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A comparison of some aspects of the U.S. and Japanese equity markets

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Abstract: Comparing Japanese and U.S. securities market, the paper shows that survivor bias affecting quantitative analysis is relatively minor in Japan and substantial in the U.S. The realized average returns vs. standard derivation curve for the two countries is also quite different. But the paper suggests that the constraint levels and estimation procedures that did best in both countries in the past will do well in the future.

Keywords: Equity market; Optimized portfolios

1. Introduction

This paper describes research of the authors developed within the Global Portfolio Research Department (GPRD) of Daiwa Securities Trust Company, a subsidiary of Daiwa Securities, Japan. The principal mission of GPRD is to develop, test and apply methods of equity portfolio selection. In this study we compare certain aspects of the results of U.S. and Japanese equity portfolio analyses. An optimized portfolio using a semi-annual composite model similar to those shown in Table 1 has been used to manage the equity component of a mixed equity fund of Japanese securities, Fund Academy, since January 1991. [1]

The portfolio selection methods tested by GPRD mostly use mean-variance analysis, although some equal weighted portfolio selection procedures have also been tested for comparison purposes. Both the mean-variance analysis and the equal weighting procedures make use of "composite methods" for estimating expected returns. These methods test to see which

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[1] The cumulative wealth ratio of the equity component of Fund Academy was 114.20 as of 30 September 1991 (17 January 1991 = 100) whereas the corresponding wealth ratio of the Topix was 107.01.

variables out of a list of fundamental variables (such as the ratio of earnings to price, book to price, etc.) have been significant predictors of total return 'recently', and then use these variables to estimate expected return for the forthcoming period. Various methods of portfolio selection which GPRD has tested differ from each other in terms of: (a) constraints imposed on choice of portfolio, such as the level of constraints for the holding of individual securities, and constraints on turnover in changing portfolios; (b) the exact way of applying composite analysis, e.g., the definition of 'recently' in the preceding sentence, and the type of statistical inference used (OLS, latent root regression, etc.); and (c) the method of picking a point from the mean-variance frontier.

Backtests start at some date, e.g., January 1, 1975 in the case of Japanese data, select a portfolio by a prescribed method, hold the portfolio for a prescribed length of time (either a quarter or half-year, perhaps with monthly rebalancing in the interim), select a new portfolio by the method, charge the portfolio a cost for purchases and sales, and repeat this process until the end of the database. The backtest keeps track of the actual, 'out of sample', performance of the method. This performance is summarized in terms of the average, standard deviation, Sharpe ratio, semi-variance and other characteristics of the method over the period.

We attempt to make the backtests 'non-anticipating' in the sense that the method has available to it, at any point in the test, only data that was in fact available at that date. However, some runs suffer from survivor bias. That is, the database does not include all securities, then in existence at the point in time, of the class from which the method selects. Rather, it includes only those which survived until the present. This violates the requirement for a non-anticipating test in that the method is assured that all selected securities will survive until the end of the database, a piece of information which is not available in fact.

The reason that our initial backtests on Japanese data used a database without survivors was that this database was most readily available to us. Months later, when a database with non-survivors, therefore without survivor bias, was obtained and installed, we tested the effects of this bias. We also tested the effect of survivor bias for U.S. securities using annual Compustat data for fundamental variables and monthly data for prices. The principal reason for testing the effect of survivor bias in the U.S. was because quarterly Compustat data (for the top 1000 market-capitalized securities) does not contain non-survivors. We used the annual data, with and without non-survivors, to test the direction and magnitude of the survivor bias effect to help us judge how serious would be the error from this source if we used quarterly Compustat data. We were surprised, momentarily, to find that the direction of the effect of survivor bias is different for the U.S. than it is for Japan. On reflection, the difference seemed quite reasonable.

We have backtested many methods of portfolio selection, including some proprietary methods for estimating expected return not described here. Despite the fact that our composite modeling reflected regression techniques previously estimated in Guerard (1987, 1990) and Guerard and Stone (1992), all regression techniques received equal testing. Our policy in practice is based on the best method we found; that is, the method which would have done best historically. There is a question as to how to estimate the likely future performance of this policy. If we had tested only one policy, and are willing to assume that the future will be drawn from the same distribution as the past, then the best estimate of a mean would be the average of past observations. But, even assuming that the future will continue to draw from the same distributions as the past, the past average performance of the historically best policy is not a good estimate of how well it does in the future. This is because the historically best method may have been so in part because it was 'lucky'. A paper by Markowitz and Xu (1991) on 'Data Mining Corrections' presents adjustments for this effect. We will have occasion to use these data mining corrections in the present paper, but refer the reader to the Markowitz and Ku paper for their derivation.

