = \bar{\alpha}_p + \bar{\beta}_p \bar{f} + \overline{(\beta_{pt-1} - \beta_p) f_t} + \bar{\varepsilon}_p, \tag{10}$$

where the overline stands for the average over time. (That is, for any random variable x_t, the notation $\bar{x}$ stands for the sample mean of x_t.) Based on (10), there are four sources or components of the average return on the strategy. The first and last components, $\bar{\alpha}_p$ and $\bar{\varepsilon}_p$, are due to the pricing errors of the factor model. That is, $\bar{\alpha}_p$ comes from the intercepts α_is in (9) and $\bar{\varepsilon}_p$ arises from the regression errors

[10] In the multifactor setting, the conventional risk adjustment procedure is also widely applied (e.g., Fama and French (1996), Haugen and Baker (1996), Grundy and Martin (2001), and Jegadeesh and Titman (2001)).

ε_{it}s in (9).[11] If the factor model correctly explains the returns on the basis assets, both $\bar{\alpha}_p$ and $\bar{\varepsilon}_p$ should vanish as the sample size becomes large. In evaluating the strategy's performance, a key hypothesis to be tested is whether both parts of the abnormal return $\bar{\alpha}_p$ and $\bar{\varepsilon}_p$ are equal to 0.

The second and third terms on the right-hand side of (10) are attributed to the factors. The component $\bar{\beta}_p\bar{f}$ is the product of average betas and factor premiums, while the term $\overline{(\beta_{pt-1} - \beta_p)f_t}$ is the sum of the covariances between the rotating betas and the factors.[12] This division is intuitively appealing. As Section II.B explains, in a rational setting the two components represent two parts of the premium for bearing risk associated with the portfolio. Common sense indicates that the level of the portfolio betas reflects risk that should be compensated. The corresponding risk premium is $\bar{\beta}_p\bar{f}$, which is consistent with the standard textbook explanation. However, the average value of the beta vector is inadequate to measure risk in the presence of dynamic trading. Given the level of the portfolio betas, how the betas vary over time also reflects risk associated with dynamic trading. This part of the risk premium is captured by the term $\overline{(\beta_{pt-1} - \beta_p)f_t}$.

Dividing the factor contribution into two parts is useful since it helps highlight the source of the problem for the conventional regression. This point is illustrated in Section II.A. In this example, there should be no abnormal return for the relative strength strategy, as the excess returns on the basis assets are perfectly captured by the factor model. Indeed, in the decomposition in (10), both $\bar{\alpha}_p$ and $\bar{\varepsilon}_p$ are equal to 0, since $\alpha_i = 0$ and $\varepsilon_{it} = 0$ for $i = 1, \ldots, n$. The second and third terms, $\bar{\beta}_p\bar{f}$ and $\overline{(\beta_{pt-1} - \beta_p)f_t}$, on the right-hand side of (10) are not equal to 0, representing the two parts of the risk premium. This example illustrates that the decomposition in (10) works because it is simply a combination, using the portfolio weights, of the regressions in (9). In contrast, the conventional procedure does not work because it ignores the portfolio weights, even though standard regressions hold for the basis assets. Without incorporating the time-varying portfolio weights, the conventional procedure is problematic because the covariance between the beta and the factor (i.e., the second part of the risk premium) is not appropriately accounted for. On a positive note, however, if one first estimates the parameters in (9) and then computes the decomposition in (10) with the portfolio weights, there is no abnormal return associated with the relative strength trading in this case, suggesting that one may circumvent the problem by using the decomposition in (10).

I propose simply to use (10) for the performance evaluation. This method of return decomposition can serve as a risk adjustment procedure since the sum of the two components, $\bar{\alpha}_p$ and $\bar{\varepsilon}_p$, represents the abnormal return, or the part of the return that is not contributed by the risk factors. It can also be viewed as a performance attribution method, when the factors are measured by returns on asset classes. Unlike Sharpe's (1992) method, my approach highlights the effects of beta rotation. That is, as the style timing strategy's betas rotate between style

[11] Even in large samples, $\bar{\varepsilon}_p$ may not converge to 0 if $E_{t-1}(\varepsilon_{it}) \neq 0$.

[12] Note that for two random variables x and y, $E[(x - E(x))y] = \text{cov}(x, y)$. So $\overline{(\beta_{pt-1} - \beta_p)f_t}$ is the sum of sample covariances between elements of β_{pt-1} and f_t. The covariances will be non-zero if the conditional risk premium, $E_{t-1}(f_t)$, is time varying and correlated with β_{pt-1}.

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betas over time, the average return of the strategy is attributable not only to the products of average betas and factor premiums, $\beta_p \bar{f}$, but also to the covariances between the betas and the factors, $\overline{(\beta_{pt-1} - \beta_p) f_t}$. In addition, this method provides a useful way to look at components of the strategy's return that are generated by the mispricing of the model. To allow for the basis assets to deviate from the factor model predictions is important since there is still considerable uncertainty on the number and identity of risk factors (e.g., Brown (1989) and MacKinlay (1995)).

I proceed in three steps to implement the method. First, I obtain the portfolio weights (w_{it-1}), which may require estimation of a forecasting model. As the next section illustrates, one may use rolling window logit model estimates to construct a style rotation strategy. Next, the parameters of the style return regressions in (9) are estimated by the standard ordinary least squares method. With the estimated intercept and betas, I obtain the fitted residuals. That is, I obtain estimates of α_i, β_i, and ε_{it}). In the third step, I obtain the return decomposition, computing the components with the inputs from the first two steps. I apply a bootstrap method for statistical inference.[13] I test whether the two parts of the abnormal return and the two parts of the risk premium are statistically significant. Using the bootstrap tests is appealing in my context. Not only does the bootstrap approach incorporate the estimation noise associated with the forecasting model in construction of the strategy (i.e., the time-varying portfolio weights), but it also accounts for the estimation noise associated with the regressions in (9). The bootstrap method is also robust to the autocorrelation structures of the style returns. Appendix B provides a detailed description of the bootstrap procedure.

Finally, the discussion can be extended to the case in which the betas of the basis assets are time varying. To emphasize the effects of cross-style beta rotation, I focus on the simplest constant beta version of a factor-based model for the style returns. In the empirical analysis discussed in the next section, I find that rotation among constant style betas successfully accounts for the performance of the style timing strategy. However, my method can also be easily applied to a conditional beta model. For example, one may assume that the row vector of betas in (9) is time varying in the form, $\beta_{it-1} = z_{t-1} C_i$, where C_i is a matrix of constant parameters and z_{t-1} is a row vector of conditioning variables (with the first element equal to 1). Even if the strategy's betas are assumed to have the same linear form, $\beta_{pt-1} = z_{t-1} C_p$, the conventional regression with the conditional beta specification cannot account for cross-style beta rotation over time. In the empirical analysis, I implement a conditional version of the Fama-French three-factor model to show that the conventional regression with the conditional betas is still problematic.

