On the Predictability of Stock Market Returns: Evidence from Industry-Rotation Strategies*

by

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Abstract

This paper evaluates historic, Bayes-Stein, Capital Asset Pricing Model (CAPM) and dividend-yield riskfree-rate estimators of asset means using statistical and economic criteria. None of the estimators exhibit much out-of-sample predictive ability when judged by statistical criteria. Yet, when combined with a discrete-time power-utility portfolio selection model, all the estimators generate economically significant returns judged in terms of compound return - standard deviation plots and accumulated wealth. Even so, the portfolios generated from dividend-yield riskfree-rate estimators perform by far the best and portfolios generated from traditional CAPM estimator perform the worst. With some notable exceptions, commonly accepted statistical measures of investment performance support these rankings.

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How do we judge whether returns are predictable? We could regress returns on past returns or on information variables that might include accounting data, dividend yields, riskfree interest rates and other macroeconomic indicators. Within this framework we could judge predictability in terms of in-sample slope coefficients and R-square values. Of course, out-of-sample measures of statistical significance—R-squares or mean square errors—would lend more credence to any claims of predictability. However, Leitch and Tanner (1991) point out that statistical measures of predictability may not shed much light on the economic value of a forecast. They show that commercial interest rate forecasts do not perform any better than naïve forecasts when evaluated in terms of out-of-sample statistical criteria. Yet, the commercial (naïve) forecasts generate economically profitable (unprofitable) trading strategies.

This paper is similar in spirit to Leitch and Tanner's. It evaluates historic, Bayes-Stein, CAPM and dividend-yield riskfree-rate estimators of asset means using statistical and economic criteria.[1] The results show that evaluating the estimators in terms of out-of-sample statistical criteria sheds little light on their economic value.

Grauer and Hakansson (1982, 1985, 1986 and 1987) and Grauer, Hakansson and Shen (1990) apply a discrete-time power-utility model in conjunction with the empirical probability assessment approach (EPAA) in domestic, global and industry-rotation asset-allocation settings. The results are noteworthy for two reasons. First, the model often generates economically and statistically significant abnormal returns. Second, no attempt is made to correct for estimation error, which is clearly present in the EPAA. It would seem prudent, therefore, to examine the effects of making corrections.

The results of applying Stein and CAPM estimators of the means are mixed. Evidence based on mean-variance (MV) portfolio selection, simulation analysis and out-of-sample portfolio performance suggests that Stein and CAPM estimators of the means can improve investment performance substantially. See, for example, Jobson, Korkie and Ratti (1979), Jobson and Korkie (1980, 1981) and Jorion (1985, 1986, 1991). On the other hand, Grauer and Hakansson (1995, 2001) find that although the Stein estimators outperform the sample (historic) estimator in an industry-rotation setting, the gains are not as great as those reported by others. Moreover, in a global setting just the opposite is true: the sample estimator outperforms the Stein estimators. In all cases, the CAPM estimator exhibits the worst performance, which is just the opposite of what Jorion (1991) finds in an industry setting using MV analysis that allows short sales.[2] In light of these contradictory results, this paper examines the effects of adding six dividend-yield riskfree-rate estimators to the mix.

Mean estimators trace their origins to different parts of the statistics and finance literature. The mean-square-error properties of the historic estimator make it an obvious choice for an estimate of a mean.[3] Stein estimators are based on purely statistical arguments that minimize the mean-square-error of a vector of means and completely ignore risk-return tradeoffs that may be helpful in predicting stock returns. CAPM estimators fill this void by drawing on the best-known financial model of asset pricing.

Dividend-yield riskfree-rate estimators, as well as estimators based on other information variables, trace their origin to the return predictability or weak form efficient markets literature, see Fama (1991). Return predictability is of interest not only because of its fundamental implications for market efficiency, but also because it is steeped in controversy. There is disagreement about whether returns are predictable and, if they are, whether predictability implies market inefficiency or is a result of rational variation in expected returns.

In the early to mid-1990s there was a consensus, based on statistical criteria, that stock market returns could be predicted from informational variables—at least over one-year to four-year decision horizons.[4] The importance of this evidence extended beyond statistical considerations as it helped renew the interest in continuous-time portfolio choice, hedging demand and non-myopic investment decisions discussed below. In one of the best known return predictability studies, Fama and French (1988) show that the power of dividend yields to forecast stock returns increases with the return horizon. The monthly and quarterly results are unimpressive, with R-squares on the order of 0.01. But, with four-year returns, the R-squares range from 0.13 to 0.64. More impressive, out-of-sample R-squares from forecasts made with coefficients estimated from 30-year rolling regressions are close to the in-sample R-squares for all return horizons.

The consensus began to crack through the 1990s and into the new century. Lo and MacKinlay (1990) and Foster, Smith and Whaley (1997) are concerned with data mining. Hodrick (1992), Goetzmann and Jorion (1993), Goyal and Welch (2003) and Ang and Bekaert (2003), among others, question the long-horizon results on statistical grounds. Goetzmann and Jorion (1993) and Stambaugh (1999) study the biases due to dependent stochastic regressors. Ferson, Sarkissian and Simin (2003) question whether there is a spurious regression bias in predictive regressions. Bossaerts and Hillion (1999) examine the statistical significance of a variety of informational variables using monthly data in an international setting. They confirm the presence of in-sample predictability, but discover that even the best prediction models have no out-of-sample forecasting power. Goyal and Welch (2003) confirm Bossaerts and Hillion's evidence, while Pesaran and Timmermann (1995) report contradictory results. Perhaps surprisingly in light of the early evidence on long-horizon predictability and the out-of-sample evidence in Bossaerts and Hillion, Goyal and Welch and Section V of this paper, Ang and Bekaert (2003) and Torous, Valkanov and Yan (2005) report that the predictive power of dividend yields is best visible at short horizons—with the short rate as an additional regressor in Ang and Bekaert's case.

The single-period MV model, the discrete-time power-utility model and the continuous-time power-utility model either are or have been combined with forecasts based on information variables in order to determine the economic significance of the forecasts.[5] Contributors to the MV literature include: Solnik (1993), Klemkosky and Bharati (1995), Connor (1997), Beller, Kling and Levinson (1998), Ferson and Seigel (2001), Marquering and Verbeek (2001), Fletcher and Hillier (2002) and Avramov and Chordia (2004), among others. They examine the portfolio returns of MV investors who exhibit "average" degrees of risk aversion and revise their portfolios monthly. While these papers report economically significant returns in U.S. bond-stock, U.S. industries and international settings, none reports results from before 1960. The benefits of the MV model include familiarity, ease of estimation—only the means, variances and covariances need to be estimated—and ease of computation.

This paper employs a discrete-time power-utility model that embodies a broad range of risk-aversion characteristics, quarterly decision horizons, borrowing and lending at different rates and an industry dataset that spans the 1934-99 period. The primary benefit of this model is the formal justification of a myopic decision rule. If returns are independent (but not necessarily stationary) from period to period, the use of a stationary myopic power-utility decision rule in each period is optimal. That is, the optimal policy only depends on next period's joint return distribution. (The single-period MV model simply assumes myopic policies are optimal.) The costs include increased complexity in estimation—the entire joint return distribution must be specified—and in computation.

Merton (1971, 1973) introduced a stochastically changing opportunity set that leads to hedging demand and non-myopic investment decisions. Recently, the (weak) evidence of in-sample return predictability based on information variables led to a resurgence of interest in the continuous-time model. A rich literature investigates hedging, the question of whether a long-horizon investor should allocate his wealth differently from a short-horizon investor, the effects of parameter and model uncertainty, the effects of transactions costs and the effects of conditioning on asset pricing models when returns are predictable.[6] Much of the computational analysis calibrates the importance of hedging demand in simulated settings where the stochastic process is consistent with a regression of returns on informational variables. And, with the exception of Brennan, Schwartz and Lagnado (1997), there is little in the way of out-of-sample results. The approach provides a great deal of insight into the multiperiod investment problem, but does not come without the added costs of predicting returns beyond the current period and still further computational complexity. In many instances, specific distributional assumptions are needed to make the model tractable, which causes problems in computing expected utility. See, for example, Barberis (2000) and Kandel and Stambaugh (1996) who constrain investors from short selling and from buying on margin to insure that the expected utility problem has a feasible solution.

Clearly, the original in-sample evidence of return predictability generated from information variables calls into question the assumption that returns are inter-temporally independent and explains the resurgence of interest in hedging and the continuous-time model. But, Bossaerts and Hillion (1999) and Goyal and Welch (2003) find no evidence of out-of-sample predictability based on information variables and in this article I find little, or no, evidence of out-of-sample predictability for *any* of the mean estimators. In light of this evidence and questions about in-sample predictability involving regressions of returns on information variables, I employ inter-temporal independence and the myopic behavior of the discrete-time power-utility model as working assumptions in this paper.

The paper proceeds as follows. Section I outlines the basic multiperiod investment model and the method employed to make it operational. The data, the estimators of the means, and the statistical measures employed to evaluate the investment performance of the portfolios generated from nine mean estimators are described in Sections II-IV, respectively. The results are reported in Sections V: the results based on statistical criteria in Section V.A, the results based on economic criteria in Section V.B, and the results based on statistical measures of investment performance in Section V.C. Section VI contains a summary and conclusions.

I. The discrete-time power-utility model

The discrete-time model is the same as the one employed in Grauer and Hakansson (1986) and the reader is referred to that paper (specifically pages 288-291) for details. It is based on the pure reinvestment version of dynamic investment theory. In particular, if $U_n(w_n)$ is the *induced* utility of wealth *w* with *n* periods to go (to the horizon) and *r* is the single-period return on the portfolio, the important convergence result

$$U_n(w_n) \to \frac{1}{\gamma} w^{\gamma}, \quad \text{for some } \gamma < 1,$$

holds for a very broad class of terminal utility functions $U_0(w_0)$ when returns are independent (but non-stationary) from period to period.[7] Convergence implies that the use of the stationary *myopic* decision rule

$$\max\ E\left[\frac{1}{\gamma}(1+r)^{\gamma}\right], \quad \text{for some } \gamma < 1,$$

in each period is optimal.

At the beginning of each period *t*, the investor chooses a portfolio $\mathbf{x}_t$ on the basis of some member γ of the family of utility functions for returns *r* given by

$$\max_{\mathbf{x}_t}\ E\ \left[\frac{1}{\gamma}(1+r_t(\mathbf{x}_t))^{\gamma}\right] = \max_{\mathbf{x}_t}\ \sum_s \pi_{ts}\frac{1}{\gamma}(1+r_{ts}(\mathbf{x}_t))^{\gamma} \tag{1}$$

subject to

$$x_{it} \geq 0,\ \ x_{Lt} \geq 0,\ \ x_{Bt} \leq 0,\ \text{all } i, \tag{2}$$

$$\sum_i x_{it} + x_{Lt} + x_{Bt} = 1\ , \tag{3}$$

$$\sum_i m_{it} x_{it} \leq 1\ , \tag{4}$$

$$1 + r_{ts}(\mathbf{x}_t) > 0,\ \text{for all s}, \tag{5}$$

where

$r_{ts}\left(\mathbf{x}_t\right)$ = $\sum_i x_{it}r_{its} + x_{Lt}r_{Lt} + x_{Bt}r_{Bt}^{d}$ is the (*ex ante*) return on the portfolio in period *t* if state *s* occurs,

$\gamma \leq 1$ = a parameter that remains fixed over time,

x_{it} = the amount invested in risky asset category *i* in period *t* as a fraction of own capital,

x_{Lt} = the amount lent in period *t* as a fraction of own capital,

x_{Bt} = the amount borrowed in period *t* as a fraction of own capital,

$\mathbf{x}_t$ = $(x_{1t},...,x_{nt}, x_{Lt}, x_{Bt})'$,[8]

r_{it} = the anticipated total return (dividend yield plus capital gains or losses) on asset category i in period t,

r_{Lt} = the return on the riskfree asset in period t,

r_{Bt}^{d} = the interest rate on borrowing at the time of the decision at the beginning of period t,

m_{it} = the initial margin requirement for asset category i in period t expressed as a fraction,

π_{ts} = the probability of state s at the end of period t, in which case the random return r_{it} will assume the value r_{its} .

Constraint (2) rules out short sales and ensures that lending (borrowing) is a positive (negative) fraction of capital. Constraint (3) is the budget constraint. Constraint (4) serves to limit borrowing (when desired) to the maximum permissible under the margin requirements that apply to the various asset categories. Constraint (5) rules out any *ex ante* probability of bankruptcy.[9]

The inputs to the model are based on the "empirical probability assessment approach" (EPAA) with quarterly revisions. At the beginning of quarter t, the portfolio problem consisting of equations (2)-(5) for that quarter uses the following inputs: the (observable) riskfree return for quarter t, the (observable) call money rate +1% at the beginning of quarter t and the (observable) realized returns for the risky asset categories for the previous k quarters. Each joint realization in quarters $t–k$ through $t–1$ is given probability $1/k$ of occurring in quarter t. Thus, under the EPAA, estimates are obtained on a moving basis and used in raw form without adjustment of any kind. On the other hand, since the whole joint distribution is specified and used, there is no information loss; all moments and correlations are implicitly taken into account. It may be noted that the empirical distribution of the past k periods is optimal if the investor has no information about the form and parameters of the true distribution, but believes that this distribution went into effect *k* periods ago.

With these inputs in place, the portfolio weights $\mathbf{x}_t$ for the various asset categories and the proportion of assets borrowed are calculated by solving equations (2)-(5) via nonlinear programming methods.[10] At the end of quarter *t*, the realized returns on the risky assets are observed, along with the realized borrowing rate r_{Bt}^{r} (which may differ from the decision borrowing rate r_{Bt}^{d}).[11] Then, using the weights selected at the beginning of the quarter, the realized return on the portfolio chosen for quarter *t* is recorded. The cycle is repeated in all subsequent quarters.[12]

All reported returns are gross of transaction costs and taxes and assume that the investor in question had no influence on prices. There are several reasons for this approach. First, as in previous studies, we wish to keep the complications to a minimum. Second, the return series used as inputs and for comparisons also exclude transaction costs (for reinvestment of interest and dividends) and taxes. Third, many investors are tax-exempt and various techniques are available for keeping transaction costs low. Finally, since the proper treatment of these items is nontrivial, they are better left to a later study.