The following two sections describe the GPRD database and its simulation of various investment strategies. The next three sections compare the differences and similarities between the U.S. and Japan with respect to the effects of survivor bias, the tradeoff between risk and return, and the optimal level of turnover permitted when reoptimizing. The next section considers whether or not a method of estimation which does well, or poorly, in one of the countries will do so in the other. A final section summarizes and suggests some broader conclusions.

2. Data

Japanese fundamental data stored in the GPRD database was collected by Nihon Keizi (Nikkei) from 1965; however, non-survivors were available only from 1970. This allowed us to begin our Japanese simulations from the beginning of 1975, since we use five years of prior returns data for the estimation of covariances. Price data was collected by the Daiwa Systems Division and was available for the period needed.

U.S. fundamental data was obtained from Compustat tapes, and price data from CRSP (Center for Research in Security Prices) tapes. Our Japanese database was set up first, and is in better shape than our U.S. data base. Specifically, our U.S. fundamental data base covers the period 1970–1990. [2]

[2] In our initial Daiwa/New York University (1991) presentation, we used 1970–1989 U.S. data. We found few data discrepancies between 1990 and 1991 Compustat databases and little simulation differences (5 basis points on average).

Non-survivors are available from Compustat for annual data only, rather than for quarterly data. Therefore our simulations use only annual U.S. fundamental data. E.g., a quarterly value for earnings to price uses the current price and the preceding annual figure for earnings, assumed known four months after the 'as of' date. A combination of considerations involving the fact that only annual fundamental data was available, the assumed four-month reporting lag and the fact that some models need five years of prior fundamental data to determine 'relatives' (e.g., the current earnings to price ratio relative to its prior five-year average) implied that some U.S. simulations could not start prior to November 1975 (denoted 7510, i.e., end of October 1975).

3. Investment methods and simulations

The underlying composite model describing total security returns is estimated using fundamental variables such as the earnings-to-price (EP), book value-to-price (BP), cash flow to price (CP), and sales-to-price-ratios (SP). We also use the current fundamental ratio relative to its five-year mean (the 'relative' variables). One may summarize the multiple regression model used to identify the determinants of U.S. equity returns in the following cross-sectional equation:

$$\mathrm{TR_T} = a_0 + a_1\mathrm{EP}_t + a_2\mathrm{BP}_t + a_3\mathrm{CP}_t + a_4\mathrm{SP}_t + a_5\mathrm{REP}_t + a_6\mathrm{RBP}_t + a_7\mathrm{RCP}_t + a_8\mathrm{RSP}_t + e_t \quad (1)$$

where: $\mathrm{TR_T}$ = ranked total returns (for six months (t to $t+6$) in semi-annual analysis and three months for quarterly data) following the calculation of fundamental financial variables, EP, BP, CP, SP, REP, RBP, RCP; RSP = previously defined ranked financial variables, a_0, a_1, ... a_8 = regression parameters, e_t = randomly distributed error terms.

The reader is referred to Guerard and Takano (1991) and Miller et al. (1991) for a complete description of the model. The benefits of the underlying model is that it is in keeping with the recent anomalies literature, particularly with the use of EP and BP variables (see Fama and French, 1991; and Jacobs and Levy, 1988). One can use ordinary least squares (OLS), an outlier-adjustment, or robust (ROB) regression procedure proposed by Beaton and Tukey (1974), latent root regression (LRR) for decomposing the correlation matrix into its non-predictive near-singularities (addressing multicollinearity), and using latent root regression on the robust-weighted data (referred to as weighted latent root regression, WLRR. An example of the application of the WLRR technique can be shown when one models total returns for the first quarter of 1990 using fundamental data as of December 1989.

The OLS-estimated equation (1) is:

$$\begin{aligned} \text{TR} = {} & \underset{(18.39)}{499.10} - \underset{(-4.49)}{0.219\text{EP}} - \underset{(-0.61)}{0.025\text{BP}} + \underset{(1.47)}{0.065\text{CP}} + \underset{(5.68)}{0.182\text{SP}} \\ & - \underset{(-0.57)}{0.023\text{REP}} + \underset{(0.55)}{0.026\text{RBP}} + \underset{(2.34)}{0.124\text{RC}} - \underset{(-2.81)}{0.141\text{RSP}}, \end{aligned}$$

(t)

$R^2 = 0.068,\ F = 8.89.$

One finds that only the sales and relative cash flow variables are statistically significant at the 10 percent level in the OLS estimation. The WLRR-estimated equation (1) for the first quarter of 1990 is:

$$\begin{aligned} \text{TR} = {} & \underset{(2.34)}{0.047\text{EP}} - \underset{(-3.83)}{0.066\text{BP}} - \underset{(-6.72)}{0.124\text{CP}} + \underset{(7.92)}{0.244\text{SP}} + \underset{(1.17)}{0.036\text{REP}} \\ & + \underset{(1.78)}{0.056\text{RBP}} + \underset{(0.22)}{0.007\text{RCP}} - \underset{(-2.39)}{0.061\text{RSP}},\ R^2 = 0.061,\ F = 12.17. \end{aligned}$$

(t)

The WLRR estimation produces a different result than the OLS estimation; earnings, sales, and relative bookvalue variables are significantly associated with total returns. The reader is referred to Gunst and Mason (1980), Guerard (1987, 1990), Guerard and Stone (1992) for a more complete discussion of regression techniques.