[13] Bootstrap methods are often applied in evaluation of trading rules (e.g., Brock, Lakonishok, and LeBaron (1992), Brown and Goetzmann (1997), and Sullivan, Timmermann, and White (1999)). I apply the stationary bootstrap of Politis and Romano (1994).

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III. An Empirical Analysis

A. Data

I use three sets of monthly data for the sample period from January 1960 to December 2000. The first set consists of the three factors, MKT, SMB, and HML, of Fama and French (1993), where MKT is the market factor, SMB is the size factor, and HML is the book-to-market factor. The second set contains four conditioning variables, DIV, YLD, TERM, and DEF, for constructing a conditional beta version of the Fama-French three-factor model, where DIV is the dividend yield, YLD is the yield on the three-month T-bill, TERM is the term spread, and DEF is the default spread. Table 1 reports details and descriptive statistics of the factors and the conditioning variables. The third set of data consists of nine style portfolios that are discussed below. The data on the three factors and the style portfolios are obtained from Kenneth French's Web site, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The set of conditioning variables is constructed following Chordia and Shivakumar (2002).

TABLE 1

Descriptive Statistics

	Fama-French Factors			Conditioning Variables			
	MKT	SMB	HML	DIV	YLD	TERM	DEF
Mean	0.51	0.13	0.40	3.37	5.98	1.34	0.99
Std. Dev.	4.40	3.16	2.83	1.05	2.62	1.22	0.44
Min	−23.09	−16.26	−12.05	1.12	2.24	−2.65	0.32
Max	16.05	21.38	13.18	6.29	16.30	4.42	2.69
First Auto.	0.05	0.10	0.18	0.99	0.98	0.95	0.97

Table 1 presents descriptive statistics for the Fama-French factors and the conditioning variables. MKT is the market factor (the excess return on the market), SMB is the size factor, and HML is the book-to-market factor. See Fama and French (1993) for details of construction. DIV is the total dividends accruing to the CRSP market index over the previous 12 months divided by the current level of the index. YLD is the yield on the three-month T-bill. TERM is the term spread, measured as the difference between the average yield of Treasury bonds with more than 10 years to maturity and the yield on the three-month T-bill. DEF is the default spread, measured as the difference between the average yield of BAA-rated corporate bonds and the average yield of AAA-rated corporate bonds. All data are monthly. The sample period is from January 1960 to December 2000. For each of the variables, the table reports the sample mean, the standard deviation, the minimum value, the maximum value, and the first autocorrelation coefficient.

Table 1 shows that Fama-French's three factors are volatile. However, the size factor and the book-to-market factor have nontrivial first autocorrelations of 0.10 and 0.18, respectively, suggesting that the lagged SMB and HML factors are correlated with the corresponding conditional factor risk premiums. This is interesting since the example in Section II.A shows that a necessary condition for the conventional regression intercept to be biased is that f_{t-1} is correlated with $E_{t-1}(f_t)$ (and hence f_t is autocorrelated). All four conditioning variables are popular predictors of stock returns (see, e.g., Chordia and Shivakumar (2002)). These predictors all have high first autocorrelation, which reflects the general finding in the literature that expected stock returns seem to have a highly persistent component. Such variables are also used to model conditional betas (see, e.g., Ferson and Schadt (1996), Ferson and Harvey (1999), and Wu (2002)).

As the next subsection explains, my empirical study is focused on a strategy that rotates among nine style portfolios. The nine portfolios are selected from

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Fama and French's (1993) 25 value-weighted size and book-to-market (BE/ME) portfolios that are double-sorted by five size quintiles and five book-to-market quintiles. The nine size BE/ME portfolios are chosen to represent nine different investment styles,

Small-Cap Growth (SZ1-BM1)	Small-Cap Neutral (SZ1-BM3)	Small-Cap Value (SZ1-BM5)
Mid-Cap Growth (SZ3-BM1)	Mid-Cap Neutral (SZ3-BM3)	Mid-Cap Value (SZ3-BM5)
Large-Cap Growth (SZ5-BM1)	Large-Cap Neutral (SZ5-BM3)	Large-Cap Value (SZ5-BM5)

where SZ1, SZ3, SZ5, and BM1, BM3, BM5 are three of the five size quintiles and three of the five book-to-market quintiles, respectively.

The investment styles represented by these portfolios are well known in practice.[14] As Mazzilli, Kittsley, Duggan, and Wang (2002) discuss, for example, the three S&P/BARRA indexes: S&P 500, Mid-Cap 400, and Small-Cap 600, which represent different size styles, have been sorted by book-to-market ratios to create an additional six style indexes: S&P 500 Growth, S&P 500 Value, Mid-Cap 400 Growth, Mid-Cap 400 Value, Small-Cap 600 Growth, and Small-Cap 600 Value. S&P/BARRA style indexes are widely accepted among practitioners, and exchange-traded funds (ETFs) are available on all of them. Another example is the recent study of Levis and Liodakis (1999) on style rotation strategies using data for the U.K. Following the procedure of Fama and French (1993), the authors construct nine style indexes of stock portfolios double-sorted by size and BE/ME.

Table 2 reports summary statistics of the nine size-BE/ME portfolios, which exhibit significant dispersion in average returns, ranging from an average monthly excess return of 0.25% for the small-growth style to 1.04% for the small-value style. Table 2 also reports the regressions of the style portfolios' excess returns on Fama and French's three factors, which capture strong common variation in the returns of the style portfolios. The R^2 is high for each of the regressions, ranging from 0.81 to 0.95. The three-factor betas exhibit well-known patterns. The market factor betas (b_i, $i = 1, \ldots, n$) are relatively flat, varying between 0.93 and 1.09. In contrast, the size factor betas (s_i, $i = 1, \ldots, n$) and the book-to-market factor betas (h_i, $i = 1, \ldots, n$) are much more dispersed, with cross-style differences clearly related to size and BE/ME, respectively. Finally, although most of the regression intercepts (α_i, $i = 1, \ldots, n$) seem small, four of them have t-statistics above two in absolute value and are not small relative to the average excess returns on the styles.

B. Logit-Based Style Timing

Style rotation includes a rich array of dynamic strategies. In general, one may first choose a model to predict the relevant style spreads over time and then construct a style rotation strategy that adjusts portfolio weights according to the prediction of relative style performance. For example, Beinstein (1995),

[14] See Leinweber, Arnott, and Luck (1997) for an introduction to different definitions of equity styles.