II. Data

The data used to estimate the probabilities of the next period's returns on risky assets and to calculate each period's realized returns on risky assets come from several sources. The returns for Standard and Poor's 500 Index come from the Ibbotson Associates database. The returns for the value-weighted industry groups are constructed from the returns on individual New York Stock Exchange firms contained in the Center for Research in Security Prices' (CRSP) monthly returns database. The firms are combined into twelve industry groups on the basis of the first two digits of the firms' SIC codes. (Grauer, Hakansson and Shen (1990) contains a detailed description of the industry data.) The riskfree asset is assumed to be 90-day U.S. Treasury bills maturing at the end of the quarter. The *Survey of Current Business* and the *Wall Street Journal* are the sources. The borrowing rate is assumed to be the call money rate +1% for decision purposes (but not for rate of return calculations). The applicable beginning of period decision rate, r_{Bt}^{d}, is viewed as persisting throughout the period and thus as riskfree. For 1934-76, the call money rates are obtained from the *Survey of Current Business.* For later periods, the *Wall Street Journal* is the source. Finally, margin requirements for stocks are obtained from the *Federal Reserve Bulletin*.[13]

III. Estimators of the means

Under the historic approach means are not used directly but are implicitly computed from the realized returns in the estimation period. The *n*-vector of historic means at the beginning of period *t* is

$$\boldsymbol{\mu}_{Ht} = \left(\bar{r}_{1t}, \ldots, \bar{r}_{nt}\right)', \tag{6}$$

where $\bar{r}_{it} = \frac{1}{k}\sum_{\tau=t-k}^{t-1} r_{i\tau}$. This EPAA approach implicitly estimates the means one at a time, relying exclusively on information contained in each of the time series.

Stein's (1955) suggestion that the efficiency of the estimate of the means could be improved by pooling the information across series leads to a number of so-called "shrinkage" estimators that shrink the historical means to some grand mean. A classic example is the James-Stein estimator, see Efron and Morris (1973, 1975 and 1977), first employed in the portfolio selection literature by Jobson, Korkie and Ratti (1979). However, because Grauer and Hakansson (1995,

2001) find that Jorion's (1985, 1986, 1991) Bayes-Stein (BS) estimator exhibits slightly better performance, this paper—like Jorion (1991)—concentrates on it. The Bayes-Stein estimator is

$$\boldsymbol{\mu}_{BSt} = (1-w_t)\boldsymbol{\mu}_{Ht} + w_t\bar{r}_{Gt}\boldsymbol{\iota}, \tag{7}$$

where $w_t = \lambda_t/(\lambda_t + k)$ is the shrinking factor, $\lambda_t = (n+2)/((\boldsymbol{\mu}_{Ht} - \bar{r}_{Gt}\boldsymbol{\iota})'\mathbf{S}_t^{-1}(\boldsymbol{\mu}_{Ht} - \bar{r}_{Gt}\boldsymbol{\iota}))$, n is the number of risky assets, $\mathbf{S}_t$ is the sample covariance matrix calculated from the k periods in the estimation period, $\bar{r}_{Gt} = \boldsymbol{\iota}'\mathbf{S}_t^{-1}\boldsymbol{\mu}_{Ht}/(\boldsymbol{\iota}'\mathbf{S}_t^{-1}\boldsymbol{\iota})$ is the grand mean and $\boldsymbol{\iota}$ is a vector of ones.[14] In this case, the grand mean is the mean of the global minimum-variance portfolio generated from the historical data.[15]

A third estimator of the means is based on the Sharpe (1964) - Lintner (1965) CAPM. The CAPM estimator is

$$\boldsymbol{\mu}_{CAPMt} = r_{Lt}\boldsymbol{\iota} + (\bar{r}_{mt} - \bar{r}_{Lt})\hat{\boldsymbol{\beta}}_t, \tag{8}$$

where $\bar{r}_{mt} = \frac{1}{k}\sum_{\tau=t-k}^{t-1} r_{m\tau}$, $\bar{r}_{Lt} = \frac{1}{k}\sum_{\tau=t-k}^{t-1} r_{L\tau}$, and $\bar{r}_{mt} - \bar{r}_{Lt}$ is an estimate of the expected excess return on the "market" portfolio and $\hat{\boldsymbol{\beta}}_t$ is the vector of estimated betas or systematic risk coefficients. At each time t, $\hat{\boldsymbol{\beta}}_t$ is estimated from the market model regressions

$$r_{i\tau} = \alpha_{it} + \beta_{it} r_{m\tau} + e_{i\tau}, \quad \text{for all } i \text{ and } \tau, \tag{9}$$

in the t–k to t–1 estimation period, where the CRSP value-weighted index is employed as the proxy for the market portfolio. This method of estimating CAPM means, employed by Jorion (1991) and Grauer and Hakansson (1995, 2001), assumes the excess return on the market is constant over the estimation period.[16] I refer to these means as the CAPM means, although it might be more accurate to refer to them as traditional CAPM means, or CAPM means that assume a constant expected return on the market.

The next six estimators use dividend yields and riskfree interest rates to forecast the means. To construct the first dividend-yield riskfree-rate estimator, the following regression is run at each time *t*

$$r_{i\tau} = b_{0i} + b_{1i} dy_{\tau-1} + b_{2i} r_{L\tau} + e_{i\tau}\text{, for all } i \text{ and } \tau, \tag{10}$$

in the *t*–*k* to *t*–1 estimation period, where the *i* subscript denotes an industry, $dy_{\tau-1}$ is the annual dividend yield on the CRSP value-weighted index lagged one month so that it is observable at the beginning of quarter *t,* and r_{Lt} is the (observable) beginning-of-quarter Treasury bill rate. Both independent variables are "de-meaned." Hence, b_{0i} is the historic average rate of return on asset (industry) *i*.

The traditional one-period ahead forecast of the mean of industry *i* is

$$\overline{r}_{DRit} = \hat{b}_{0i} + \hat{b}_{1i} dy_{t-1} + \hat{b}_{2i} r_{Lt}, \tag{11}$$

where $\hat{b}_{0i}$, $\hat{b}_{2i}$ and $\hat{b}_{2i}$ are the estimated coefficients and dy_{t-1} and r_{Lt} are observable at the beginning of period *t*+1. That is, the quarterly variable dy_{t-1} is lagged one month and there is no need to lag r_{Lt} as it is observable at the beginning of the quarter. The vector of dividend-yield riskfree-rate (DR) estimators is

$$\boldsymbol{\mu}_{DRt} = \left(\overline{r}_{DR1t}, \ldots, \overline{r}_{DRnt}\right)'. \tag{12}$$

However, this forecast is extremely variable. Therefore, in the spirit of the Stein estimators, I "shrink" the DR means in two ways: first, to CAPM means and second to historic means. Black and Litterman (1992) shrink individual investor's forecasts of means to CAPM means in a Bayesian framework. Their method attempts overcome three problems: the difficulty in estimating means; the extreme sensitivity of the solutions to slight perturbations in the means documented by Best and Grauer (1991, 1992) and Green and Hollifield (1992); and need for a set of means that would clear the market in an equilibrium setting. When the DR and CAPM means are assumed to be equally likely, the vector of dividend-yield riskfree-rate - CAPM (DRCAPM) mean estimators is[17]

$$\boldsymbol{\mu}_{DRCAPMt} = (\boldsymbol{\mu}_{DRt} + \boldsymbol{\mu}_{CAPMt})/2\,. \tag{13}$$

Alternatively, I shrink the dividend-yield riskfree-rate to historic means. Again, assuming that the DR and historic means are equally likely, the vector of dividend-yield riskfree-rate - historic (DRH) mean estimators is

$$\boldsymbol{\mu}_{DRHt} = (\boldsymbol{\mu}_{DRt} + \boldsymbol{\mu}_{Ht})/2\,. \tag{14}$$

Shrinking the dividend-yield riskfree-rate means to historic means is somewhat *ad hoc*. But it provides natural way to link to two additional estimators that help to separate out the effects of market timing and selectivity in the portfolios generated from different mean estimators.

I create a dividend-yield riskfree-rate historic estimator of the expected return on the "market" (the value-weighted CRSP) portfolio by: regressing market (instead of industry) returns on dividend-yields and riskfree-rates in equation (10); making the forecast for the market corresponding to equation (11); and averaging that forecast with the historic mean on the market as in equation (14). The DRM forecast μ_{DRMt} is combined with the discrete-time power-utility portfolio optimizer in order to ascertain whether portfolios generated from it can "time" the market. In this case, the investment universe consists of the CRSP value-weighted index, borrowing and lending—and *not* the universe of the twelve industry portfolios, borrowing and lending, which is employed in all other cases.

The next dividend-yield riskfree-rate estimator uses the "market-timing" estimator μ_{DRMt} to estimate the slope of the "security market line" in making forecasts of industry means. The dividend-yield riskfree rate market - CAPM (DRMCAPM) means are

$$\boldsymbol{\mu}_{DRMCAPMt} = r_{Lt}\boldsymbol{\iota} + (\mu_{DRMKTt} - r_{Lt})\hat{\boldsymbol{\beta}}_t, \tag{15}$$

where μ_{DRMt} is estimated by the method just described and $\hat{\boldsymbol{\beta}}_t$ is estimated from equation (9).

I expect that the portfolios generated from the DRM means will time the market. However, because the investment universe consists of the market, borrowing and lending only, I expect that these portfolios will not earn returns as high as the industry-rotation portfolios generated from the DRH and DRCAPM means. Furthermore, I expect that portfolios generated from the DRMCAPM industry-rotation means will exhibit market-timing ability, while the portfolios employing the DRH and DRCAPM industry-rotation means will not.

Finally, most of the power-utility (MV) asset-allocation literature estimates the joint return distribution (mean vector and covariance matrix) from a moving window. It has been suggested, however, that the analysis should be based on an "expanding" window. To investigate this possibility, I consider a sixth dividend-yield riskfree-rate estimator shrunk to the historic mean estimator based on the full sample from the first quarter of 1926 to time *t*-1. I call this a DRHAOH estimator to indicate that the dividend-yield riskfree-rate regression and the joint return distribution are estimated from an *expanding all-of-history* window.

IV. Statistical measures of investment performance

In Section V we will see that the compound return – standard deviation plots and cumulative wealth values provide convincing evidence that: (1) all the mean estimators provide economic value when combined with the discrete-time power-utility model, and (2) the dividend-yield riskfree-rate estimators perform better than the traditional CAPM estimator. While the figures and wealth values get to the heart of the matter, they do not give us a sense of how much of the difference can be attributed to randomness. In order to shed light on this issue I report the results from a number of commonly accepted statistical measures of performance. Unfortunately, none is without problems. First, the industry-rotation strategies examined here are neither the pure selectivity strategies implicit in Jensen's (1968) test, nor the pure market-timing strategies embodied in Treynor and Mazuy's (1966) and Henriksson and Merton's (1981) tests of market timing. Second, Roll (1978) argues that Jensen's test is ambiguous because the choice of the benchmark (market) portfolio affects both systematic risk (beta) and abnormal return (alpha).[18] Third, expected returns and risk measures may vary with economic conditions.

In light of these problems, I employ an eclectic mix of performance measures that include conditional and unconditional versions of the Jensen, Henriksson-Merton and Treynor-Mazuy tests as well as Grinblatt and Titman's (1993) portfolio change measure that gauges performance without reference to a proxy for the market portfolio. The null hypothesis is that there is no superior investment performance and the alternative hypothesis is that there is. Thus, I report the results of one-tailed tests. All regressions are corrected for heteroskedasticity using White's (1980) correction.

The unconditional Jensen (1968) test is based on the regression

$$R_{pt} = \alpha_p + \beta_p R_{mt} + u_{pt} \,, \tag{16}$$

where $R_{pt} = r_{pt} - r_{Lt}$ is the excess return on portfolio p over the Treasury bill rate, $R_{mt} = r_{mt} - r_{Lt}$ is the excess return on the CRSP value-weighted index, α_p is the unconditional measure of performance and β_p is the unconditional measure of risk. However, expected returns and betas almost certainly change over time. Therefore, Ferson and Schadt (1996) and Ferson and Warther (1996), among others, building on the earlier work of Shanken (1990), advocate conditional performance measures. I follow their suggestion that a portfolio's risk is related to dividend yields and short-term Treasury yields postulating that

$$\beta_p = b_{0p} + b_{1p} dy_{t-1} + b_{2p} r_{Lt}, \tag{17}$$

where dy_{t-1} is the CRSP value-weighted index annual dividend yield at the beginning of period t and r_{Lt} is the (observable) beginning-of-quarter Treasury bill rate, both measured as deviations from their estimation-period means. Substituting equation (17) into equation (16), yields the conditional Jensen test

$$R_{pt} = \alpha_{cp} + b_{0p} R_{mt} + b_{1p}[dy_{t-1} R_{mt}] + b_{2p}[r_{Lt} R_{mt}] + e_{pt}, \tag{18}$$

where α_{cp} is the conditional measure of performance, b_{0p} is the conditional beta and b_{1p} and b_{2p} measure how the conditional beta varies with dividend yields and Treasury bill rates.

The unconditional regression specification for the Treynor and Mazuy (1966) test is

$$R_{pt} = \alpha_p + \beta_p R_{mt} + \gamma_p R_{mt}^2 + u_{pt}, \tag{19}$$

where α_p is the measure of selectivity, β_p is the unconditional beta and γ_p is the market-timing coefficient. Substituting for β_p, the conditional regression specification is

$$R_{pt} = \alpha_{cp} + b_{0p} R_{mt} + b_{1p}[dy_{t-1} R_{mt}] + b_{2p}[r_{Lt} R_{mt}] + \gamma_p R_{mt}^2 + e_{pt}, \tag{20}$$

where α_{cp}, b_{0p}, b_{1p}, b_{2p} and γ_p are defined above.