In our initial Japanese analysis, we estimate quarterly models using semi-annual Japanese data with quarterly prices to create quarterly ratios. The statistically significant and the coefficients having the 'correct' sign were used in the next period model. We find support for the four-quarter smoothed model described in Miller et al. (1991) using the WLRR procedure. The four-quarter smoothed composite models were used as an input to the mean-variance optimization analysis. We believed that our proposed methods of estimating expected returns might not be applicable to financial corporations. Therefore, we excluded these from all analyses performed thus far except for some Japanese analyses, not reported here, wherein we analyze the effect of indexing the financials as part of the portfolio. Specifically, the universe of securities used in the Japanese analyses reported here consist of the first section of the Tokyo Stock Exchange (TSE) less the financial firms, for a total of approximately 1000 firms. The universe for the U.S. analyses consists of the 1000 largest firms on the New York and American Stock Exchanges, again ignoring the financial firms.

Figure 1 summarizes the inputs and outputs of a mean-variance analysis. Inputs consist of estimates of expected returns for each security; estimates of variances and covariances (or the equivalent) and constraints on the choice of portfolio. The output includes the set of efficient mean and variance (or standard deviation) combinations. There is an efficient portfolio associated with any choice of efficient mean-variance combination.

Our experimentation included various combinations of expected return estimation procedure and levels of constraints on turnover and individual

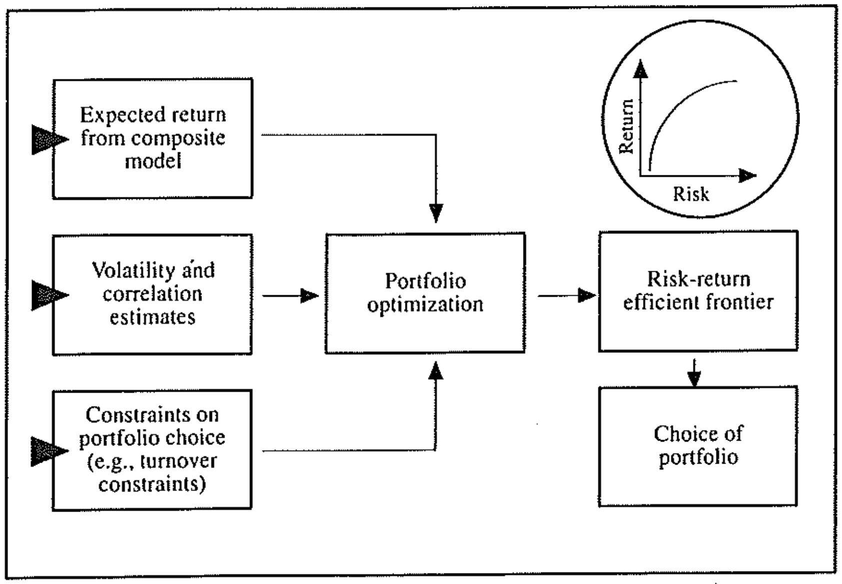

Fig. 1. Investment process.

holdings. Table 1 presents some of the simulations we have run against the Japanese database. Each line summarizes one simulation. The first column presents a simulation ID (SID); the second indicates whether the portfolio was reoptimized (OP) quarterly (3) or semiannually (6). Table 1 is sorted first by OP and then by geometric mean return (GM) in the next to last column.

After the first optimization, the optimizer is told to constrain the level of turnover in subsequent reoptimizations. For example, our first Japanese simulations used semi-annual reoptimization with a 50% turnover constraint.

Estimated future annual geometric mean (after data mining adjustment)

$$= \text{Antilog of } [(\bar{Y} + \beta^{est}(\bar{Y}_b - \bar{Y})] - 1$$
$$= \text{Antilog of } [0.2899 + 0.5944\,(0.2280 - 0.1899)] - 1$$
$$= 23.68\%$$

where:

$\bar{Y}$ = the overall overage of logarithm of one plus return for all models = 0.1899

$\bar{Y}_b$ = the average of logarithm of one plus return for the Best Model = 0.2280

β^{est} = 0.5944

Fig. 2. Data mining adjustment.

We found that a 20% turnover constraint worked best for simulations with semi-annual reoptimizations, and 10% did best with quarterly reoptimizations. The turnover constraints (TOV) of various simulations is shown in the third column of Table 1. The term RP = 1 in the fourth column indicates that

Table 1
D-POS, Japan. Simulation results: sorted by geometric mean. Let UL = 2.0 TCR = 2.0 PM = −1 PPar = 0.90 Begin = 7412 End = 9012.