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TABLE 2
Style Portfolios

			Three-Factor Regression				
Portfolio	Mean	Std. Dev.	α	b	s	h	R^2
SZ1-BM1	0.25	7.97	−0.35 (−3.2)	1.03 (37.8)	1.41 (38.8)	−0.27 (−6.5)	0.91
SZ1-BM3	0.74	6.04	0.01 (0.1)	0.93 (59.1)	1.13 (53.7)	0.28 (11.6)	0.95
SZ1-BM5	1.04	5.86	0.12 (2.0)	0.98 (64.3)	1.09 (54.2)	0.68 (28.8)	0.95
SZ3-BM1	0.41	6.69	−0.07 (−0.9)	1.09 (61.9)	0.73 (31.1)	−0.43 (−15.7)	0.95
SZ3-BM3	0.66	4.93	−0.11 (−1.4)	1.02 (56.7)	0.43 (18.1)	0.48 (17.1)	0.90
SZ3-BM5	0.93	5.23	−0.04 (−0.5)	1.09 (60.3)	0.52 (21.6)	0.84 (29.9)	0.91
SZ5-BM1	0.48	4.79	0.17 (3.0)	0.97 (68.3)	−0.25 (−13.4)	−0.39 (−17.8)	0.93
SZ5-BM3	0.58	4.31	0.00 (0.0)	0.99 (52.9)	−0.27 (−10.8)	0.27 (9.4)	0.86
SZ5-BM5	0.65	4.61	−0.20 (−2.1)	1.03 (44.5)	−0.07 (−2.4)	0.83 (23.1)	0.81

Table 2 presents sample means and standard deviations for excess returns on the nine style portfolios that are selected from the 25 value-weighted size and book-to-market sorted portfolios of Fama and French. The nine portfolios are SZ1-BM1, SZ1-BM3, SZ1-BM5, SZ3-BM1, SZ3-BM3, SZ3-BM5, SZ5-BM1, SZ5-BM3, and SZ5-BM5, where (SZ1, SZ3, SZ5) and (BM1, BM3, BM5) are three out of the five size quintiles and three out of the five book-to-market quintiles, respectively. The sample period is from January 1960 to December 2000. See Fama and French (1993) for details on the portfolio construction. The table also reports the ordinary least squares regressions for the styles, $r_{it} = \alpha_i + b_i \text{MKT}_t + s_i \text{SMB}_t + h_i \text{HML}_t + \varepsilon_{it}$, where r_{it} is the excess return on the ith style portfolio, for $i = 1, \ldots, n$; MKT_t, SMB_t, and HML_t are time-t values of the market, the size, and the book-to-market factors of Fama and French, respectively. The t-statistics are reported in parentheses.

Fan (1995), Sorensen and Lazzara (1995), Kao and Shumaker (1999), Levis and Liodakis (1999), and Asness et al. (2000) investigate models that forecast differences between returns on growth and value strategies according to measures of aggregate economic and financial conditions. These studies focus on variables such as the earnings yield on the S&P 500, the slope of the yield curve, corporate credit spreads, corporate profits, spreads in valuation multiples, expected earnings growth spreads, and other macroeconomic measures.

I use a logit model with Fama-French's three factors (lagged by one month) to predict relative style performance. This has certain intuitive appeal, as predictions are derived from the recent relative performance of asset classes. To my knowledge, the three factors have never been used as predictors in the existing literature on style rotation.[15] The goal in this paper is not to promote a particular style timing strategy, but rather to show the strategy serves to illustrate the problem with the conventional evaluation method.

The style timing strategy is constructed as follows. Let Small_t be the sum of time-t returns on the styles SZ1-BM1, SZ1-BM3, and SZ1-BM5. Let Large_t be the sum of time-t returns on the styles SZ5-BM1, SZ5-BM3, and SZ5-BM5. Moreover, let Growth_t be the sum of time-t returns on the styles SZ1-BM1, SZ3-BM1, and SZ5-BM1, and let Value_t be the sum of time-t returns on the styles SZ1-

[15]Levis and Liodakis (1999) use a logit model to construct style rotation strategies. They do not consider Fama-French's three factors for prediction of relative performance. Furthermore, none of the studies cited use the Fama-French model for risk adjustment of style timing strategies.

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BM5, SZ3-BM5, and SZ5-BM5. A logit model is applied to obtain conditional probabilities about the signs of the size spread and the value spread,

$$(11) \quad p_{1t-1} = \text{Prob}(\text{Small}_t > \text{Large}_t | x_{t-1}) = \frac{\exp(a_1 x_{t-1})}{1 + \exp(a_1 x_{t-1})},$$

$$(12) \quad p_{2t-1} = \text{Prob}(\text{Value}_t > \text{Growth}_t | x_{t-1}) = \frac{\exp(a_2 x_{t-1})}{1 + \exp(a_2 x_{t-1})},$$

where $x_{t-1} = (1 \ \text{MKT}_{t-1} \ \text{SMB}_{t-1} \ \text{HML}_{t-1})'$. The variables MKT_{t-1}, SMB_{t-1}, and HML_{t-1} are the one-month lagged values of the market, the size, and the book-to-market factors of Fama and French (1993), and a_1 and a_2 are two 1×4 parameter vectors. The model is estimated by the maximum likelihood method. See Maddala (1983) for details about the logit model and the estimation method.

The rotation strategy is constructed with rolling window estimates. The strategy's return for any given month t is based on the logit model parameter estimates that are obtained over a 10-year window from month $t - 120$ to month $t - 1$.[16] The conditional probability estimates $\hat{p}_{1t-1}$ and $\hat{p}_{2t-1}$ are obtained from the parameter estimates. Given the estimated logit probabilities, I construct a strategy (denoted by PW−PL) that buys the predicted winner style and short sells the predicted loser style. This timing strategy is composed of two strategies. The first one, the predicted winner strategy (PW), is defined as follows. It selects SZ1 if $\hat{p}_{1t-1} > 0.55$, SZ3 if $0.45 \leq \hat{p}_{1t-1} \leq 0.55$, and SZ5 if $\hat{p}_{1t-1} < 0.45$. At the same time, the PW strategy selects BM5 if $\hat{p}_{2t-1} > 0.55$, BM3 if $0.45 \leq \hat{p}_{2t-1} \leq 0.55$, and BM1 if $\hat{p}_{2t-1} < 0.45$. The combination of the predicted winners in the size and BE/ME quintiles gives rise to the predicted winner. The second strategy (PL) buys the predicted loser, which is the opposite of PW, that is, the combination of the predicted size quintile loser and predicted BE/ME quintile loser defines the PL.

I apply the maximum likelihood method to estimate the logit models. Panel A of Table 3 reports descriptive statistics of the conditional probabilities based on the 10-year rolling window estimates. Panel A shows that the conditional probabilities vary in wide ranges, and the first autocorrelations suggest that they are not very persistent over time. The correlation between $\hat{p}_{1t-1}$ and $\hat{p}_{2t-1}$ is modest. These features of the conditional probabilities $\hat{p}_{1t-1}$ and $\hat{p}_{2t-1}$ suggest that the timing strategy rotates frequently among the styles.