The unconditional Henriksson and Merton (1981) test is given by

$$R_{pt} = \alpha_p + \beta_{dp} R_{mt} + \gamma_p \max(0, R_{mt}) + u_{pt}, \tag{21}$$

where α_p is the measure of selectivity, β_{dp} is the down-market beta, γ_p is the market-timing coefficient, in this case the difference between the up- and down-market beta, and $\max(0, R_{mt})$ is the payoff on a call option on the market with exercise price equal to the riskfree rate of interest. Following Ferson and Schadt (1996), the conditional Henriksson-Merton test is

$$R_{pt} = \alpha_{cp} + b_{dp}R_{mt} + b_{1p}[dy_{t-1}R_{mt}] + b_{2p}[r_{Lt}R_{mt}] + \gamma_p R^*_{mt} + b^*_{1p}[dy_{t-1}R^*_{mt}] + b^*_{2p}[r_{Lt}R^*_{mt}] + e_{pt}\,, \qquad (22)$$

where R^*_{mt} is the product of the excess return on the CRSP value-weighted index and an indicator dummy for positive values of the difference between the excess return on the index and the conditional mean of the excess return. (The conditional mean is estimated by a linear regression of the excess return of the CRSP value-weighted index on dy_{t-1} and r_{Lt}.) The most important coefficients are b_{dp}, the conditional down-market beta, and γ_p, the market-timing coefficient, which in this case is the difference between the up- and down-market conditional betas.

In contrast to most other performance measures, Grinblatt and Titman's (1993) portfolio change measure employs portfolio holdings as well as rates of return and does not require an external benchmark (market) portfolio. In order to motivate the portfolio change measure, assume that uninformed investors perceive that the vector of expected returns is constant, while informed investors can predict whether expected returns vary over time. Informed investors can profit from changing expected returns by increasing (decreasing) their holdings of assets whose expected returns have increased (decreased). The holding of an asset that increases with an increase in its conditional expected rate of return will exhibit a positive unconditional covariance with the asset's returns. The portfolio change measure is constructed from an aggregation of these covariances. For evaluation purposes, let

$$PCM_t = \sum_i r_{it}(x_{it} - x_{i,t-j})\,,$$

where r_{it} is the quarterly rate of return on asset *i* time *t*, x_{it} and $x_{i,t-j}$ are the holdings of asset *i* at time *t* and time *t–j*, respectively. This expression provides an estimate of the covariance between returns and weights at a point in time. Alternatively, it may be viewed as the return on a zero-weight portfolio. The portfolio change measure is an average of the PCM_t's

$$\overline{PCM} = \sum_t \sum_i \left[r_{it} \left(x_{it} - x_{i,t-j} \right) / T \right], \tag{23}$$

where T is the number of time-series observations. The portfolio change measure test itself is a simple t-test based on the time series of zero-weight portfolio returns, i.e.,

$$t = \left(\overline{PCM} / \sigma\left(PCM \right) \right) \sqrt{T} \ , \tag{24}$$

where $\sigma(PCM)$ is the standard deviation of the time series of PCM_t's. In their empirical analysis of mutual fund performance, Grinblatt and Titman work with two values of j that represented one- and four-quarter lags. This paper employs the same two lags.

The portfolio change measure is particularly apropos in the present study because the portfolio weights are chosen according to a pre-specified set of rules over the same quarterly time interval as performance is measured. Thus, I do not have to worry about possible gaming or window-dressing problems that face researchers trying to gauge the performance of mutual funds.

V. Results

A. Results based on statistical criteria

Table I depicts the symbols used in the figures and tables. The out-of-sample forecasting results are reported in Table II. The findings confirm Bossaerts and Hillion's (1999) and Goyal and Welch's (2003) results that there is little, or no, out-of-sample short-horizon forecasting ability with information variables. Surprisingly, there is little to distinguish between any of the forecasts and even the small differences are counterintuitive. The total mean square error of the DRH means is indistinguishable from the total mean square errors of the historic and CAPM means. The DRMCAPM—not the Bayes-Stein—estimator has the smallest total mean square error. The average out-of-sample R-squares are below 0.01 for all but the CAPM estimator. Yet, the results in Section B show that when this estimator is combined with the power-utility model it generates the worst economic performance. Equally surprising, the Bayes-Stein estimator, noted for minimizing the total mean square error, exhibits the smallest average out-of-sample R-square.

Tables I and II here

B. Results based on economic criteria

Table III shows the compound return - standard deviation pairs for two sets of benchmarks in three time periods: 1934-99, 1966-99 and 1966-81. The first set of benchmarks is a set of passive buy-and-hold policies—one for each industry. The second set of benchmarks consists of leveraged holdings of the CRSP value-weighted portfolio which, as noted, proxies for the "market" portfolio. The market portfolio, VW, earned on the order of 12 percent in the 1934-99 and 1966-99 periods and 6.62 percent in the 1966-81 period. V20 consists of an investment of 200 percent in the market financed by borrowing 100 percent at the call money rate plus one percent. Leverage increased the market's return by over 3 percent to 15.5 percent in the full period. In the 1966-99 period, investing in V20 increased the market's return marginally, from 12.15 to 12.52 percent; but decreased the market's return by over 4 percent to 2.48 percent in the 1966-81 period.

Table III here

Figure 1 plots the <u>annual</u>[19] compound return and standard deviation[20] of the realized returns for four sets of ten power-utility strategies, based on γ's in equation (1) ranging from -50 (extremely risk averse) to 1 (risk-neutral), for the 66-year period from 1934-99. Portfolios are chosen each quarter, employing a 32-quarter estimation period, from an investment universe that includes the twelve value-weighted U.S. industry indices, lending and borrowing. The first set of strategies (black circles) shows the returns generated using historic means. The second set (open squares) displays the returns based on Bayes-Stein means. The third set (open triangles) depicts those based on CAPM means and the fourth set (open circles) presents the returns obtained employing the DR forecasts of the means. The figure also shows the benchmarks: RL, V5, VW, V15 and V20 as open diamonds. Figure 2 plots the corresponding results for the 30-year sub-period from 1966-99. Finally, Figure 3 displays the results for the (inflationary) 16-year sub-period from 1966-81, a period which experienced a one-half percent per year negative realized risk premium on the value-weighted portfolio of risky assets.

Figures 1-3 show three main results. In the 1934-99 and 1966-99 periods, portfolios generated from the DR means "outperform" portfolios that employ the historic, Bayes-Stein and CAPM means. The portfolios based on the CAPM means are "dominated" by the other three *and* by the benchmark portfolios. However, in the 1966-81 period, portfolios employing historic and Bayes-Stein means do not so obviously dominate portfolios based on the CAPM means.[21]

Figures 1, 2 and 3 here

In order to shed light on whether timing or selectivity or a combination of the two cause the performance of the DR portfolios, and to examine the robustness of the results, five additional dividend-yield riskfree-rate estimators are examined. The compound return - standard deviation pairs of the portfolios generated from these estimators of the means and from the levered market benchmark portfolios are plotted over the same three periods in Figures 4, 5 and 6, respectively. For ease of comparison the DR portfolios are also plotted in the figures.

The main results in Figures 4-6 may be summarized as follows. First, the portfolios generated from the DRCAPM, DRMCAPM and DRH means perform even better than the portfolios generated from the DR means. Second, the portfolios generated from the DRM means (which simply combine the market with borrowing or lending) are characterized by less compound return and variance than the portfolios generated from all the dividend-yield riskfree-rate industry-rotation means. In addition, the less risk-averse power-utility portfolios generated from the DRM market-timing means incur either less, or slightly more, standard deviation than the market in the post-1966 period, but earn far higher rates of return. Fourth, given that the portfolios employing DRCAPM, DRH, DRMCAPM and DR industry-rotation means earn higher returns than the portfolios employing the DRM market-timing means, it appears that something more than—or other than—market timing is involved in performance of the portfolios generated from the industry-rotation means. (The portfolio weights and market-timing tests reported in the next section support this conclusion.) Finally, portfolios generated from the DRAOH expanding-window method do not perform nearly as well as the DRCAPM, DRH, DRMCAPM, DR and DRM portfolios, which speaks well for the moving window approach.

Figures 4, 5 and 6 here

C. Results based on statistical measures of investment performance

With some notable exceptions, the statistical measures of investment performance support the conclusions drawn from the figures and cumulative wealth values. For the sake of brevity, I focus on results that either support or contradict the central conclusions.

Table IV summarizes the average alphas and betas for the ten power strategies obtained from conditional and unconditional Jensen tests over the 1934-99, 1966-99 and 1966-81 periods. The results of the Jensen tests are consistent with conclusions drawn from the figures and cumulative wealth values. The alphas of the portfolios generated from the DR, DRH, DRCAPM and DRMCAPM estimators are much larger and more statistically significant than those of the other five estimators, particularly in the 1934-99 and 1966-99 periods. Consistent with the figures and wealth rankings, the portfolios generated these industry-rotation estimators outperform (i.e., have larger alphas than) the portfolios based on the DRM means, which combine the market with borrowing or lending. In addition, the conditional Jensen test uniformly ranks the performance of the historic, Bayes-Stein and CAPM portfolios higher than the unconditional Jensen test, which is consistent with Ferson and Schadt's (1996) and Ferson and Warther's (1996) mutual fund results. For the dividend-yield riskfree-rate portfolios, just the opposite is true.

Table IV here

Tables V and VI contain the results of unconditional and conditional Henriksson-Merton and Treynor-Mazuy market-timing tests, respectively. In the 1966-99 period, there is strong evidence of market-timing ability for the DRM and DRMCAPM estimators. The four tests indicate that ten of the DRM portfolios and nine of the DRMCAPM portfolios exhibit statistically significant market-timing ability at the five percent level. The evidence is mixed for the other estimators, with little or no evidence of statistically significant market-timing ability according to the unconditional tests, and some evidence of statistically significant market-timing ability according to the conditional tests. Surprisingly, the conditional tests indicate more market-timing ability for the historic estimator than for the DR and DRH estimators.

In the 1934-99 period, both conditional tests show the same overwhelming evidence of market-timing ability for the DRM and DRMCAPM estimators, and almost no market-timing ability for any of the other estimators. The case for the market-timing ability of the DRM and DRMCAPM estimators, however, is less strongly supported by the unconditional tests. In the

1966-81 period, the results are anomalous. The conditional tests, especially the Treynor-Mazuy conditional test, show strong evidence of market-timing ability for the historic, Bayes-Stein and CAPM estimators, and no evidence of market-timing ability for any of the dividend-yield riskfree-rate estimators.

Tables V and VI here

The results of the timing tests are supported by an examination of the portfolio weights presented in Table VII. The table shows the percent of time that the power-utility investors either: (1) lend 100 percent of their wealth; or (2) combine lending or borrowing with investment in one to six industries; or (3) combine lending or borrowing with investment in seven to twelve industries in the 1934-99 period. Two results stand out. First, an investor who wishes to time the market, must be willing to move in or out of equities. The DRM investors (not shown in Table VII as the investment universe consists of the market, borrowing and lending only) and DRMCAPM investors do! Specifically, the DRMCAPM (and DRM) investors lend 100 percent of their wealth 18.9 percent of the time—50 times out of the 264 quarters from 1934-99. The DR investors lend 100 percent of their wealth 10.6 percent of the time. None of the investors employing the other six estimators of the means lend 100 percent of their wealth over 5.3 percent of the time. Second, the CAPM and DRMCAPM investors diversify far more than those employing the other six industry-rotation estimators of the means. Thus, the DR, DRH, and DRCAPM investors achieve their returns in very different ways from the DRMCAPM investors. The DR, DRH and DRCAPM investors lend 100 percent of their wealth 10.6, 4.2, and 3.8 percent of the time, respectively, and *never* invest in as many as seven industries at any point in time. On the other hand, the DRMCAPM investors commit 100 percent of their wealth to lending 18.9 percent of the time and the more risk-averse investors, with powers ranging from -50 to -3, invest in seven to twelve industries over 50 percent of the time.

Table VII here

The results of the portfolio change measure test are presented in Table VIII. The tests encompass 1-quarter and 4-quarter lags for each of the estimators. As noted, these two lags are the same as those employed by Grinblatt and Titman (1993) in their study of mutual funds. The results of the 4-quarter test are consistent with the conclusions drawn from the figures. The DR, DRH, DRCAPM and DRMCAPM portfolios exhibit much larger portfolio change measure values than the historic, Bayes-Stein, CAPM and DRAOH portfolios in the 1934-99 and 1966-99 periods. In the 1934-99 period, PCMs for all but the CAPM portfolios are highly statistically significant. The Grinblatt-Titman test also gives rise to two anomalous results. The portfolios generated from historic and Bayes-Stein means are characterized by statistically significant performance, while the portfolios generated from dividend-yield riskfree-rate estimators perform abysmally in all three periods according to the 1-quarter PCM.[22] In the 1966-81 period, all the portfolios generated from dividend-yield riskfree-rate estimators perform poorly according to the 4-quarter PCM, which is almost completely at odds with Figures 3 and 6.

Table VIII here

VI. Summary and concluding comments

This paper evaluates historic, Bayes-Stein, CAPM and dividend-yield riskfree-rate estimators of asset means employing statistical and economic criteria. With one exception, the analysis is conducted in an industry-rotation setting using quarterly data. None of the estimators exhibit much out-of-sample predictive ability when judged by statistical criteria. The average out-of-sample R-squares are below 0.01 for all but the CAPM estimator. And, there is little difference in the mean square errors of the eight industry-rotation mean estimators. Yet, when the mean estimators are combined with a discrete-time power-utility portfolio selection model, all the resulting portfolios earn economically significant returns. Nonetheless, judged in terms of the compound return - standard deviation plots in Figures 1-6, or in terms of accumulated wealth, some of the portfolios perform appreciably better than others. With the exception of the DRAOH portfolios, where the estimates are based on an expanding window all-of-history approach, the dividend-yield riskfree-rate portfolios perform by far the best, and the traditional CAPM portfolios perform the worst.

The DR industry-rotation means are based on regressions of industry returns on CRSP-index dividend yields and riskfree interest rates. The DRH and DRCAPM estimators combine historic and CAPM means with the DR means. An examination of the portfolio weights indicates that portfolios generated from these estimators do not attempt to time the market nor do they diversify widely. The DR, DRH, and DRCAPM portfolios lend 100 percent of their wealth 10.6, 4.2 and 3.8 percent of the time, respectively; and all of them hold less than seven industries at any point in time. The DRM market-timing estimator is based on a regression of CRSP value-weighted index returns on CRSP index dividend yields and riskfree interest rates. An examination of portfolio weights—in an investment universe consisting of the market, borrowing and lending—shows that the DRM portfolios attempt to time the market, lending 100 percent of their wealth 18.9 percent of the time. The DRMCAPM industry-rotation estimators uses the DRM means to set the slope of the security market line in a CAPM framework. The portfolios weights indicate that the DRMCAPM portfolios time the market and diversify much more widely than their dividend yield – riskfree rate brethren. Like the DRM portfolios, they lend 100 percent of their wealth up to 18.9 percent of the time; and six of the DRCAPM portfolios hold more than six twelve industries over 50 percent of the time.