SID	OP	TOV	RP	Rtri	ERET	GM	Shrp
900869	3	10.00	1	25.0	PROPRIETARY	25.60	0.89
900867	3	10.00	0	0.0	PROPRIETARY	25.39	0.89
900868	3	10.00	1	20.0	PROPRIETARY	25.32	0.87
900860	3	15.00	1	25.0	PROPRIETARY	24.28	0.84
900853	3	15.00	0	0.0	PROPRIETARY	24.19	0.85
900858	3	10.00	1	25.0	PROPRIETARY	24.04	0.85
900852	3	12.50	0	0.0	PROPRIETARY	23.94	0.85
900855	3	10.00	1	20.0	PROPRIETARY	23.93	0.86
900856	3	12.50	1	20.0	PROPRIETARY	23.90	0.84
900854	3	17.50	0	0.0	PROPRIETARY	23.89	0.84
900859	3	12.50	1	25.0	PROPRIETARY	23.89	0.83
900857	3	15.00	1	20.0	PROPRIETARY	23.81	0.82
900819	3	10.00	0	0.0	REGR(WLRR,4Q,4)	22.74	0.83
900820	3	10.00	1	25.0	REGR(WLRR,4Q,4)	22.68	0.82
900944	3	10.00	0	0.0	BPR	22.43	0.78
900908	3	10.00	1	20.0	REGR(LRR,4Q,9.1)	22.23	0.75
900874	3	10.00	0	0.0	REGR(OLS,4Q,8)	22.16	0.79
900878	3	10.00	0	0.0	REGR(OLS,4Q,9.1)	22.16	0.79
900903	3	10.00	0	0.0	REGR(OLS,4Q,8)	22.16	0.79
900914	3	10.00	0	0.0	REGR(OLS,4Q,9.1)	22.16	0.79
900841	3	10.00	1	25.0	REGR(WLRR,1Q,4)	22.00	0.79
900817	3	10.00	0	0.0	REGR(LRR,4Q14)	21.99	0.76
900983	3	10.00	1	20.0	REGR(WLRR,4Q,9.1)	21.93	0.75
900984	3	10.00	1	20.0	REGR(WLRR,4Q,9.1)	21.86	0.75
900794	3	15.00	1	20.0	REGR(WLRR,1Q,4)	21.84	0.76
900818	3	10.00	1	25.0	REGR(LRR,4Q,4)	21.84	0.75
900877	3	10.00	0	0.0	REGR(WLRR,4Q,8)	21.84	0.78
900906	3	10.00	0	0.0	REGR(WLRR,4Q,8)	21.84	0.78
900985	3	12.50	1	20.0	REGR(WLRR,4Q,9.1)	21.84	0.75
900913	3	10.00	0	0.0	REGR(WLRR,4Q,9.2)	21.83	0.77
900793	3	12.50	1	20.0	REGR(WLRR,1Q,4)	21.78	0.78
900791	3	12.50	0	0.0	REGR(WLRR,1Q,4)	21.75	0.79
900792	3	15.00	0	0.0	REGR(WLRR,1Q,4)	21.68	0.77
900982	3	10.00	1	20.0	REGR(WLRR,4Q,9.1)	21.66	0.75
900842	3	10.00	1	25.0	REGR(WLRR,10,4)	21.55	0.79
900766	3	10.00	1	20.0	REGR(WLRR,1Q,4)	21.49	0.78
900810	3	15.00	0	0.0	REGR(WLRR,1Q,4)	21.47	0.76
900901	3	10.00	0	0.0	REGR(LRR,4Q,9.1)	21.45	0.72
900813	3	10.00	0	0.0	REGR(OLS,4Q,4)	21.42	0.78
900840	3	10.00	1	25.0	REGR(WLRR,1Q,4)	21.41	0.76
900838	3	10.00	1	25.0	REGR(WLRR,1Q,4)	21.40	0.76
900909	3	10.00	1	20.0	REGR(WLRR,4Q,9.1)	21.40	0.75
900910	3	10.00	0	0.0	REGR(LRR,4Q,9.2)	21.34	0.75
900816	3	10.00	1	25.0	REGR(ROB,4Q,4)	21.30	0.76
900839	3	10.00	1	25.0	REGR(WLRR,1Q,4)	21.30	0.75

Table 1 (continued)