Panel B of Table 3 reports the performance of the PW−PL strategy. The intercept from the conventional Fama-French three-factor regression, FF α, is included along with the sample mean of the raw return. Since I use a 10-year estimation window, the strategy starts to operate in January 1970, and its performance is impressive. PW generates a monthly average return that is significantly higher than that of PL. The average monthly difference (1.12%) is equivalent to an annual average difference of more than 13 percentage points. It is also surprising that the conventional risk adjustment regression gives rise to an intercept of 1.00%; that is, according to the conventional three-factor regression, PW earns an average risk-adjusted annual return 12 percentage points higher than that of PL.

[16] The construction of w_{it-1} only makes use of the data up to month $t - 1$. I checked the results in all the tables with the five- and 15-year rolling window estimates. The results are robust.

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TABLE 3

Logit-Based Style Rotation

Panel A. Conditional Probabilities from the Logit Model

Probabilities	Mean	Std. Dev.	Min	Max	First Auto.	corr(p_{1t-1}, p_{2t-1})
p_{1t-1}	0.49	0.17	0.01	0.99	0.27	−0.15
p_{2t-1}	0.58	0.11	0.05	0.86	0.31	

Panel B. Performance of the PW−PL Strategy

1970–2000		1970–1981		1982–2000		1970–1993		1994–2000	
Mean	FF α	Mean	FF α	Mean	FF α	Mean	FF α	Mean	FF α
1.12	1.00	1.42	1.06	0.93	0.90	1.09	0.80	1.22	1.53
(3.9)	(3.6)	(3.3)	(2.8)	(2.5)	(2.4)	(4.0)	(3.3)	(1.4)	(1.8)

Table 3 presents results for the logit-based style timing. Panel A reports descriptive statistics of the conditional probabilities, p_{1t-1} and p_{2t-1}, defined by (11) and (12), that are based on 10-year rolling window maximum likelihood estimates. The month t performance of the PW−PL strategy is based on the estimates of p_{1t-1} and p_{2t-1} that use the 10-year data up to month $t-1$. For several sample periods, Panel B reports the mean return difference between strategies PW and PL, where PW is the strategy of buying the predicated winner and PL is the strategy of buying the predicted loser. It also includes the Fama-French three-factor regression intercept (FF α) for the PW−PL strategy. The numbers in parentheses are t-statistics.

According to the t-statistics, both the raw return and the three-factor regression alpha are highly statistically significant.

Panel B of Table 3 also reports subsample results. I divide the sample period and consider four subsample periods: 1970–1981 vs. 1982–2000 and 1970–1993 vs. 1994–2000. My choice of subsamples is motivated by Banz (1981), who attracted a great deal of attention to the size effect and possibly to other asset class performances, and Fama and French (1993), who also generated considerable notice as their paper quickly became well known among financial economists and practitioners. As the rotation strategy is based on the three factors of Fama and French, the 1994–2000 period after the publication of this influential article may be, to some extent, viewed as an out-of-sample period. As the table shows, the results are fairly stable over the subsamples. Although both the raw return and the conventional three-factor regression alpha for the 1994–2000 period are even higher than those for the 1970–1993 period, I need to be cautious since the t-statistics are insignificant (probably due to the short subsample size of the post-1993 period).[17]

C. Multifactor Evaluation

This subsection discusses the risk adjustment results, using both the conventional Fama-French three-factor regression and the new method. To be precise, the conventional procedure is to run the following three-factor regression,

$$r_{pt} = \alpha_p + b_p \mathrm{MKT}_t + s_p \mathrm{SMB}_t + h_p \mathrm{HML}_t + \varepsilon_{pt}, \tag{13}$$

where r_{pt} is the excess return on the strategy or return difference between two strategies, b_p, s_p, and h_p are the factor loadings or betas, and α_p is the regression

[17] It should be noted that I have ignored constraints on trading in practice. For the strategy's performance, I do not adjust for transaction costs due to lack of data. In terms of transaction costs, however, the 1994–2000 period is of particular interest, since it is associated with the rapid development of exchange-traded funds (ETFs) that provide a convenient and cost-effective tool for implementing style rotation strategies (e.g., for short selling). For example, see Wiandt and McClatchy (2002) and Mazzilli et al. (2002) for discussion about ETFs.

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intercept that is interpreted as the risk-adjusted return. As Table 3 shows, the results based on the conventional risk adjustment procedure are impressive for the PW−PL timing strategy. It should be noted that since the factors reflect asset class performances, the results can also be interpreted in terms of performance attribution. An insignificant intercept or Jensen's alpha, for instance, is interpreted as evidence that the strategy's return is explained by risk or is attributable to the asset class performances represented by the factors. According to this widely applied procedure, the large intercepts reported in Table 3 give rise to the conclusion that for the most part the performance of the PW−PL strategy cannot be attributed to the factors.

Panel A of Table 4 provides a closer look, showing that PW generates high raw returns, with an average excess return of 1.03% per month. In contrast, PL produces an average excess return of −0.09% per month. However, the Fama-French three-factor betas deliver a mixed ranking. According to the book-to-market factor betas, PW is riskier than PL, but PL has higher market and size factor betas. Jointly, the three-factor regression produces an intercept or a risk-adjusted return difference of 1.00% for PW−PL, which is not much different from the unadjusted value of 1.12%. Clearly, the conventional procedure is grossly inadequate to account for the performance of the logit-based style timing.

TABLE 4

Multifactor Evaluation of Style Rotation

Panel A. Conventional Regression

		Three-Factor Regression				
	Mean	α	b	s	h	R^2
PW	1.03	0.27	0.95	0.46	0.47	0.69
	(4.2)	(1.7)	(24.4)	(9.2)	(8.0)	
PL	−0.09	−0.73	1.10	0.59	−0.01	0.81
	(−0.3)	(−4.8)	(30.2)	(12.4)	(−0.1)	
PW−PL	1.12	1.00	−0.15	−0.12	0.48	0.14
	(4.5)	(3.6)	(−2.3)	(−1.4)	(4.8)	

Panel B. Return Decomposition

	PW	PL	PW−PL
$\bar{r}_p$	$1.03^{(3)}$	$-0.09^{(0)}$	$1.12^{(3)}$
$\bar{\alpha}_p$	$-0.06^{(3)}$	$-0.12^{(3)}$	$0.06^{(2)}$
$\bar{\beta}_p\bar{f}$	$0.83^{(2)}$	$0.52^{(1)}$	$0.30^{(3)}$
$\overline{(\beta_{pt-1} - \bar{\beta}_p)f_t}$	$0.30^{(2)}$	$-0.41^{(3)}$	$0.71^{(2)}$
$\bar{\varepsilon}_p$	$-0.03^{(0)}$	$-0.08^{(3)}$	$0.04^{(0)}$

Panel A reports the results from the Fama-French three-factor regressions (13) for strategies PW, PL, and PW−PL (i.e., buying PW and short selling PL). The mean excess returns on the strategies are also included. The *t*-statistics are reported in parentheses. Panel B reports results from decomposing each strategy's return into four components, $\bar{r}_p = \bar{\alpha}_p + \bar{\beta}_p\bar{f} + \overline{(\beta_{pt-1} - \bar{\beta}_p)f_t} + \bar{\varepsilon}_p$, using the portfolio weights based on the rolling window estimates and the regression estimates for the nine styles. For the return and the four components, a bootstrap test, described in Appendix B, is conducted in each case. The superscript of the mean is assigned to be 0, 1, 2, or 3. Superscript 0 indicates that the bootstrap test does not reject that the mean is equal to 0 at the 10% significance level. Superscripts 1, 2, and 3 indicate that the bootstrap test rejects at the 10%, 5%, and 1% levels, respectively.