With some notable exceptions, commonly accepted statistical measures of performance support the market-timing ability of the DRM and DRMCAPM portfolios and their compound return - standard deviation and wealth rankings. The Treynor-Mazuy and Henriksson-Merton market-timing tests show statistically significant market-timing ability for the DRM and DRMCAPM portfolios in the 1934-99 and 1966-99 periods, and little or no market-timing ability for the portfolios based on the other estimators. Furthermore, the Jensen and 4-quarter lag Grinblatt-Titman tests support the compound return - standard deviation and wealth rankings, especially in the 1934-99 and 1966-99 periods.

The anomalous results tend to cluster in, but are not confined to, the 1966-81 period. In the 1966-81 period, the unconditional Jensen test assigns statistically significant performance to all the DR and DRCAPM portfolios, while the conditional test sees no statistically significant performance. In the same period, the conditional Treynor-Mazuy and Henriksson-Merton tests find *negative* market-timing ability for the DRM and DRMCAPM portfolios, and statistically significant market-timing ability for the traditional CAPM portfolios, which appears to be at complete odds with the results reported in Figures 3 and 6. The Grinblatt-Titman tests give rise to two anomalous results. First, all the dividend-yield riskfree-rate portfolios perform abysmally in all three periods according to the 1-quarter PCM. Second, in the 1966-81 period, all the dividend-yield riskfree-rate estimators perform poorly according to the 4-quarter PCM.

It is an open question as to whether these anomalies are a sign of a true lack of performance, or of differences in performance, or simply reflect shortcomings in statistical measures of investment performance. It is well known, for example, that the performance measures do not agree on the performance of passive portfolios or professional money managers and that they suffer from a number of conceptual and empirical shortcomings. Equally important, Grauer (2006b) benchmarks popular measures of investment performance with two extremes: perfect-foresight asset-allocation strategies, which yield returns beyond one's wildest dreams, and bankrupt MV asset-allocation strategies, which lose everything. Unfortunately, many of the measures cannot differentiate between them. In addition, the timing measures confound selectivity and market-timing ability.

So, are returns predictable? Clearly, the answer depends on the length of the decision horizon examined and metric chosen. With quarterly returns, the out-of-sample statistical answer is a clear no—and the economic answer is a resounding yes. In this case, I argue that the economic answer is compelling. You can't spend a slope coefficient, a *t*-statistic, an R-square, or a mean square error. But, four of the more risk-tolerant power-utility portfolios generated from DRCAPM means grew from one dollar to $28,000, $301,000, $1,213,000 or $228,000 over the 1934-99 period. These portfolios provided investors with real spending opportunities—especially when compared to an investment in the market that grew to only $3,600, or an investment of 200% in the market financed by 100% borrowing that grew to $9,700 over the same period. In this case, Leitch and Tanner (1991, page 580) are correct in suggesting that: "… least-squares regression analysis may not be appropriate for many studies of economic behavior."

Footnotes

[1] The paper is similar to Leitch and Tanner's work in that it evaluates forecasts employing statistical and economic criteria. But the details are quite different. This paper employs the forecasts in a portfolio optimizer, whereas Leitch and Tanner use a forecast to form a trading rule more like the trading rules employed in the papers listed in footnote 5.

[2] Alternatively, it has been suggested that one might adjust for estimation risk by constraining portfolio weights. Again, the results are somewhat mixed. Employing simulation and MV analysis with short sales permitted, Frost and Savarino (1988) report that imposing upper bounds both reduces estimation bias and improves performance. In a companion paper, Grauer (2006a) shows that the portfolios of less risk-averse MV investors generated from dividend-yield riskfree-rate estimators of the means bankrupt in an out-of-sample industry rotation setting when short sales are permitted. Yet, when short sales are precluded, the dividend-yield riskfree-rate portfolios of these less risk-averse MV investors exhibit the best performance. Moreover, portfolios generated from the CAPM estimator, which display the best performance when short sales are permitted, exhibit the worst performance when short sales are precluded. On the other hand, Grauer and Shen (2000), employing the discrete-time power-utility model in an out-of-sample setting with short sales precluded, report that constraining the portfolio weights further leads to appreciably more diversification and less realized risk, but at the cost of less realized return.

[3] As noted above, the use of historic data in conjunction with the discrete-time power-utility model has proven quite successful in various asset allocation settings. However, the use of sample estimators has been widely criticized as the optimizing process has a tendency to maximize the effects of errors in the inputs. See Michaud (1989).

[4] See the references in Fama and French (1988, 1989), Fama (1991) and Hawawini and Keim (1995).

[5] Alternatively, Breen, Glosten and Jagannathan (1989), Fuller and Kling (1990), Pesaran and Timmermann (1994), Larsen and Wozniak (1995), Pelaez (1998) and Schwert (2003), among others, investigate the economic value of trading rules based on predictive regressions, when the predictions are not combined with an MV or power-utility portfolio selection model. The results are mixed and sample-period dependent. Schwert, for example, examines a strategy of investing in short-term bonds when a dividend yield model predicts stock returns are lower than interest rates. The model predicts poorly during the 1990s when stock returns were high and the dividend yield model predicted low stock returns. Schwert (2003, page 953) concludes: "In short, the out-of-sample prediction performance of this model would have been disastrous." By way of contrast, this paper shows that when dividend-yield riskfree-rate forecasts are combined with the discrete-time power-utility model, the results through the 1990s are anything but disastrous.

[6] See, for example, Kandel and Stambaugh (1996), Kim and Omberg (1996), Brennan, Schwartz and Lagnado (1997), Balduzzi and Lynch (1999), Brandt (1999), Campbell and Viceira (1999), Barberis (2000), Pastor (2000), Pastor and Stambaugh (2000), Lynch (2001), Lynch and Balduzzi (2001), Avramov (2002) and Brennan and Xia (2002).

[7] See Hakansson (1974). Other contributors to the discrete-time power-utility literature include Mossin (1968), Hakansson (1971), Leland (1972), Ross (1974) and Huberman and Ross (1983).

[8] In this paper, matrices and vectors are in bold and scalars in italics. Vectors are column vectors and a prime indicates transposition e.g. **x**' is the row vector corresponding to the column vector **x**.

[9] The solvency constraint (5) is not binding for the power functions, with $\gamma \leq 0$ and discrete probability distributions with a finite number of outcomes, because the marginal utility of zero wealth is infinite. Nonetheless, it is convenient to explicitly consider equation (5) so that the nonlinear programming algorithm used to solve the investment problem does not attempt to evaluate an infeasible policy as it searches for the optimum.

[10] The nonlinear programming algorithm employed is described in Best (1975).

[11] The realized borrowing rate is calculated as a monthly average.

[12] Note that if k = 32 under quarterly revision, then the first quarter for which a portfolio can be selected is b+32, where b is the first quarter for which data is available.

[13] There is no practical way to take maintenance margins into account in our programs. In any case, it is evident from the results that they would come into play only for the more risk-tolerant strategies and for them only occasionally and that the net effect would be relatively neutral.

[14] The λ_t does not contain an adjustment for degrees of freedom in estimating the covariance matrix as in Jorion (1985, 1986, 1991), for example. We chose to model the problem this way to allow for the possibility of combining a Stein estimator with a set of non-equal probabilities for the states of nature used to estimate the joint distribution of security returns.

[15] Having calculated the Bayes-Stein and historic means for asset i, we add the difference $(\bar{r}_{BSit} - \bar{r}_{it})$ where $\bar{r}_{BSit}$ and $\bar{r}_{it}$ are the Bayes-Stein and historic means for asset i at time t, to each actual return on asset i in the estimation period. That is, in each estimation period, we replace the raw return series with the adjusted return series $r^A_{i\tau} = r_{i\tau} + (\bar{r}_{BSit} - \bar{r}_{it})$, for all i and τ. No adjustment is made to the EPAA variance-covariance structure or to the other moments. Thus, the mean vector of the adjusted series is equal to the Bayes-Stein means of the original series; all other moments are unchanged. The same procedure is followed for the CAPM and dividend-yield riskfree-rate estimators discussed below.

[16] Alternatively, the ratio of the excess return on the market to the market's standard deviation or variance might be assumed to be constant. See, for example, Merton (1980) and Best and Grauer (1985). Or, we could estimate the expected return on the market using, say, a dividend-yield riskfree-rate estimator as in equations (10)-(12).

[17] I estimate the CAPM means from equation (8). Black and Litterman estimate them in a slightly different way. They estimate what they call equilibrium (and Best Grauer (1985) call $(\mathbf{\Sigma}, \mathbf{x})$ - compatible) means from $\boldsymbol{\mu} = r_L \boldsymbol{\iota} + \delta \mathbf{\Sigma x}$, where $\mathbf{\Sigma}$ is the covariance matrix of asset returns and $\mathbf{x}$ is a vector of portfolio weights. When these means and $\mathbf{\Sigma}$ are inputs to a MV problem, subject only to a budget constraint, **x** is the optimal solution.

[18] See also Dybvig and Ross (1985), Grauer (1991) and Green (1986).

[19] Annual returns were obtained by compounding the quarterly realized returns.

[20] For consistency with the compound return (geometric mean), the standard deviation is based on the log of one plus the rate of return. This quantity is very similar to the standard deviation of the rate of return for levels less than 25 percent.

[21] In results not reported in the figures or tables, I examined the robustness of the dividend-yield riskfree-rate forecasts employing dividend yields from the 12 industries themselves (i.e., petroleum returns were forecast from petroleum dividend yields) and from the S&P500 index rather than from the CRSP value-weighted index. Somewhat surprisingly, portfolios generated from the industry dividend yields did not perform as well as the original DR portfolios generated from the CRSP dividend yields. But, the portfolios generated from the S&P500 dividend yields performed better than the CRSP DR portfolios.

[22] In their study of mutual funds, Grinblatt and Titman (1993) also found more credible results with the 4-quarter PCM.

References

Andrew Ang and Geert Bekaert. "Stock Return Predictability: Is it There?" Manuscript, Columbia University, July 2003.

Doron Avramov. "Stock Return Predictability and Model Uncertainty." *Journal of Financial Economics*, 64 (2002), 423-458.

Doron Avramov and Tarun Chordia. "Predicting Stock Returns." Manuscript, University of Maryland, current version May 2004.

Pierluigi Balduzzi and Anthony W. Lynch. "Transaction Costs and Predictability: Some Utility Cost Calculations." *Journal of Financial Economics*, 52 (April 1999), 47-78.

Nicholas Barberis. "Investing for the Long Run when Returns are Predictable." *Journal of Finance*, 55 (February 2000) 225-264.

Kenneth R. Beller, John L. Kling and Michael Levinson. "Are Industry Stock Returns Predictable?" *Financial Analysts Journal*, 54 (September/October 1998) 42-57.

Michael J. Best. "A Feasible Conjugate Direction Method to Solve Linearly Constrained Optimization Problems." *Journal of Optimization Theory and Applications*, 16 (July 1975), 25-38.

Michael J. Best and Robert R. Grauer. "Capital Asset Pricing Compatible with Observed Market Value Weights." *Journal of Finance*, 40 (March 1985), 85-103.

Michael J. Best and Robert R. Grauer. "On the Sensitivity of Mean-Variance-Efficient Portfolios to Changes in Asset Means: Some Analytical and Computational Results." *Review of Financial Studies*, 4 (1991), 315-342.

Michael J. Best and Robert R. Grauer. "Positively Weighted Minimum-Variance Portfolios and the Structure of Asset Expected Returns." *Journal of Financial and Quantitative Analysis*, 27 (December 1992), 513-537.

Fischer Black and Robert Litterman. "Global Portfolio Optimization." *Financial Analysts Journal*, 48 (September/October 1992) 28-43.

Peter Bossaerts and Pierre Hillion. "Implementing Statistical Criteria to Select Return Forecasting Models: What Do We Learn?" *Review of Financial Studies*, 12 (Summer 1999), 405-428.

Michael W. Brandt. "Estimating Portfolio and Consumption Choice: A Conditional Euler Equations Approach." *Journal of Finance*, 54 (October 1999), 1609-1645.

Michael J. Brennan, Eduardo S. Schwartz and Ronald Lagnado. "Strategic Asset Allocation." *Journal of Economic Dynamics & Control*, 21 (June 1997), 1377-1403.

Michael J. Brennan and Yihong Xia. "Dynamic Asset Allocation under Inflation." *Journal of Finance*, 57 (June 2002), 1201-1238.

John Campbell and Louis Viceira. "Consumption and Portfolio Decisions When Expected Returns are Time Varying." *Quarterly Journal of Economics*, 114 (May 1999), 433-495.

Gregory Connor. "Sensible Return Forecasting for Portfolio Management." *Financial Analysts Journal*, 53 (September/October 1997) 44-51.

Philip H. Dybvig and Stephen A. Ross. "The Analytics of Performance Measurement Using a Security Market Line." *Journal of Finance*, 40 (June 1985), 401-416.

Eugene F. Fama and Kenneth R. French. "Dividend Yields and Expected Stock Returns." *Journal of Financial Economics*, 22 (1988) 3-25.

Eugene F. Fama and Kenneth R. French. "Business Conditions and Expected Returns on Stocks and Bonds." *Journal of Financial Economics*, 25 (November 1989) 23-49.

Wayne E. Ferson and Rudi W. Schadt. "Measuring Fund Strategy and Performance in Changing Economic Conditions." *Journal of Finance*, 51 (June 1996), 425-462.

Wayne E. Ferson and V.A. Warther. "Evaluating Fund Performance in a Dynamic Market." *Financial Analysts Journal*, 52 (1996), 20-28.

Wayne E. Ferson and Andrew F. Siegel. "The Efficient Use of Conditioning Information in Portfolios." *Journal of Finance* 56, (June 2001), 967-982.

Wayne E. Ferson, Sergei Sarkissian and Timothy Simin. "Spurious Regressions in Financial Economics?" *Journalof Finance*, 58 (August 2003), 1393-1413.