SID	OP	TOV	RP	Rtri	ERET	GM	Shrp
900912	3	10.00	0	0.0	REGR(LRR,4Q,9.2)	21.29	0.71
900765	3	10.00	0	0.0	REGR(WLRR,1Q,4)	21.24	0.76
900815	3	10.00	0	0.0	REGR(ROB,4Q,4)	21.23	0.76
900902	3	10.00	0	0.0	REGR(WLRR,4Q,9.1)	21.16	0.74
900986	3	15.00	1	20.0	REGR(WLRR,4Q,9.1)	21.09	0.72
900954	3	10.00	0	0.0	REGR(OLS,4Q,4)	20.91	0.72
900876	3	10.00	0	0.0	REGR(LRR,4Q,8)	20.90	0.74
900905	3	10.00	0	0.0	REGR(LRR,4Q,8)	20.90	0.74
900911	3	10.00	0	0.0	REGR(ROB,4Q,9.2)	20.66	0.72
900907	3	10.00	1	20.0	REGR(ROB,4Q,9.1)	20.36	0.74
900763	3	10.00	0	0.0	REGR(LRR,1Q,4)	20.21	0.71
900875	3	10.00	0	0.0	REGR(ROB,4Q,8)	20.15	0.71
900904	3	10.00	0	0.0	REGR(ROB,4Q,8)	20.15	0.71
900787	3	12.50	0	0.0	REGR(LRR,1Q,4)	20.08	0.71
900900	3	10.00	0	0.0	REGR(ROB,4Q,9.1)	20.07	0.72
900781	3	12.50	1	20.0	REGR(OLS,1Q,4)	19.96	0.71
900788	3	15.00	0	0.0	REGR(LRR,1Q,4)	19.92	0.70
900764	3	10.00	1	20.0	REGR(LRR,1Q,4).	19.88	0.70
900790	3	15.00	1	20.0	REGR(LRR,1Q,4)	19.81	0.70
900789	3	12.50	1	20.0	REGR(LRR,1Q,4)	19.78	0.70
900779	3	12.50	0	0.0	REGR(OLS,1Q,4)	19.77	0.67
900786	3	15.00	1	20.0	REGR(ROB,1Q,4)	19.76	0.71
900780	3	15.00	0	0.0	REGR(OLS,1Q,4)	19.72	0.69
900784	3	15.00	0	0.0	REGR(ROB,1Q,4)	19.67	0.71
900782	3	15.00	1	20.0	REGR(OLS,1Q,4)	19.41	0.69
900759	3	10.00	0	0.0	REGR(OLS,1Q,4)	19.40	0.67
900785	3	12.50	1	20.0	REGR(ROB,1Q,4)	19.33	0.69
900760	3	10.00	1	20.0	REGR(OLS,1Q,4)	19.31	0.66
900783	3	12.50	0	0.0	REGR(ROB,1Q,4)	19.10	0.69
900761	3	10.00	0	0.0	REGR(ROB,1Q,4)	19.03	0.68
900931	3	10.00	0	0.0	CPR	19.01	0.68
900762	3	10.00	1	20.0	REGR(ROB,1Q,4)	19.00	0.67
900932	3	10.00	0	0.0	SPR	18.63	0.61
900716	3	10.00	1	20.0	benchmark	17.25	0.60
900927	3	10.00	0	0.0	EPR	16.82	0.57
900826	6	20.00	3	25.0	PROPRIETARY	24.63	0.84
900709	6	20.00	3	20.0	PROPRIETARY	23.61	0.81
900710	6	20.00	3	25.0	PROPRIETARY	23.44	0.82
900733	6	25.00	1	20.0	PROPRIETARY	23.34	0.80
900773	6	17.50	3	20.0	PROPRIETARY	23.26	0.78
900707	6	20.00	3	20.0	PROPRIETARY	23.08	0.79
900847	6	20.00	0	0.0	PROPRIETARY	22.62	0.81
901030	6	20.00	3	20.0	BPR	22.42	0.78
900796	6	20.00	3	20.0	REGR(OLS,2S,4)	22.33	0.79
901047	6	20.00	3	20.0	BPR	22.20	0.77
900770	6	22.50	0	0.0	REGR(OLS,1S,4)	22.17	0.77
900795	6	20.00	0	0.0	REGR(OLS,2S,4)	22.14	0.79
900749	6	20.00	3	25.0	REGR(OLS,1S,4)	22.03	0.78
900800	6	20.00	3	20.0	REGR(LRR,2S,4)	21.98	0.78
900849	6	20.00	0	0.0	REGR(LRR,3S,4)	21.98	0.77

Table 1 (continued)