Panel B of Table 4 presents a different view by reporting results from my return decomposition method, which highlights the role of beta rotation. The panel shows that the average excess returns for both PW and PL are mainly due to two factor-related components, $\bar{\beta}_p\bar{f}$ and $\overline{(\beta_{pt-1} - \beta_p)f_t}$. The difference between

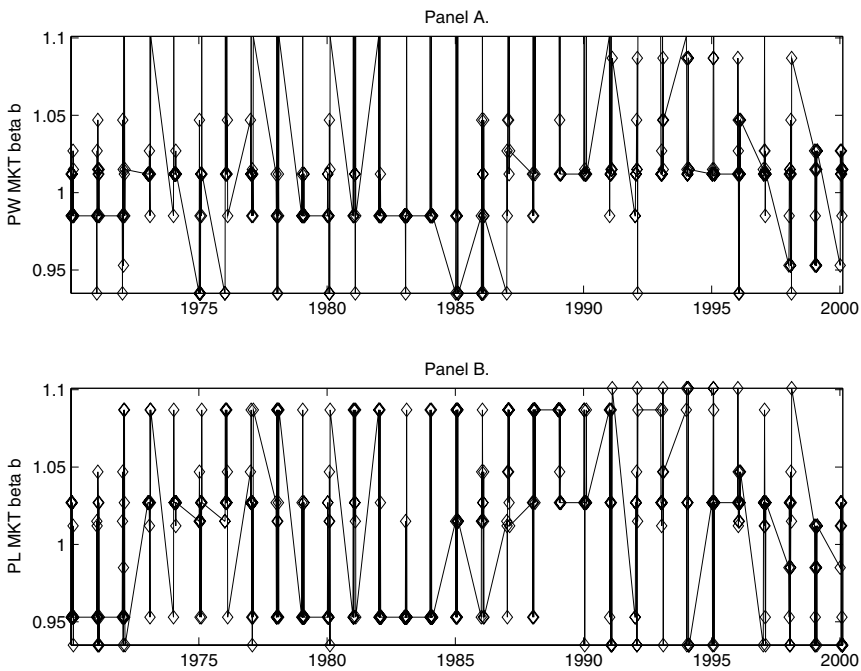
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PW and PL, however, is largely attributed to the latter. As Panel B shows, more than half of the average return difference between PW and PL is from the covariances between the rotating betas and the factors (i.e., $\overline{(\beta_{pt-1} - \beta_p)f_t}$). According to the bootstrap test, this covariance component is statistically significant at the 5% level. The second largest component for the PW−PL strategy is $\overline{\beta}_p\overline{f}$ (i.e., the products of average betas and factor risk premiums), which is significant at the 1% level by the bootstrap test. In this case, the pricing errors of the Fama-French three-factor model, whether regression intercepts or residuals, contribute little to the performance of the timing strategy.[18]

The sharp contrast between the two panels of Table 4 is due to beta rotation. To demonstrate it visually, I plot the three-factor betas through time for PW and PL in Figures 1, 2, and 3. As different styles take turns being the predicted winner and the predicted loser over time, the three-factor betas of the strategies rotate among the betas of the nine styles. The figures vividly show that the dynamic strategies are associated with significant beta rotation.

FIGURE 1

Market Factor Betas of Strategies PW and PL



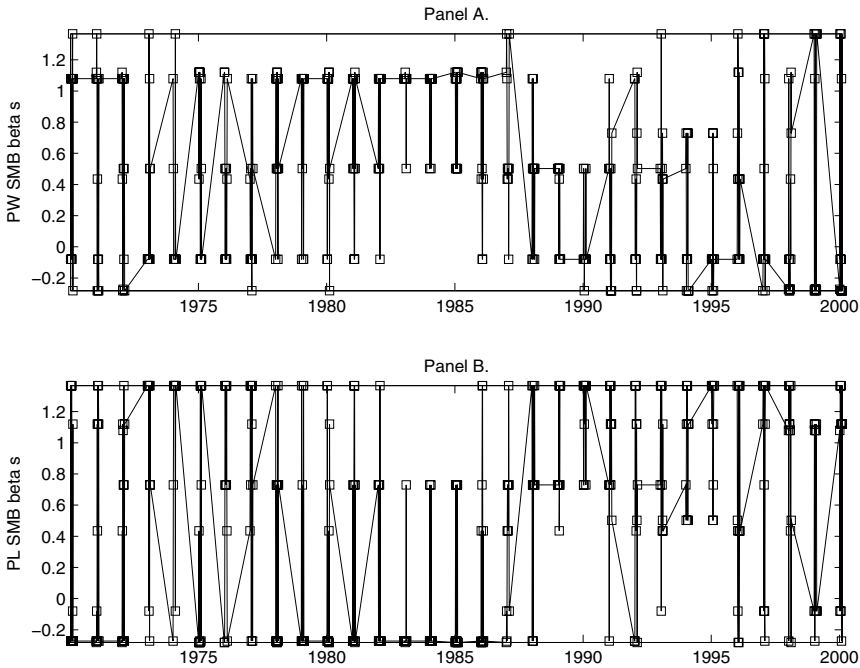
The market factor beta for the PW strategy is $b_{pt-1} = \sum_{i=1}^{n} w_{it-1}b_i$ where $w_{it-1} = 1$ if style i is the predicted winner at time $t-1$ and $w_{it-1} = 0$ otherwise. The weights for the PL strategy are such that $w_{it-1} = 1$ if style i is the predicted loser at time $t-1$ and $w_{it-1} = 0$ otherwise. The market factor betas for the style portfolios (b_i, $i = 1, \ldots, n$) are estimated by the three-factor time-series regressions. The regression estimates are reported in Table 2.

[18] Although the contribution from the intercepts is statistically significant at the 5% level based on the bootstrap p-value, its value is only 0.06.