Peter A. Frost and James E Savarino. "For Better Performance: Constrain Portfolio Weights." *Journal of Portfolio Management*, (1988) 29-34.

William N. Goetzmann and Philippe Jorion. "Testing the Predictive Power of Dividend Yields." *Journal of Finance*, 48 (June 1993), 663-680.

Robert R. Grauer. "Further Ambiguity When Performance Is Measured by the Security Market Line." *Financial Review*, 26 (November 1991), 569-585.

Robert R. Grauer. "Benchmarking Performance Measures with Perfect-Foresight and Bankrupt Asset-Allocation Strategies." Manuscript, Simon Fraser University, current version July 2006a.

Robert R. Grauer. "Extreme Mean-Variance Solutions: Estimation Error versus Modeling Error?" Manuscript, Simon Fraser University, current version July 2006b.

Robert R. Grauer and Nils H. Hakansson. "Higher Return, Lower Risk: Historical Returns on Long-Run, Actively Managed Portfolios of Stocks, Bonds and Bills, 1936-1978." *Financial Analysts Journal*, 38 (March-April 1982), 39-53.

Robert R. Grauer and Nils H. Hakansson. "Returns on Levered, Actively Managed Long-Run Portfolios of Stocks, Bonds, and Bills, 1934-1984." *Financial Analysts Journal*, 41 (September-October 1985), 24-43.

Robert R. Grauer and Nils H. Hakansson. "A Half-Century of Returns on Levered and Unlevered Portfolios of Stocks, Bonds, and Bills, with and without Small Stocks." *Journal of Business*, 59 (April 1986), 287-318.

Robert R. Grauer and Nils H. Hakansson. "Gains from International Diversification: 1968-85 Returns on Portfolios of Stocks and Bonds." *Journal of Finance*, 42 (July 1987), 721-739.

Robert R. Grauer and Nils H. Hakansson. "Stein and CAPM Estimators of the Means in Asset Allocation." *International Review of Financial Analysis*, 4 (1995), 35-66.

Robert R. Grauer and Nils H. Hakansson. "Applying Portfolio Change and Conditional Performance Measures: The Case of Industry Rotation via the Dynamic Investment Model." *Review of Quantitative Finance and Accounting*, 17 (November 2001), 237-265.

Robert R. Grauer, Nils H. Hakansson and Frederick C. Shen. "Industry Rotation in the U.S. Stock Market: 1934-1986 Returns on Passive, Semi-passive, and Active Strategies." *Journal of Banking and Finance,* 14 (August 1990), 513-535.

Robert R. Grauer and Frederick C. Shen. "Do Constraints Improve Portfolio Performance?" *Journal of Banking and Finance*, 24 (August 2000), 1253-1274.

Richard C. Green. "Benchmark Portfolio Inefficiency and Deviations from the Security Market Line." *Journal of Finance*, 41 (June 1986), 295-312.

Richard C. Green and Burton Hollifield. "When Will Mean-Variance Efficient Portfolios Be Well-Diversified?", *Journal of Finance,* 47 (December 1992)1785-1810.

Mark Grinblatt and Sheridan Titman. "Performance Measurement Without Benchmarks: An Examination of Mutual Fund Returns." *Journal of Business*, 66 (January 1993) 47-68.

Nils H. Hakansson. "On Optimal Myopic Portfolio Policies, With and Without Serial Correlation of Yields." *Journal of Business*, 44 (July 1971), 324-34.

Nils H. Hakansson. "Convergence to Isoelastic Utility and Policy in Multiperiod Portfolio Choice." *Journal of Financial Economics,* 1 (September 1974), 201-24.

Gabriel Hawawini and Donald B. Keim. "On the Predictability of Common Stock Returns: World Wide Evidence." In R. A. Jarrow, V. Maksimovic and W. T. Ziemba, editors: *Finance*, Handbooks in Operations Research and Management Science, 9 Amsterdam: North Holland, (1995), 497-544.

Roy D. Henriksson and Robert C. Merton. "On Market Timing and Investment Performance II. Statistical Procedures for Evaluating Forecasting Skills." *Journal of Business*, 54 (October 1981), 513-533.

Robert J. Hodrick. "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement." *Review of Financial Studies,* 5 (1992), 357-386.

Gur Huberman and Stephen Ross. "Portfolio Turnpike Theorems, Risk Aversion and Regularly Varying Utility Functions." *Econometrica*, 51 (September 1983), 1104-19.

Michael C. Jensen. "The Performance of Mutual Funds in the Period 1945-1964." *Journal of Finance*, 23 (March 1968), 389-416.

J.D. Jobson, B. Korkie and V. Ratti. "Improved Estimation for Markowitz Portfolios using James-Stein Type Estimators." *Proceedings of the American Statistical Association*, Business and Economics Statistics Section, 41 (1979), 279-284.

J.D. Jobson and B. Korkie. "Estimation for Markowitz Efficient Portfolios." *Journal of the American Statistical Association*, 75 (September 1980), 544-554.

J.D. Jobson and B. Korkie. "Putting Markowitz Theory to Work." *Journal of Portfolio Management*, 7 (Summer 1981), 70-74.

Philippe Jorion. "International Portfolio Diversification with Estimation Risk." *Journal of Business*, 58 (July 1985), 259-278.

Philippe Jorion. "Bayes-Stein Estimation for Portfolio Analysis." *Journal of Financial and Quantitative Analysis* 21, (1986), 279-292.

Philippe Jorion. "Bayesian and CAPM Estimators of the Means: Implications for Portfolio Selection." *Journal of Banking and Finance*, 15 (1991) 717-727.

Robert C. Klemkosky and Rakesh Bharati. "Time-Varying Expected Returns and Asset Allocation." *Journal of Portfolio Management*, 21 (Summer 1995), 80-88.

Gordon Leitch and J. Ernest Tanner. "Economic Forecast Evaluation: Profits versus the Conventional Error Measures." *American Economic Review*, 81 (June 1991), 580-599.

Hayne Leland. "On Turnpike Portfolios." In *Mathematical Methods in Investment and Finance*. Karl Shell, G.P. Szego, eds., Amsterdam, North-Holland, 1972.

John Lintner. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics*, 47 (December 1965), 13-47.

Anthony W. Lynch. "Portfolio Choice and Equity Characteristics: Characterizing the Hedging Demands Induced by Return Predictability." *Journal of Financial Economics*, 62 (October 2001), 67-130.

Anthony W. Lynch and Pierluigi Balduzzi . "Predictability and Transaction Costs: The Impact on Rebalancing Rules and Behavior." *Journal of Finance*, 55 (October 2000), 2285-2309.

Wessel Marquering and Marno Verbeek. "The Economic Value of Predicting Stock Index Returns and Volatility." Manuscript, Erasmus University

Robert C. Merton. "Optimum Consumption and Portfolio Rules in a Continuous Time Model." *Journal of Economic Theory*, 3 (December 1971), 373-413.

Robert C. Merton. "An Intertemporal Capital Asset Pricing Model. *Econometrica*, 41 (September 1973), 867-888.

Robert C. Merton. "On Estimating the Expected Return on the Market: An Exploratory Investigation." *Journal of Financial Economics*, 8 (December 1980), 323-361.

Richard O. Michaud. "The Markowitz Optimization Enigma: Is 'Optimized' Optimal?" *Financial Analysts Journal*, 45 (January-February 1989), 31-42

Jan Mossin. "Optimal Multiperiod Portfolio Policies." *Journal of Business*, 41 (April 1968), 215-229.

Rolando F. Pelaez. "Economically Significant Stock Market Forecasts." *Financial Review*, 33 (1998), 65-76.

Lubos Pastor. "Portfolio Selection and Asset Pricing Models." *Journal of Finance*, 55 (February 2000), 179-223.

Lubos Pastor and Robert F. Stambaugh. "Comparing Asset Pricing Models: An Investment Perspective." *Journal of Financial Economics*, 56 (June 2000), 335-381.

Richard Roll. "Ambiguity When Performance Is Measured by the Securities Market Line." *Journal of Finance*, 33 (September 1978), 1051-1069.

Stephen Ross. "Portfolio Turnpike Theorems for Constant Policies." *Journal of Financial Economics*, 1 (July 1974), 171-98.

G. William Schwert. "Anomalies and Market Efficiency." In George M. Constantinides, Milton Harris and Rene Stultz, editors: *Handbook in the Economics of Finance*, Amsterdam: Elsevier Science B.V. (2003), 939-972.

J. Shanken. "Intertemporal Asset Pricing: an Empirical Investigation." *Journal of Econometrics*, 45 (1990), 99-120.

William F. Sharpe. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance*, 19 (September 1964), 425-442.

Bruno Solnik. "The Performance of International Asset Allocation Strategies Using Conditioning Information." *Journal of Empirical Finance*, 1 (June 1993), 33-55.

C. Stein. "Inadmissibility of the Usual Estimator for the Mean of a Multivariate Normal Distribution." *Proceedings of the 3rd Berkeley Symposium on Probability and Statistics I*, Berkeley: University of California Press, 1955.

Robert F. Stambaugh. "Predictive Regressions." *Journal of Financial Economics*, 54 (December 1999), 375-421.

J.L. Treynor and K. Mazuy. "Can mutual funds outguess the market?" *Harvard Business Review*, 44 (1966), 131-136.

Walter Torous, Rossen Valkanov and Shu Yan. "On Predicting Stock Returns with Nearly Integrated Explanatory Variables." *Journal of Business*, 78 (2005) in press.

H. White. "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity." *Econometrica*, 48 (1980), 817-838.

Table I
Definitions of the Symbols in the Tables and Figures

The investment universe consists of twelve value-weighted industries, borrowing, and lending. In the case of the DRM means, the investment universe consists of the market (VW), borrowing and lending. Quarterly portfolio revision with a 32-quarter estimation period is employed.

	Benchmarks
RL	Riskfree lending at the three month Treasury bill rate
VW	Market (value-weighted CRSP index)
V5	50% in VW, 50% in lending
V15	150% in VW, 50% in borrowing at the call money rate plus 1%
V20	200% in VW, 100% in borrowing at the call money rate plus 1%
	Estimators of the Means
Historic	Historic means
Bayes-Stein	Bayes-Stein means
CAPM	CAPM means
DR	Dividend yield – riskfree rate means
DRH	Dividend yield – riskfree rate means shrunk to historic means
DRCAPM	Dividend yield – riskfree rate means shrunk to CAPM means
DRM	Dividend yield – riskfree rate means for the market portfolio
DRMCAPM	CAPM means with slope from DRM means
DRHAOH	DRH means from an expanding window

Table II

Out-of-Sample R-squares and Mean Squared Forecast Errors for Eight Estimators of Industry Returns

At a point in time, each estimator bases its forecast on data from the previous 32-quarters. R-square values are formed by squaring the correlation coefficient between the forecast and the realized return. Mean squared errors are in units of percent squared per quarter. See Table 1 for definitions of the symbols.

	Historic		Bayes-Stein		CAPM		DR	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
Petroleum	0.004	91.7	0.004	92.4	0.004	92.0	0.004	99.3
Finance & Real Estate	0.014	102.5	0.006	102.3	0.020	102.5	0.004	121.0
Consumer Durables	0.005	124.4	0.002	123.5	0.022	125.2	0.021	131.2
Basic Industries	0.004	84.5	0.002	84.6	0.010	85.1	0.005	92.5
Food & Tobacco	0.002	64.5	0.002	64.8	0.002	65.0	0.008	73.0
Construction	0.004	142.0	0.000	139.4	0.020	142.3	0.017	148.8
Capital Goods	0.005	98.3	0.002	98.1	0.008	98.0	0.008	107.1
Transportation	0.016	142.0	0.002	139.7	0.009	142.0	0.005	162.6
Utilities	0.000	52.4	0.000	53.1	0.006	52.8	0.001	64.4
Textiles & Trade	0.002	112.1	0.000	111.3	0.002	111.1	0.006	125.5
Services	0.000	214.3	0.004	212.7	0.005	211.4	0.008	236.7
Leisure	0.031	178.8	0.004	175.7	0.033	177.9	0.005	200.8
Average R^2	0.007		0.002		0.012		0.008	
Sum MSE		1,407.4		1,397.6		1,405.2		1,562.8

	DRH		DRCAPM		DRMCAPM		DRHAOH	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
Petroleum	0.001	91.8	0.002	91.40	0.001	91.6	0.001	90.40
Finance & Real Estate	0.001	103.8	0.001	103.80	0.001	102.5	0.002	101.70
Consumer Durables	0.014	120.1	0.013	120.10	0.009	120.9	0.003	121.40
Basic Industries	0.002	84.2	0.001	84.10	0.002	84.2	0.000	82.90
Food & Tobacco	0.008	64.9	0.005	65.30	0.002	65.6	0.006	63.70
Construction	0.011	137.8	0.010	137.20	0.013	136.2	0.003	138.60
Capital Goods	0.004	97.5	0.005	96.90	0.002	97.8	0.002	97.20
Transportation	0.002	142.9	0.002	142.00	0.005	138.5	0.001	140.70
Utilities	0.001	54.7	0.000	55.00	0.001	53.2	0.004	54.30
Textiles & Trade	0.004	112.4	0.005	111.50	0.019	107.9	0.001	111.20
Services	0.005	215.0	0.005	212.00	0.007	207.9	0.000	216.20
Leisure	0.001	179.0	0.001	177.40	0.004	174.3	0.000	175.40
Average R^2	0.005		0.004		0.006		0.002	
Sum MSE		1,404.1		1,396.7		1,380.6		1,393.7

Table III

Performance of Selected Benchmark Portfolios

At each point in time, the borrowing portfolio V15 (V20) invests a minimum of 150% (200%) of wealth in VW, or the applicable maximum percentage dictated by the initial margin constraints set by the Federal Reserve. These portfolios borrow at the call money rate plus 1%. See Table 1 for definitions of the symbols.