SID	OP	TOV	RP	Rtri	ERET	GM	Shrp
900748	6	20.00	3	20.0	REGR(OLS,1S,4)	21.80	0.77
900754	6	20.00	3	20.0	REGR(LRR,12,4)	21.68	0.74
900747	6	20.00	0	0.0	REGR(OLS,1S,4)	21.65	0.77
900802	6	20.00	3	20.0	REGR(WLRR,2S,4)	21.60	0.79
901029	6	20.00	0	0.0	BPR	21.59	0.76
900755	6	20.00	3	25.0	REGR(LRR,1S,4)	21.52	0.74
900799	6	20.00	0	0.0	REGR(LRR,2S,4)	21.51	0.77
901046	6	20.00	0	0.0	BPR	21.49	0.76
900801	6	20.00	0	0.0	REGR(WLRR,2S,4)	21.40	0.79
900769	6	17.50	0	0.0	REGR(OLS,1S,4)	21.34	0.76
900778	6	22.50	3	20.0	REGR(WLRR,1S,4)	21.30	0.79
900772	6	22.50	0	0.0	REGR(LRR,1S,4)	21.26	0.72
900753	6	20.00	0	0.0	REGR(LRR,1S,4)	21.20	0.72
900756	6	20.00	0	0.0	REGR(WLRR,1S,4)	21.10	0.77
900757	6	20.00	3	20.0	REGR(WLRR,1S,4)	21.06	0.78
900758	6	20.00	3	25.0	REGR(WLRR,1S,4)	21.02	0.78
900777	6	17.50	3	20.0	REGR(WLRR,1S,4)	20.95	0.78
900771	6	17.50	0	0.0	REGR(LRR,1S,4)	20.93	0.71
900848	6	20.00	0	0.0	REGR(ROB,3S,4)	20.74	0.76
900776	6	22.50	3	20.0	REGR(ROB,1S,4)	20.37	0.76
900797	6	20.00	0	0.0	REGR(ROB,22,4)	20.24	0.75
900798	6	20.00	3	20.0	REGR(ROB,2S,4)	20.12	0.76
900752	6	20.00	3	25.0	REGR(ROB,1S,4)	19.56	0.73
900751	6	20.00	3	20.0	REGR(ROB,1S,4)	19.35	0.73
900750	6	20.00	0	0.0	REGR(ROB,1S,4)	19.29	0.72
900775	6	17.50	3	20.0	REGR(ROB,1S,4)	19.26	0.72
901049	6	20.00	3	20.0	CPR	18.99	0.68
901051	6	20.00	3	20.0	SPR	18.69	0.61
901048	6	20.00	0	0.0	CPR	18.65	0.67
901050	6	20.00	0	0.0	SPR	17.87	0.59
901045	6	20.00	3	20.0	EPR	17.55	0.59
901044	6	20.00	0	0.0	EPR	17.34	0.59

SID = simulation ID; OP = period of re-optimization; TOV = turnover constraint; Rtri = rebalancing trigger; ERET = model description; GM = geometric mean; Shrp = Sharpe ratio.

REGR (technique, period, equation)

Technique = OLS for ordinary least-squares regression analysis,
LRR for latent root regression,
ROB for robust regression,
WLRR for weighted latent root regression;

Period = 1S for one-period semi-annual analysis,
2S for two-period semi-annual analysis,
3S for three-period semi-annual analysis,
1Q for one-period quarterly analysis,
4Q for four-period quarterly analysis;

Equation = 4; $\text{TRR} = a_0 + a_1\text{EPR} + a_2\text{BPR} + a_3\text{CPR} + a_4\text{SPR} + a_5\text{REPR} + a_6\text{RPBR} + a_7\text{RCPR} + a_8\text{RSPR} + e_t$

8; $\text{TRR} = a_0 + a_1\text{EPR} + a_2\text{BPR} + a_3\text{CPR} + a_4\text{SPR} + e_t$

9.1; $\text{TRR} = a_0 + a_1\text{EPR} + a_2\text{BPR} + a_3\text{CPR} + a_4\text{SPR} + a_5\text{REPR}(2) + a_6\text{RPBR}(2) + a_7\text{RCPR}(2) + a_8\text{RSPR}(2) + e_t,$

where (2) denotes 2-year averages of relative variables.

9.2; $\text{TRR} = a_0 + a_1\text{EPR} + a_2\text{BPR} + a_3\text{CPR} + a_4\text{SPR} + a_5\text{REPR}(3) + a_6\text{RPBR}(3) + a_7\text{RCPR}(3) + a_8\text{RSPR}(3) + e_t,$

where (3) denotes 3-year averages of relative variables.