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FIGURE 2

Size Factor Betas of Strategies PW and PL



The size factor beta for the PW strategy is $s_{pt-1} = \sum_{i=1}^{n} w_{it-1} s_i$ where $w_{it-1} = 1$ if style i is the predicted winner at time $t - 1$ and $w_{it-1} = 0$ otherwise. The weights for the PL strategy are such that $w_{it-1} = 1$ if style i is the predicted loser at time $t - 1$ and $w_{it-1} = 0$ otherwise. The size factor betas for the style portfolios (s_i, $i = 1, \ldots, n$) are estimated by the three-factor time-series regressions. The regression estimates are reported in Table 2.

Time variation in the strategies' betas is also reflected in the descriptive statistics of Table 5. As Table 5 shows, PW and PL have the same range (maximum and minimum values) for each of the three betas. The autocorrelation coefficients of all the betas are not large, indicating that the betas vary significantly over time with weak serial dependence. Interestingly, the correlation coefficients between the size and book-to-market factor betas and the corresponding factors are positive for PW and negative for PL. This suggests that the effects of beta rotation are associated with the SML and HML factors (rather than the MKT factor).

In sum, the evidence shows that the raw return of the PW−PL strategy is impressive over the sample period. According to the Fama-French three-factor model, the conventional procedure delivers the conclusion that the strategy's return is not explained by risk at all. In contrast, my new method concludes that the logit timing strategy's return is largely captured by the Fama-French model and little can be attributed to the mispricing of the model for the underlying styles.

D. Conditional Evaluation

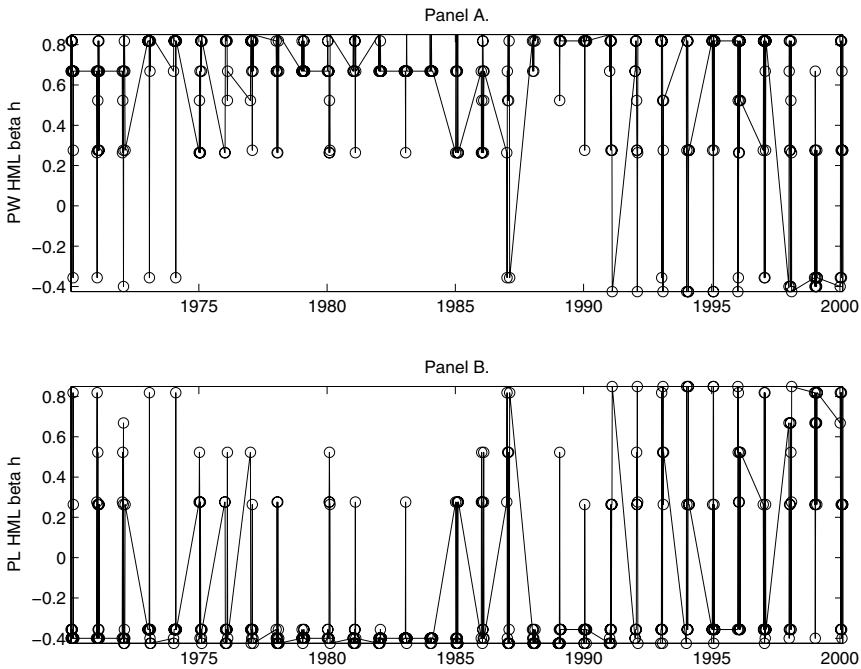
Does it make any difference if the factor betas vary with business conditions? In this subsection, I consider a case in which the factor model (13) is extended to

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FIGURE 3

Book-to-Market Factor Betas of Strategies PW and PL



The book-to-market factor beta for the PW strategy is $h_{pt-1} = \sum_{i=1}^{n} w_{it-1} h_i$ where $w_{it-1} = 1$ if style i is the predicted winner at time $t-1$ and $w_{it-1} = 0$ otherwise. The weights for the PL strategy are such that $w_{it-1} = 1$ if style i is the predicted loser at time $t-1$ and $w_{it-1} = 0$ otherwise. The book-to-market factor betas for the style portfolios (h_i, $i = 1, \ldots, n$) are estimated by the three-factor time-series regressions. The regression estimates are reported in Table 2.

TABLE 5

Cross-Style Beta Rotation

	Strategy PW			Strategy PL		
	b_{pt-1}	s_{pt-1}	h_{pt-1}	b_{pt-1}	s_{pt-1}	h_{pt-1}
Mean	1.02	0.47	0.57	1.01	0.59	−0.13
Std. Dev.	0.05	0.55	0.37	0.05	0.68	0.42
Min	0.93	−0.28	−0.43	0.93	−0.28	−0.43
Max	1.10	1.37	0.85	1.10	1.37	0.85
First Auto.	0.06	0.27	0.31	0.12	0.32	0.32
$\text{corr}(\beta^j_{pt-1}, f^j_t)$	−0.09	0.10	0.10	−0.04	−0.13	−0.11
	(−1.6)	(2.0)	(1.9)	(−0.8)	(−2.4)	(−2.1)

Table 5 presents descriptive statistics for the three betas, b_{pt-1}, s_{pt-1}, and h_{pt-1}, of strategies PW and PL that buy the predicted winner and the predicted loser, respectively. The three betas are then given by $b_{pt-1} = \sum_{i=1}^{n} w_{it-1} b_i$, $s_{pt-1} = \sum_{i=1}^{n} w_{it-1} s_i$, and $h_{pt-1} = \sum_{i=1}^{n} w_{it-1} h_i$, where w_{it-1} are the portfolio weights of a strategy, and the style betas b_i, s_i, and h_i take the values of the estimates reported in Table 2. As for the correlation coefficient $\text{corr}(\beta^j_{pt-1}, f^j_t)$, the beta β^j_{pt-1} represents b_{pt-1}, s_{pt-1}, and h_{pt-1}, for $j = 1, 2, 3$, while the factor f^j_t represents MKT_t, SMB_t, and HML_t, for $j = 1, 2, 3$, respectively.

have time-varying betas. Following Ferson and Schadt (1996), Ferson and Harvey (1999), and Wu (2002), I apply a popular conditional performance evaluation procedure that assumes that the betas of the strategies are linear functions of conditioning variables. More precisely, the excess return on a portfolio (or return difference between two portfolios) is given by

$$(14) \qquad r_{pt} = \alpha_{pt-1} + b_{pt-1}\mathrm{MKT}_t + s_{pt-1}\mathrm{SMB}_t + h_{pt-1}\mathrm{HML}_t + \varepsilon_{pt},$$

and the time-varying alpha and betas are of the form, $[\alpha_{pt-1}\ b_{pt-1}\ s_{pt-1}\ h_{pt-1}] = z_{t-1}[\alpha_p\ b_p\ s_p\ h_p]$, where α_p, b_p, s_p, and h_p are 5×1 vectors of constant parameters. The conditioning instruments are given in a 1×5 row vector $z_{t-1} = (1\ \mathrm{DIV}_{t-1}\mathrm{YLD}_{t-1}\mathrm{TERM}_{t-1}\mathrm{DEF}_{t-1})$. This specification is convenient, since the right-hand side of (14) is still linear in the parameters, and hence one can run the standard ordinary least squares regression for parameter estimation. The time-varying term α_{pt-1} is the conditional risk-adjusted return.