	1934 - 1999		1966 - 1999		1966 - 1981	
	Compound Return (%)	St Dev ln(1+r)	Compound Return (%)	St Dev ln(1+r)	Compound Return (%)	St Dev ln(1+r)
Panel A: Industry Portfolios						
Petroleum	12.63	17.70	12.08	18.00	11.03	23.54
Finance & Real Estate	12.64	19.60	12.34	18.00	7.90	20.47
Consumer Durables	12.94	22.13	11.67	20.51	4.15	25.38
Basic Industries	12.02	16.82	11.55	14.44	5.82	15.47
Food & Tobacco	12.37	16.67	14.22	17.74	7.64	16.76
Construction	11.94	21.46	13.17	21.32	5.10	23.96
Capital Goods	12.27	19.18	10.38	17.58	6.09	22.42
Transportation	9.61	21.99	8.48	20.12	4.62	22.49
Utilities	11.26	15.31	11.70	13.95	5.78	13.64
Textiles & Trade	12.24	21.97	12.09	23.70	3.80	26.96
Services	13.45	28.36	12.78	22.65	8.92	31.36
Leisure	12.95	26.32	13.04	25.04	8.93	33.61
Panel B: Levered Value-Weighted (VW) Portfolios						
Treasury Bills (RL)	4.12	3.25	6.75	2.47	6.98	2.78
50% VW, 50% Lending (V5)	8.53	8.29	9.83	7.76	7.25	9.27
100% in Market (VW)	12.27	16.49	12.15	15.66	6.62	18.81
150% VW, 50% Borrowing (V15)	14.21	24.68	12.51	23.73	4.45	28.55
200% VW, 100% Borrowing (V20)	15.50	31.35	12.52	31.11	2.48	36.86

Table IV
Unconditional and Conditional Jensen Alphas for Ten Power Portfolios Estimated from Nine Sets of Means

The alphas are in units of percent per quarter. The p-values measure the significance of the coefficients relative to zero and are heteroskedasticity consistent. The alphas and p-values are averages calculated over ten power portfolios. See Table 1 for definitions of the symbols.

	Unconditional				Conditional			
	Alpha	Number Negative	1-tail p-value	Number ≤ 0.05	Alpha	Number Negative	1-tail p-value	Number ≤ 0.05
Panel A: Historic Means								
1934-1999	0.50	0	0.11	3	0.48	1	0.11	8
1966-1999	0.57	1	0.13	5	0.76	0	0.07	7
1966-1981	-0.20	4	0.56	0	0.62	0	0.13	0
Panel B: Bayes-Stein Means								
1934-1999	0.54	0	0.08	4	0.54	1	0.08	9
1966-1999	0.70	0	0.09	6	0.81	0	0.05	9
1966-1981	0.06	1	0.37	0	0.62	0	0.08	3
Panel C: CAPM Means								
1934-1999	0.17	0	0.27	0	0.13	1	0.27	0
1966-1999	0.11	1	0.33	0	0.20	1	0.21	0
1966-1981	0.06	8	0.61	0	0.86	0	0.11	3
Panel D: DR Means								
1934-1999	0.80	0	0.06	4	0.73	0	0.06	6
1966-1999	1.40	0	0.04	8	0.90	0	0.10	1
1966-1981	1.75	0	0.06	4	0.53	0	0.33	0
Panel E: DRH Means								
1934-1999	0.86	0	0.02	10	0.84	0	0.02	9
1966-1999	1.30	0	0.01	10	1.05	0	0.02	10
1966-1981	1.27	0	0.07	4	0.75	0	0.15	1
Panel F: DRCAPM Means								
1934-1999	0.90	0	0.01	9	0.88	0	0.02	9
1966-1999	1.28	0	0.01	10	1.16	0	0.01	9
1966-1981	1.07	0	0.09	3	0.89	0	0.07	2
Panel G: DRMCAPM Means								
1934-1999	0.66	0	0.02	10	0.60	0	0.03	9
1966-1999	1.28	0	0.01	10	0.66	0	0.04	7
1966-1981	1.60	0	0.02	10	-0.08	9	0.63	0
Panel H: DRHAOH Means								
1934-1999	0.15	0	0.12	7	0.10	1	0.15	6
1966-1999	0.21	0	0.12	0	0.18	0	0.17	0
1966-1981	0.07	1	0.40	0	0.02	2	0.48	0
Panel I: DRM Means								
1934-1999	0.53	0	0.02	10	0.46	0	0.02	8
1966-1999	0.87	0	0.00	10	0.52	0	0.02	10
1966-1981	0.87	0	0.02	10	-0.08	8	0.60	0

Table V
Unconditional and Conditional Henriksson-Merton Alphas and Timing Coefficients
for Ten Power Portfolios Estimated from Nine Sets of Means

The alphas are in units of percent per quarter. Gamma is the timing coefficient. The p-values measure the significance of the coefficients relative to zero and are heteroskedasticity consistent. The alphas, gammas, and p-values are averages calculated over ten power portfolios. See Table 1 for definitions of the symbols.

	Unconditional							Conditional						
	Alpha	Number Negative	2-tail p-value	Gamma	Number Negative	1-tail p-value	Number ≤ 0.05	Alpha	Number Negative	2-tail p-value	Gamma	Number Negative	1-tail p-value	Number ≤ 0.05
Panel A: Historic Means														
1934-1999	0.35	1	0.40	0.04	6	0.49	0	0.17	0	0.67	0.09	1	0.30	0
1966-1999	-0.05	8	0.81	0.18	1	0.25	0	-0.19	9	0.64	0.29	1	0.09	8
1966-1981	0.17	6	0.89	-0.10	3	0.54	0	0.21	0	0.85	0.17	1	0.11	6
Panel B: Bayes-Stein Means														
1934-1999	0.51	1	0.24	0.01	8	0.57	0	0.25	0	0.49	0.08	1	0.33	0
1966-1999	0.07	3	0.91	0.19	1	0.27	0	0.01	7	0.88	0.63	0	0.10	7
1966-1981	0.25	1	0.84	-0.06	2	0.47	0	0.26	0	0.64	0.14	1	0.12	3
Panel C: CAPM Means														
1934-1999	0.13	1	0.52	0.01	8	0.54	0	-0.01	2	0.77	0.05	0	0.38	0
1966-1999	-0.16	9	0.73	0.08	1	0.34	0	-0.15	9	0.55	0.15	0	0.17	0
1966-1981	0.13	7	0.57	-0.02	3	0.44	0	0.16	8	0.24	0.27	0	0.02	9
Panel D: DR Means														
1934-1999	-0.32	9	0.65	0.33	0	0.10	2	0.05	6	0.61	0.20	0	0.17	1
1966-1999	-0.04	6	0.46	0.43	0	0.08	5	0.26	6	0.45	0.19	0	0.21	3
1966-1981	0.38	0	0.83	0.38	0	0.21	0	0.09	6	0.88	0.13	0	0.40	0
Panel E: DRH Means														
1934-1999	0.23	1	0.50	0.19	0	0.27	0	0.35	1	0.58	0.14	0	0.21	0
1966-1999	0.32	5	0.65	0.29	0	0.11	4	0.42	5	0.58	0.18	1	0.16	5
1966-1981	0.94	0	0.42	0.09	2	0.44	0	0.29	1	0.73	0.12	0	0.32	0
Panel F: DRCAPM Means														
1934-1999	0.41	1	0.23	0.15	0	0.37	1	0.28	1	0.35	0.18	0	0.17	1
1966-1999	0.33	6	0.63	0.28	0	0.10	4	0.39	6	0.47	0.24	0	0.08	6
1966-1981	0.77	0	0.43	0.08	2	0.44	0	0.26	0	0.82	0.20	0	0.12	1
Panel G: DRMCAPM Means														
1934-1999	-0.88	10	0.43	0.46	0	0.05	4	-0.62	10	0.25	0.37	0	0.04	9
1966-1999	-1.13	10	0.12	0.71	0	0.01	9	-0.45	9	0.25	0.41	0	0.03	9
1966-1981	-0.75	10	0.61	0.66	0	0.10	0	0.23	0	0.70	-0.08	9	0.72	0
Panel H: DRHAOH														
1934-1999	-0.16	8	0.86	0.09	0	0.25	0	0.26	0	0.20	-0.05	6	0.71	0
1966-1999	0.32	0	0.37	-0.03	3	0.56	0	0.29	0	0.36	-0.05	8	0.70	0
1966-1981	0.03	6	0.87	0.01	2	0.41	0	0.05	1	0.90	-0.03	6	0.59	0
Panel I: DRM Means														
1934-1999	-0.49	10	0.47	0.30	0	0.05	4	-0.38	10	0.26	0.25	0	0.02	10
1966-1999	-0.97	10	0.01	0.54	0	0.00	10	-0.60	10	0.02	0.38	0	0.00	10
1966-1981	-0.51	10	0.36	0.38	0	0.04	9	-0.05	10	0.90	-0.02	6	0.56	0

Table VI
Unconditional and Conditional Treynor-Mazuy Alphas and Timing Coefficients for Ten Power Portfolios Estimated from Nine Sets of Means

The alphas are in units of percent per quarter. Gamma is the timing coefficient. The p-values measure the significance of the coefficients relative to zero and are heteroskedasticity consistent. The alphas, gammas, and p-values are averages calculated over ten power portfolios. See Table 1 for definitions of the symbols.

	Unconditional							Conditional						
	Alpha	Number Negative	2-tail p-value	Gamma	Number Negative	1-tail p-value	Number ≤ 0.05	Alpha	Number Negative	2-tail p-value	Gamma	Number Negative	1-tail p-value	Number ≤ 0.05
Panel A: Historic Means														
1934-1999	0.54	1	0.11	-0.0006	9	0.65	0	0.28	1	0.26	0.0029	1	0.28	0
1966-1999	0.18	0	0.73	0.0050	1	0.27	0	0.19	0	0.65	0.0083	0	0.09	7
1966-1981	-0.07	9	0.87	-0.0015	2	0.50	0	0.21	0	0.75	0.0074	0	0.04	9
Panel B: Bayes-Stein Means														
1934-1999	0.66	1	0.06	-0.0016	9	0.73	0	0.35	1	0.17	0.0027	0	0.31	0
1966-1999	0.34	0	0.51	0.0046	1	0.30	0	0.33	0	0.41	0.0069	0	0.12	2
1966-1981	0.09	0	0.92	-0.0004	1	0.39	0	0.32	0	0.51	0.0052	1	0.07	9
Panel C: CAPM Means														
1934-1999	0.32	1	0.20	-0.0020	9	0.71	0	0.05	1	0.61	0.0011	1	0.40	0
1966-1999	-0.04	9	0.76	0.0020	1	0.33	0	-0.05	9	0.62	0.0037	0	0.20	0
1966-1981	0.02	8	0.52	0.0004	2	0.41	0	0.32	6	0.50	0.0097	0	0.00	10
Panel D: DR Means														
1934-1999	0.15	2	0.67	0.0087	0	0.10	1	0.35	4	0.64	0.0054	1	0.17	6
1966-1999	0.75	2	0.54	0.0084	0	0.12	4	0.67	2	0.56	0.0032	3	0.28	1
1966-1981	1.45	0	0.21	0.0036	2	0.42	0	1.16	0	0.27	-0.0113	10	0.93	0
Panel E: DRH Means														
1934-1999	0.60	0	0.20	0.0035	6	0.46	1	0.63	0	0.16	0.0029	1	0.22	0
1966-1999	0.92	0	0.29	0.0048	1	0.19	0	0.88	0	0.29	0.0024	2	0.25	3
1966-1981	1.47	0	0.09	-0.0024	9	0.69	0	1.33	0	0.10	-0.0105	10	0.94	0
Panel F: DRCAPM Means														
1934-1999	0.81	1	0.08	0.0012	8	0.60	1	0.65	0	0.12	0.0032	0	0.21	0
1966-1999	0.84	0	0.29	0.0057	0	0.16	0	0.81	0	0.25	0.0051	0	0.12	6
1966-1981	1.16	0	0.12	-0.0011	9	0.65	0	1.14	0	0.09	-0.0045	10	0.79	0
Panel G: DRMCAPM Means														
1934-1999	-0.17	4	0.32	0.0112	0	0.12	3	-0.13	3	0.63	0.0104	0	0.03	9
1966-1999	-0.11	9	0.59	0.0179	0	0.02	9	-0.19	9	0.49	0.0123	0	0.03	9
1966-1981	0.39	1	0.57	0.0145	0	0.17	0	0.03	3	0.71	-0.0021	8	0.79	0
Panel H: DRHAOH Means														
1934-1999	-0.15	4	0.86	0.0041	0	0.17	0	0.17	0	0.24	-0.0010	5	0.59	0
1966-1999	0.27	0	0.24	-0.0008	6	0.58	0	0.28	0	0.24	-0.0015	10	0.71	0
1966-1981	0.07	1	0.86	0.0001	2	0.48	0	0.05	1	0.89	-0.0005	8	0.57	0
Panel I: DRM Means														
1934-1999	0.04	3	0.24	0.0065	0	0.13	4	0.01	3	0.62	0.0064	0	0.01	10
1966-1999	-0.12	10	0.56	0.0127	0	0.00	10	-0.17	10	0.42	0.0100	0	0.00	10
1966-1981	0.27	0	0.49	0.0072	0	0.09	1	0.07	0	0.74	-0.0027	10	0.80	0

Table VII
Profile of Portfolio Weights

The table shows the percentage of time that the power-utility portfolios either lend 100% of their wealth or combine lending or borrowing with investment in either 1 to 6 industries or 7 to 12 industries. Percentage of times is taken with respect to the 264 quarters in the 1934-1999 period. Percentages may not add to 100% due to rounding. See Table 1 for definitions of the symbols.