investment policy included monthly rebalancing between optimizations; = 3 indicates quarterly rebalancing between (semi-annual) reoptimizations; = 0 indicates no rebalancing. 'Rtri' indicates the deviation between the actual weight of a security in the portfolio, as compared to target weight, which 'triggers' the rebalancing. For example, Rtri = 0.25 indicates that if the target weight is 1.00 percent and the actual weight is 1.25 percent then some of the security will be sold to bring the weight back to one percent. (The story is slightly more complicated, as a corollary of the fact that the portfolio is kept fully invested.) At first we tried rebalancing with 5 and 10 percent trigger points, but found trigger points in the neighborhood of 25 percent worked more satisfactorily. The last two columns show the actual ('out of sample') geometric mean and Sharpe ratio (Shrp) for each run. The third from last run indicates the expected return estimation technique (ERET). For example, BPR in this column for the nineteenth simulation listed indicates that essentially each security's rank in a book to price listing was used as the estimate of its expected return. The ERET for the 17th run in Table 1 is characterized as 'REGR(WLRR,4Q,4)'. This indicates that expected return is essentially estimated by a regression of actual return ranking against several variables. WLRR indicates that a weighted latent root regression technique is used as compared to, e.g., ordinary least squares, OLS. '4Q' indicates that the coefficients used to estimate expected return are the average of four quarterly cross sectional regressions (setting to zero any coefficients in a cross sectional regression which are not significant at the 10 percent level or have the 'wrong' sign). The final '4' indicates that equation 4 of Table 1 is used in each cross sectional regression. [3] The REGR

[3] We use the 'conventional' approach to fundamental variables; that is, the earnings-to-price formulation, rather than the 'traditionally'-analyzed price-to-earnings formulation. The use of the traditional approach produces almost identical results to the conventional approach (see Table 2). For a description of the traditional approach, the 'lower P/B' or 'low P/E' model, see Guerard (1990).

Table 2
Survivor-biased-free universe, traditional modeling.

Model	GM	Sharpe
WLRR	22.51	0.83
LRR	22.30	0.80
ROB	19.87	0.71
OLS	20.90	0.73
PBR	21.65	0.77

We find no significant difference between the traditional and conventional modeling formulations. Significant excess returns are produced out-of-sample with the quarterly-based models. Furthermore, the use of the traditional modeling approach produces models that can well discriminate with respect to the average model performance, producing Markowitz and Xu, 1991) data-mining beta of 0.76 ($t = 4.25$). Thus, the best model, the REGR(WLRR,4Q), is significantly better than the average of the models.

(WLRR,4Q,4) produces the highest GM of any non-proprietary, or public, Japanese model in our analysis.

The ERET labelled PROPRIETARY, used in SID = 900869, is like REGR(WLRR,4Q,4) except that it includes two proprietary features. The only thing which we say about these two features is that they are not the result of experimentation with dozens of features. They were the results of certain theoretical considerations, and were added to John Guerard's work with composite modeling (1990, 1991). The second line in the heading of the table notes certain parameters which were the same in all the runs of Table 1. The term UL = 2.0 indicates that in all runs in this table a two percent upper limit on the holding of any one security was imposed at each optimization; TCR = 2.0 indicates that the simulation charged a two percent each way transaction cost, including estimated market impact. A pick parameter (PPar) of 1.00 would indicate that the portfolio with maximum expected return was picked from the frontier at each optimization; a zero PPar would indicate that the minimum variance portfolio was chosen each time. The indicated PPar = 0.90 means that the selected portfolio was ninety percent of the way (on the expected return axis) from the minimum variance to the maximum expected return portfolio. UNID = 150 indicates that this is the latest, unbiased Japanese database. The 'start' and 'end' parameters indicate that all these runs began at the end of 7412 and ended at the end of 9012. Also, all runs reported here used historical covariances for the preceding 60 months.

Figures 3 and 4 illustrate the value added by the REGR(WLRR,4Q,4) and proprietary model methods of expected return estimation, and by the mean-variance process. [4] Each point in the figure shows the average return and standard deviation realized ('out of sample') by an investment policy in a 7412 through 9012 Japanese simulation. (The y-axis is actually twelve times the average monthly return. This common method of 'annualizing' average monthly returns gives a lower figure than the more accurate method: annualized = $\exp(12*(\text{monthly mean}-1/2*\text{monthly variance}))$. The x-axis is the square root of 12 times monthly standard deviation. Much smoother curves are observed using these essentially monthly numbers than when the means

[4] The equally-weighted portfolio created in Figure 3 may appear somewhat strange in that there is little spread between the portfolio returns using PPar = 0.20 and PPar = 1.00. The use of a PPar of 0.20 implies that you would purchase a security if its composite score was in the highest 20 percent and sell it when it fell below the 20th percentile. One can easily imagine a security could be purchased one quarter with a composite percentile ranking of 20 and sold the next quarter with a composite percentile ranking of 21. Few managers would implement such a strategy. If one purchased securities in the upper quintile and sold when their respective composite scores fell into the lowest quintile, rebalancing every quarter to produce equally-weighted portfolios, the portfolio average annual return for REGR(WLRR,4Q,4) is 27.17 percent for the 1974–1990 period and the corresponding Sharpe ratio is 0.81. The turnover for the revised quintile strategy is 38 percent as opposed to 167 percent for the PPar strategy shown in Figure 3.