Table 6 reports the conditional Fama-French regressions for the PW and PL strategies. An inspection of Panel A, which reports the parameter estimates and corresponding *t*-statistics, suggests that the conditional alpha and betas of PW have quite different time-varying patterns than those of PL. In fact, the three conditional betas of PW are negatively correlated with the corresponding ones of PL, while the conditional alphas of the two strategies have a correlation coefficient of 0.18. (These correlations are not reported in the table.) The descriptive statistics of Panel B show that there is significant time variation in all of the conditional alphas and betas. Consistent with the results of Table 4, PW has a higher average value of the book-to-market factor beta than PL, but it has (slightly) lower average values of the market beta and the size factor beta. The difference between the average alphas of PW and PL is 0.74%, which is quite large compared to the average return difference of 1.12% for the PW−PL strategy. Thus, the results lead to the conclusion that the conditional Fama-French three-factor regressions still cannot explain most of the PW−PL strategy's return.

I decompose the returns using the conditional Fama-French regressions. I run regression (14) for each individual style portfolio to estimate the conditional alpha and conditional betas for the nine style portfolios. Then I repeat the performance attribution analysis in Table 4, with the estimated time-varying alphas and betas. The results, reported in Table 7, are remarkably similar to those of Table 4. A minor difference is that the component $\bar{\varepsilon}_p$ is 0.13, compared to the value of 0.04 in Table 4. Clearly, it is still the case that beta rotation plays a key role. Most of the PW−PL strategy's return can be attributed to the component $\overline{(\beta_{pt-1} - \beta_p)f_t}$, that is, the covariances between the rotating betas and the corresponding factors. Very little of the strategy's return can be attributed to the pricing errors of the conditional Fama-French three-factor model.

The results of Tables 6 and 7 help highlight that the key feature of my approach is to explicitly incorporate the time-varying portfolio weights. Without using the weights directly to model conditional betas and alphas, the popular conditional approach that assumes betas vary with business cycle variables still fails to account for the performance of the style timing strategy.

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TABLE 6

Conditional Three-Factor Risk Adjustment

Panel A. Conditional Three-Factor Regressions

	Regression Estimates				*t*-Statistics			
	α	*b*	*s*	*h*	α	*b*	*s*	*h*
Strategy PW:								
CONST	0.41	1.05	0.16	0.57	0.64	6.54	0.66	2.39
DIV	−0.30	0.08	0.08	0.20	−1.32	1.59	1.39	2.64
YLD	−0.10	−0.01	0.00	0.01	−0.82	−0.42	0.09	0.13
TERM	−0.25	0.06	0.05	0.02	−1.36	1.41	0.80	0.38
DEF	1.72	−0.36	−0.04	−0.77	2.99	−2.47	−0.20	−3.66
Strategy PL:								
CONST	−1.78	0.91	1.32	0.57	−3.05	6.19	5.96	2.65
DIV	−0.12	−0.08	0.09	−0.15	−0.57	−1.82	1.68	−2.14
YLD	0.18	0.06	−0.07	−0.06	1.56	2.24	−1.82	−1.62
TERM	0.20	−0.01	−0.13	−0.12	1.15	−0.27	−2.18	−2.11
DEF	0.14	0.08	−0.35	0.40	0.26	0.61	−2.08	2.09

Panel B. Summary Statistics of Conditional Alphas and Betas

	Strategy PW				Strategy PL			
	α	*b*	*s*	*h*	α	*b*	*s*	*h*
Mean	0.20	0.95	0.52	0.49	−0.54	1.06	0.56	−0.07
Std. Dev.	0.53	0.15	0.12	0.25	0.35	0.13	0.24	0.21
Min	−0.97	0.32	0.23	−0.34	−1.03	0.84	−0.27	−0.60
Max	1.98	1.24	0.86	1.13	0.55	1.58	0.95	0.51
First Auto.	0.90	0.94	0.98	0.93	0.99	0.96	0.98	0.95

Table 6 presents the results from the conditional Fama-French three-factor regressions, defined in (14), for strategies PW and PL. Panel A reports the parameter estimates and the corresponding *t*-statistics for the regressions. Panel B reports descriptive statistics for the time-varying conditional alphas and conditional betas, based on the estimates from Panel A.

TABLE 7

Performance Attribution Using the Conditional Three-Factor Model

	PW	PL	PW−PL
$\bar{r}_p$	$1.03^{(3)}$	$-0.09^{(0)}$	$1.12^{(3)}$
$\bar{\alpha}_p$	$-0.10^{(3)}$	$-0.10^{(3)}$	$0.00^{(0)}$
$\bar{\beta}_p\bar{f}$	$0.81^{(3)}$	$0.51^{(1)}$	$0.30^{(3)}$
$(\beta_{pt-1} - \bar{\beta}_p)f_t$	$0.34^{(2)}$	$-0.36^{(3)}$	$0.69^{(2)}$
$\bar{\varepsilon}_p$	$-0.02^{(0)}$	$-0.14^{(3)}$	$0.13^{(0)}$

Table 7 reports the performance attribution results using the conditional Fama-French three-factor model, defined in (14), for strategies PW, PL, and PW−PL (buying PW and short selling PL). We run conditional Fama-French three-factor regression (as in Table 6) for each of the nine styles to obtain the style's conditional betas and the conditional alpha. Accordingly, each strategy's return is divided into four components, $\bar{r}_p = \bar{\alpha}_p + \bar{\beta}_p\bar{f} + (\beta_{pt-1} - \bar{\beta}_p)f_t + \bar{\varepsilon}_p$, using the portfolio weights based on the rolling window estimates and the conditional regression estimates for the nine styles. For the return and the four components, a bootstrap test, described in Appendix B, is conducted in each case. The superscript of the mean is assigned to be 0, 1, 2, or 3. Superscript 0 indicates that the bootstrap test does not reject that the mean is equal to 0 at the 10% significance level. Superscripts 1, 2, and 3 indicate that the bootstrap test rejects at the 10%, 5%, and 1% levels, respectively.

IV. Conclusion

Relative performance differences across styles have been unstable in recent years. While this lack of style consistency leads investors to question the importance of style investing, a growing number of studies demonstrate significant benefits of style rotation in tactical asset allocation and equity style management. For example, Ahmed, Lockwood, and Nanda (2002) find that even moderate multi-style rotation gives a portfolio an excellent chance of outperforming the market index.