	-50	-30	-15	-10	-5	-3	-1	0	0.5	1
					Panel A: Historic Means					
100% Lending	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
in 1 to 6 industries	99.5	99.6	99.3	99.2	99.6	99.6	99.6	99.6	99.6	99.6
in 7 to 12 industries	0.0	0.0	0.4	0.4	0.0	0.0	0.0	0.0	0.0	0.0
					Panel B: Bayes-Stein Means					
100% Lending	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3
in 1 to 6 industries	94.3	94.4	94.3	94.3	93.9	94.3	94.4	94.7	94.8	94.7
in 7 to 12 industries	0.4	0.4	0.4	0.4	0.8	0.4	0.4	0.0	0.0	0.0
					Panel C: CAPM Means					
100% Lending	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3	5.3
in 1 to 6 industries	11.4	11.7	13.6	15.9	27.3	35.7	52.7	73.5	85.6	94.7
in 7 to 12 industries	83.2	82.9	81.0	78.7	67.4	59.2	42.0	21.3	9.1	0.0
					Panel D: DR Means					
100% Lending	10.6	10.6	10.6	10.6	10.6	10.6	10.6	10.6	10.6	10.6
in 1 to 6 industries	89.3	89.4	89.5	89.5	89.3	89.4	89.4	89.5	89.4	89.4
in 7 to 12 industries	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
					Panel E: DRH Means					
100% Lending	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2
in 1 to 6 industries	95.8	95.8	95.9	95.7	95.9	95.8	95.9	95.8	95.9	95.8
in 7 to 12 industries	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
					Panel F: DRCAPM Means					
100% Lending	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8
in 1 to 6 industries	95.9	96.3	96.1	96.2	96.2	96.1	96.2	96.3	96.3	96.3
in 7 to 12 industries	0.4	0	0	0	0	0	0	0	0	0
					Panel G: DRMCAPM Means					
100% Lending	18.9	18.9	18.9	18.9	18.9	18.9	18.9	18.9	18.9	18.9
in 1 to 6 industries	15.2	15.9	16.6	17.0	22.3	29.6	45.5	63.6	72.3	81.1
in 7 to 12 industries	66.0	65.2	64.3	64.0	58.6	51.4	35.7	17.4	8.7	0.0
					Panel H: DRHAOH Means					
100% Lending	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
in 1 to 6 industries	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6
in 7 to 12 industries	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table VIII
Grinblatt-Titman Portfolio Change Measures for Ten Power Portfolios Estimated from Nine Sets of Means

The Grinblatt-Titman portfolio change measure (PCM) is based on one quarter and four quarter lags. PCM is in units of percent per quarter. The p-values measure the significance of the PCM relative to zero. The PCM and p-values are averages calculated over ten power portfolios. See Table 1 for definitions of the symbols.

	One Quarter Lag				Four Quarter Lag			
	PCM	Number Negative	1-tail p-value	Number ≤ 0.05	PCM	Number Negative	1-tail p-value	Number ≤ 0.05
Panel A: Historic Means								
1934-1999	0.27	0	0.06	7	0.82	0	0.01	10
1966-1999	0.39	0	0.06	8	1.00	0	0.01	10
1966-1981	0.32	1	0.11	7	0.72	0	0.08	6
Panel B: Bayes-Stein Means								
1934-1999	0.29	0	0.04	9	0.75	0	0.01	9
1966-1999	0.41	0	0.05	9	1.03	0	0.01	10
1966-1981	0.36	0	0.07	8	0.96	0	0.02	9
Panel C: CAPM Means								
1934-1999	0.09	1	0.19	1	0.05	8	0.58	1
1966-1999	0.19	0	0.10	2	0.21	1	0.27	0
1966-1981	0.18	0	0.16	1	0.26	1	0.40	0
Panel D: DR Means								
1934-1999	0.09	4	0.51	0	1.55	0	0.00	10
1966-1999	0.20	5	0.52	0	2.16	0	0.03	9
1966-1981	-0.11	7	0.64	0	1.18	4	0.34	1
Panel E: DRH Means								
1934-1999	0.12	1	0.40	0	1.27	0	0.00	10
1966-1999	0.16	0	0.38	0	1.80	0	0.01	10
1966-1981	-0.28	10	0.66	0	0.97	0	0.26	0
Panel F: DRCAPM Means								
1934-1999	0.27	0	0.15	1	1.00	0	0.00	10
1966-1999	0.22	0	0.25	0	1.33	0	0.01	10
1966-1981	-0.19	10	0.61	0	0.85	0	0.22	0
Panel G: DRMCAPM Means								
1934-1999	0.22	2	0.35	1	0.96	0	0.01	10
1966-1999	0.29	0	0.26	0	1.44	0	0.01	10
1966-1981	0.16	6	0.49	0	0.92	0	0.27	0
Panel H: DRHAOH Means								
1934-1999	-0.01	3	0.38	0	0.34	0	0.05	9
1966-1999	0.08	0	0.15	0	0.47	0	0.01	10
1966-1981	0.25	0	0.09	0	0.24	0	0.23	0
Panel I: DRM Means								
1934-1999	0.12	0	0.33	0	0.68	0	0.01	10
1966-1999	0.17	0	0.28	0	0.97	0	0.02	10
1966-1981	0.15	0	0.34	0	0.56	0	0.22	0

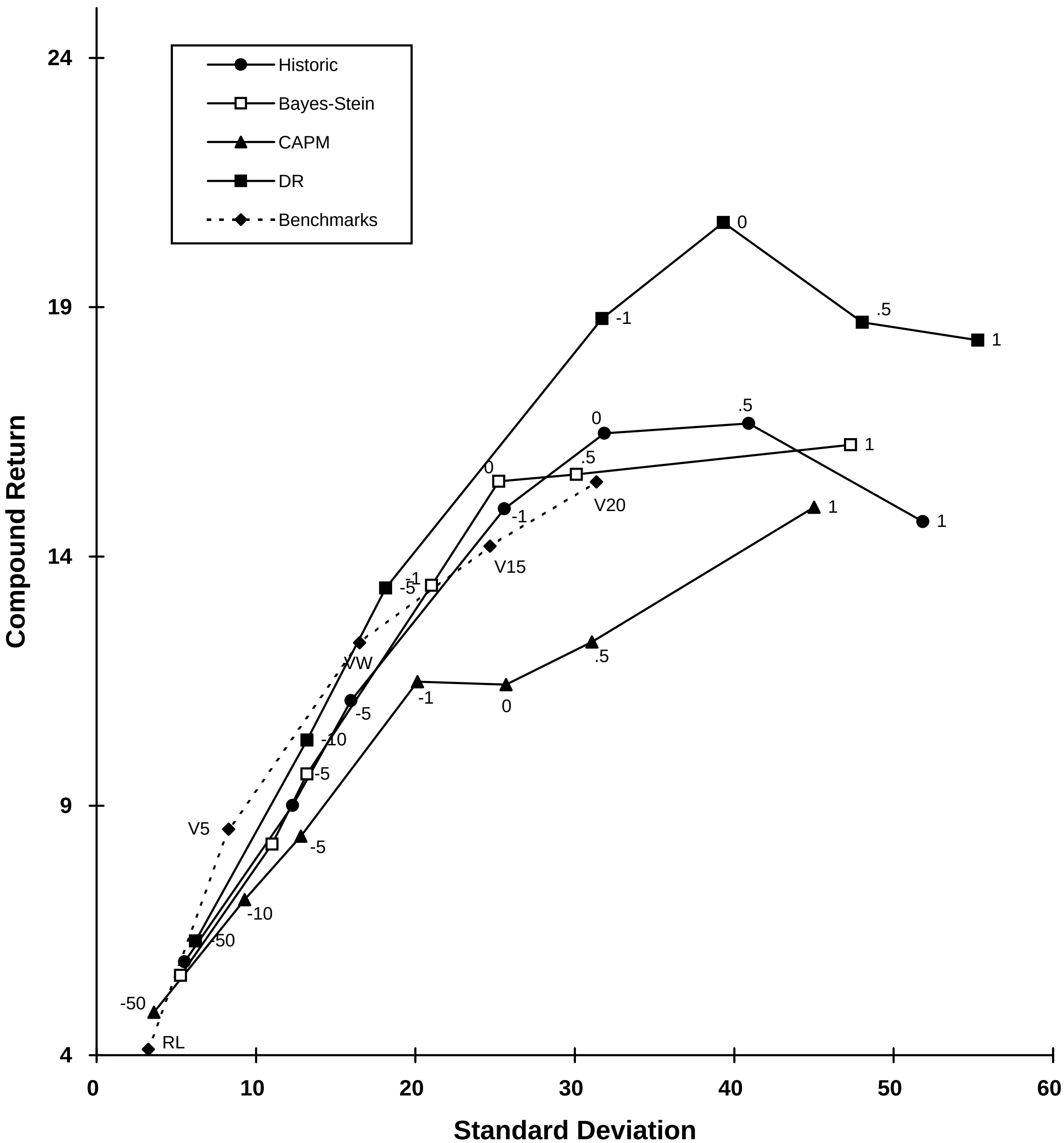

Figure 1. Annual compound return versus the standard deviation (of the log of one plus return) for five benchmarks and four sets of power-utility portfolios constructed from historic, Bayes-Stein, CAPM, and dividend yield – riskfree rate (DR) estimators of the means in the 1934-1999 period.

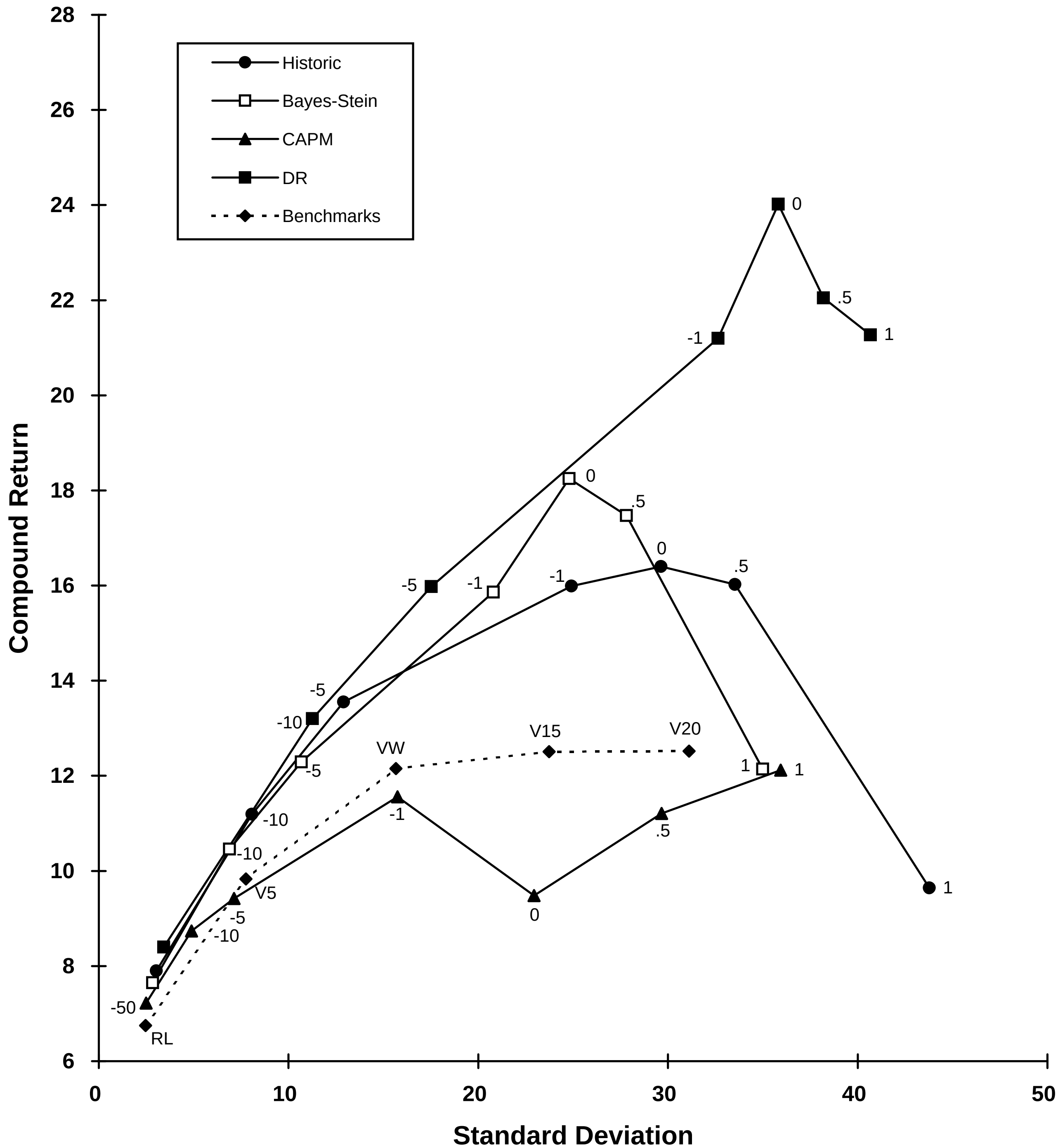

Figure 2. Annual compound return versus the standard deviation (of the log of one plus return) for five benchmarks and four sets of power-utility portfolios constructed from historic, Bayes-Stein, CAPM, and dividend yield – riskfree rate (DR) estimators of the means in the 1966-1999 period.

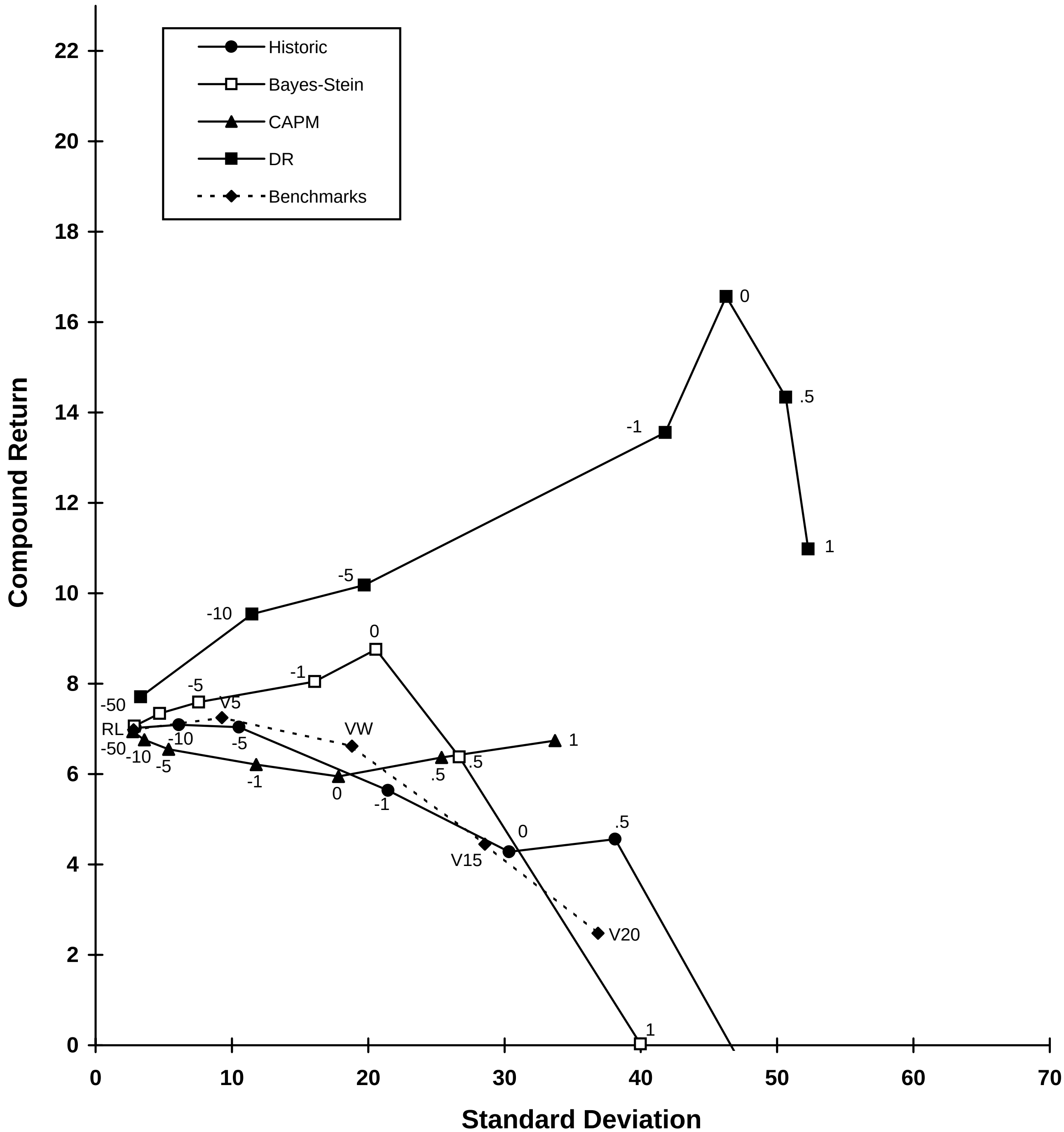

Figure 3. Annual compound return versus the standard deviation (of the log of one plus return) for five benchmarks and four sets of power-utility portfolios constructed from historic, Bayes-Stein, CAPM, and dividend yield – riskfree rate (DR) estimators of the means in the 1966-1981 period.

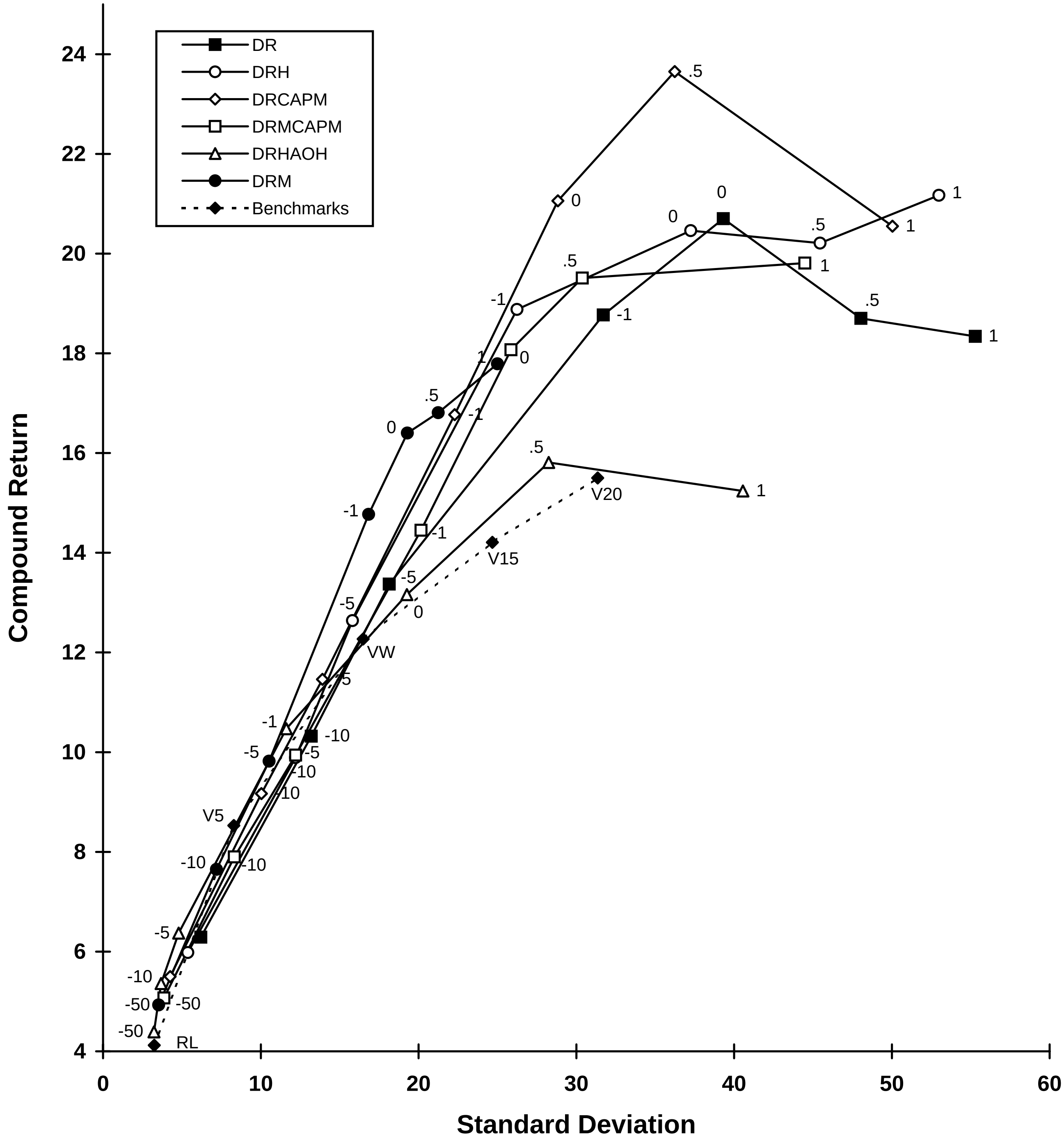

Figure 4. Annual compound return versus the standard deviation (of the log of one plus return) for five benchmarks and six sets of power-utility portfolios constructed from dividend-yield riskfree-rate estimators of the means in the 1934-1999 period. See Table 1 for definitions of the symbols.

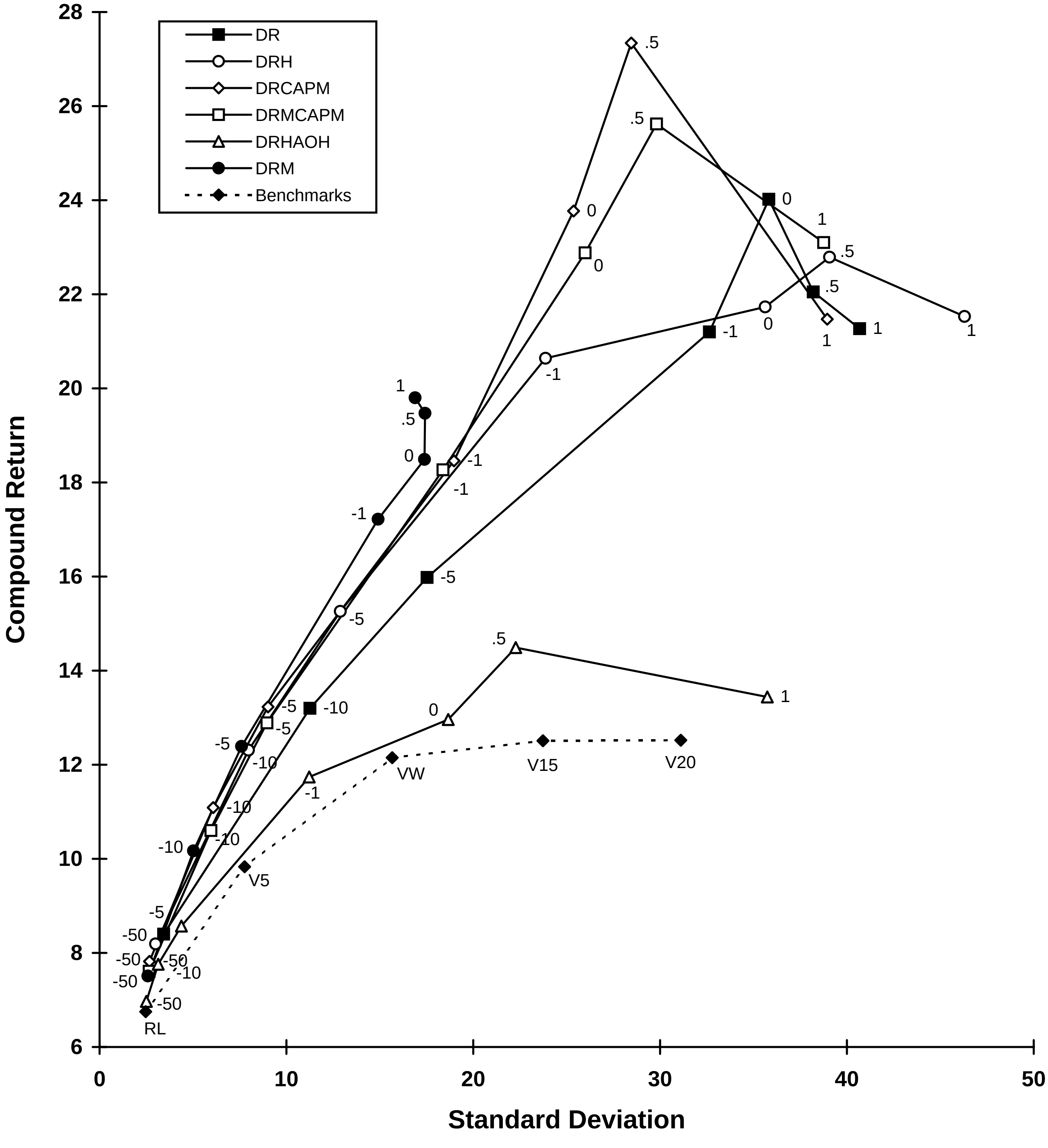

Figure 5. Annual compound return versus the standard deviation (of the log of one plus return) for five benchmarks and six sets of power-utility portfolios constructed from dividend-yield riskfree-rate estimators of the means in the 1966-1999 period. See Table 1 for definitions of the symbols.

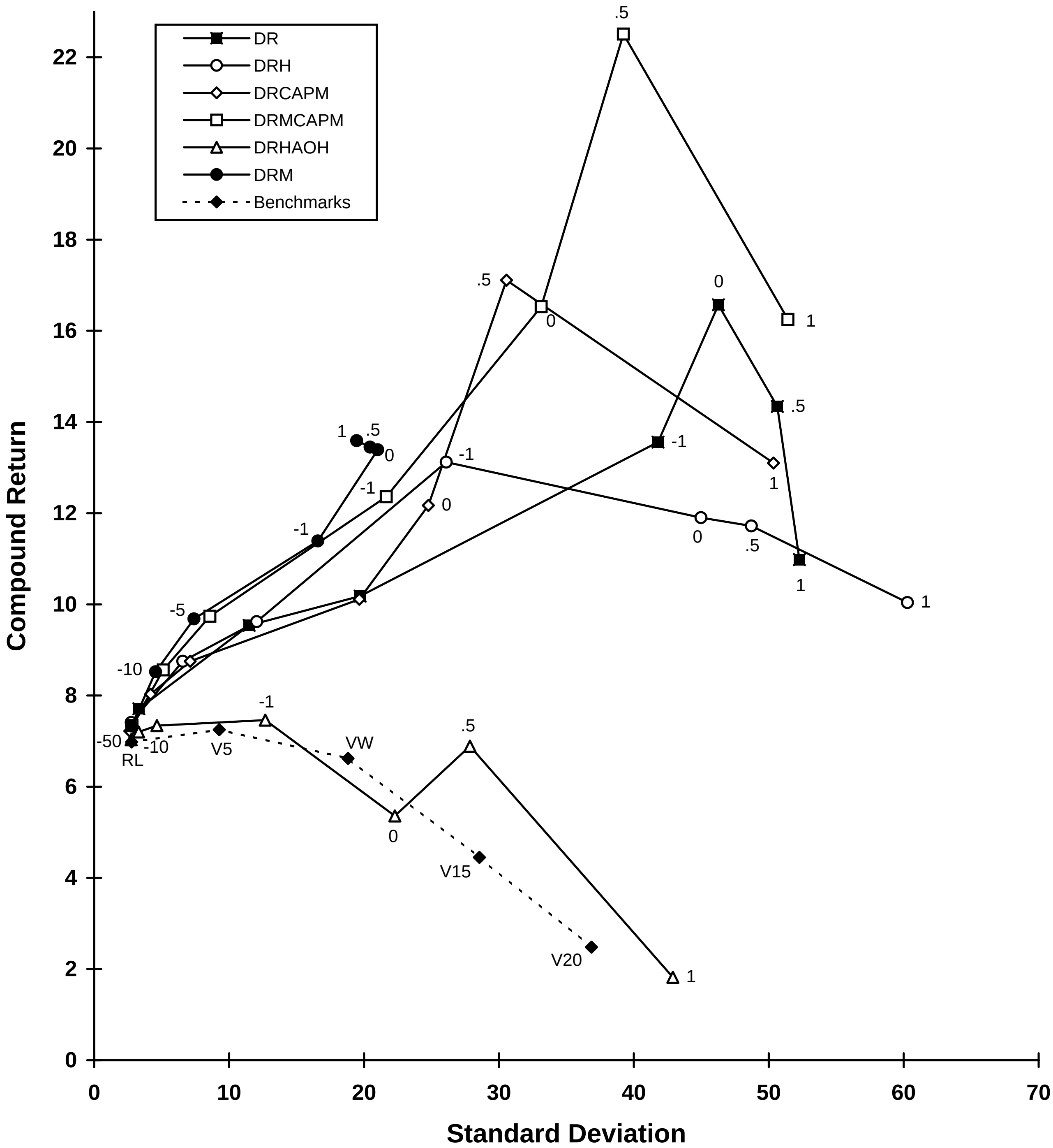

Figure 6. Annual compound return versus the standard deviation (of the log of one plus return) for five benchmarks and six sets of power-utility portfolios constructed from dividend-yield riskfree-rate estimators of the means in the 1966-1981 period. See Table 1 for definitions of the symbols.