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This article proposes a new approach to multifactor evaluation of style rotation strategies. This is a simple weight-based approach designed to decompose returns on trading strategies. Analyzing a logit-based style timing strategy, I find that the conventional procedure generates misleading results and my approach yields the opposite conclusion. The findings show that the average values of the factor betas are grossly inadequate to explain the strategy's performance, even though much of the variation in the style returns is well captured by the Fama-French three-factor model. The covariances between the rotating betas and the factors are the most important source of the strategy's return.

The problem of the conventional risk adjustment procedure caused by time-varying asset weights may be relevant to a wide range of trading strategies. An interesting possibility is the momentum strategy of Jegadeesh and Titman (1993). On one hand, applying the conventional procedure with the Fama-French three-factor model, Fama and French (1996) and Jegadeesh and Titman (2001) find that the momentum payoff after risk adjustment is even higher, giving rise to the conclusion that none of the momentum payoff can be attributed to compensation for risk. On the other hand, it is reasonable to conjecture that there is large dispersion of individual stocks in multifactor betas, and the beta rotation associated with the momentum strategy may cause significant bias in the conventional risk adjustment regression. However, it is likely to be a difficult task to obtain a clear test of this conjecture, since a large number of stocks may have highly non-stationary factor betas. Whenever a feasible method is developed to effectively capture betas of individual stocks, it will be intriguing to test whether multifactor beta rotation among individual stocks explains the momentum effect.

Appendices

A. Alpha of the Relative Strength Strategy

This appendix provides a proof for the results (3), (4), and (5) for the relative strength strategy. The expressions (3) and (4) for a_p and b_p follow from an extension of Stein's lemma. Let x, y, and z be jointly normally distributed. Then, $\text{cov}(x, yz) = \text{cov}(x, y)E(z) + \text{cov}(x, z)E(y)$. This result can be established with Stein's lemma. The proof is omitted for brevity, but available upon request.

Since the portfolio weights defined in (1) are linear in the excess returns, the beta β_{pt-1} is normally distributed, given the normality of the risk factor. Thus, $\text{cov}(\beta_{pt-1}f_t, f_t) = \text{cov}(\beta_{pt-1}, f_t)E(f_t) + E(\beta_{pt-1})\text{var}(f_t)$.

With this equation, one can show that b_p can be expressed as

$$b_p = \frac{\text{cov}(r_{pt}, f_t)}{\text{var}(f_t)} = E(\beta_{pt-1}) + \mu\frac{\text{cov}(\beta_{pt-1}, f_t)}{\text{var}(f_t)}.$$

Then, it is straightforward to show that

$$a_p = E(r_{pt}) - b_pE(f_t) = \text{cov}(\beta_{pt-1}, f_t)\left(1 - \frac{\mu^2}{\sigma^2}\right).$$

Finally,

$$\begin{aligned}\operatorname{cov}(\beta_{pt-1}, f_t) &= \operatorname{cov}\left(\sum_{i=1}^{n} w_{it-1}\beta_i, f_t\right)\\ &= \operatorname{cov}\left(\frac{1}{n}\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}\right)\beta_i f_{t-1}, f_t\right)\\ &= \frac{1}{n}\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}\right)^2 \operatorname{cov}(f_{t-1}, f_t),\end{aligned}$$

and similarly,

$$\begin{aligned}E(\beta_{pt-1}) &= E\left(\sum_{i=1}^{n} w_{it-1}\beta_i\right) = E\left(\frac{1}{n}\sum_{i=1}^{n}\left(\beta_i - \bar{\beta}\right)\beta_i f_{t-1}\right)\\ &= \frac{1}{n}\sum_{i=1}^{n}(\beta_i - \bar{\beta})^2\mu.\end{aligned}$$

The results (3), (4), and (5) are established after putting everything together.

B. Bootstrap for Statistical Testing

To draw statistical inference about the abnormal return and the risk premium, one needs to take into account estimation errors associated with the strategy's construction and the underlying factor pricing model (i.e., the noise in estimation of (9), (11), and (12)). In addition, the returns of the style portfolios may be correlated over time in complicated ways. A bootstrap testing procedure, described below, is applied to address these concerns.

For notational convenience, let y_t denote the vector of all the relevant variables including the style excess returns $r_{1t}, \ldots, r_{nt}$ and the factors in the vector f_t, for $t = 1, \ldots, T$. In the conditional evaluation analysis, the vector of conditioning variables z_t is also included in y_t. Let STAT denote a t-statistic for the sample mean (of the return or a component in the decomposition) that is computed by the standard procedure. I resample the data to obtain B time series $\{y_{jt}^b\}$, $t = 1, \ldots, T$, for $j = 1, \ldots, B$. For each resampled time series, I compute a t-statistic, denoted by STAT_j^b, which is a resampled version of STAT. Then, the following statistics are used to compute the p-value associated with STAT, $\sqrt{T}(\text{STAT}_j^b - \text{STAT})$, for $j = 1, \ldots, B$. I compare $\sqrt{T}(\text{STAT})$ to the quantiles of $\sqrt{T}(\text{STAT}_j^b - \text{STAT})$ to obtain the p-value. The bootstrap p-value may be defined as the probability in favor of the null hypothesis that the mean is equal to 0, i.e., $\text{Prob}[\sqrt{T}(\text{STAT}_j^b - \text{STAT}) > \sqrt{T}(\text{STAT})]$. By this definition, a p-value that is close to 0 indicates evidence that the mean is statistically significant. For example, if the p-value is 0.04, then it indicates that the mean is significantly different from 0 at the 5% level.

The series $\{y_{jt}^b\}$ is generated according to the stationary bootstrap algorithm of Politis and Romano (1994). For $t = 1, \ldots, T$, and $j = 1, \ldots, B$, y_{jt}^b is defined by $y_{jt}^b = y_{\eta_{jt}}$, where η_{jt} is a random index chosen according to the stationary bootstrap algorithm of Politis and Romano. To implement this method, I choose a smoothing parameter q and then proceed as follows.

Step 1. For t=1, draw η_{j1} as a random variable, uniformly distributed over $\{1, \ldots, T\}$, independently of other variables.

Step 2. Increase t by 1. If $t > T$, stop. Otherwise, draw a standard uniform random variable u, independently of other variables.

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If $u < q$, draw η_{jt} as a random variable, uniformly distributed over $\{1, \ldots, T\}$, independently of other variables.

If $u \geq q$, set $\eta_{jt} = \eta_{jt-1} + 1$; if $\eta_{jt} > T$, set $\eta_{jt} = 1$.

Repeat Step 2.

Theoretically, the parameter q should change with the sample size (i.e., $q \equiv q_T$), such that $0 < q_T \leq 1$, $q_T \to 0$, and $Tq_T \to \infty$, as $T \to \infty$. Following Sullivan, Timmermann, and White (1999) and Wang (2003), I set $q = 0.1$, which corresponds to an average block length of 10. I have tried various values of q in the empirical analysis. The results are not sensitive to the choice of q.

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