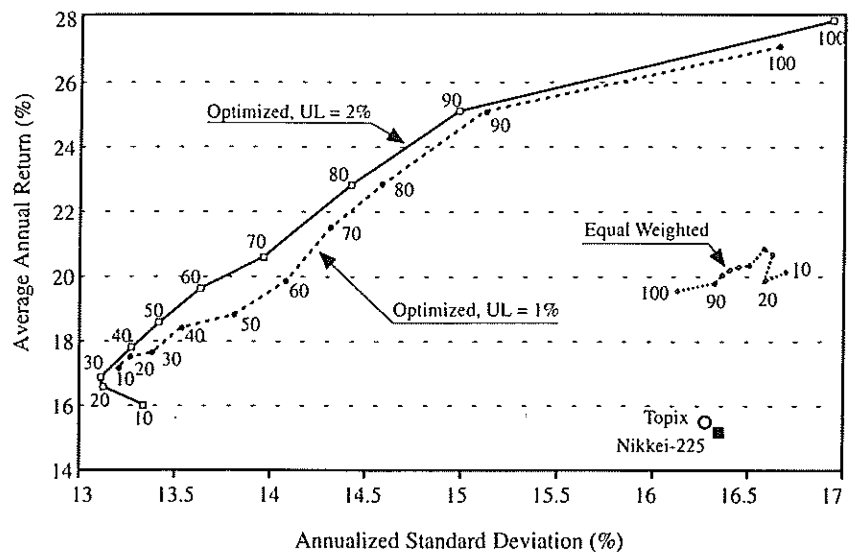

Fig. 3. Observed risk-return tradeoff, Japan. REGR(WLRR,4Q,4), TCR = 2%.

and standard deviations of (the relatively few) annual returns are plotted.) Points on the upper curve show the monthly means and standards deviation, 'annualized', for policies like that of simulation SID = 900869, except for

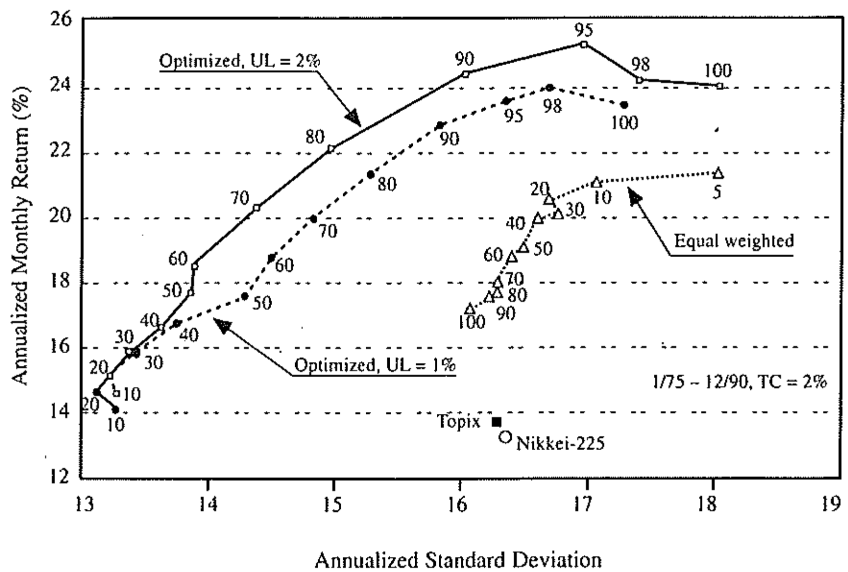

Fig. 4. Observed risk-return tradeoff. TSE Section 1, standard composite model.

choice of portfolio from the efficient frontier. The point labelled 90 represents PPar = 0.90, i.e., SID = 900869 on the first line of Table 1. We see that, by and large, the curve of actual average returns and standard deviations looks roughly like an ex ante mean-variance frontier. One difference is that the realized average return which resulted when anticipated expected return was maximized was less than the realized average return for some portfolios with lower anticipated expected return. Presumably this is due to 'sampling error' which we would expect to be greater for portfolios at the high variance end of the efficient frontier.

The second curve, labelled UL = 1%, is like the first except that an upper limit of one percent on the holdings of any one security is imposed by the optimizer in tracing out the efficient frontier. The third curve shows realized average and standard deviations of return for equal weighted portfolios. Securities are ranked according to their expected returns. For the point labelled '10', the top 10 percent are equal weighted in the portfolio; twenty percent for the point labelled '20'; etc. There is no turnover constraint associated with this method, which is one reason why the average returns for the optimized curves are much higher, for a given level of standard deviation, than those for the equal weighted portfolios. The realized average and standard deviation of returns for the Topix and the Nikkei-225, with dividends, without transaction costs, are also shown.

In Figures 5 and 6 we show the observed risk–return relationship for the REGR(WLRR,4Q,4) model in the U.S. using two and one percent transac-

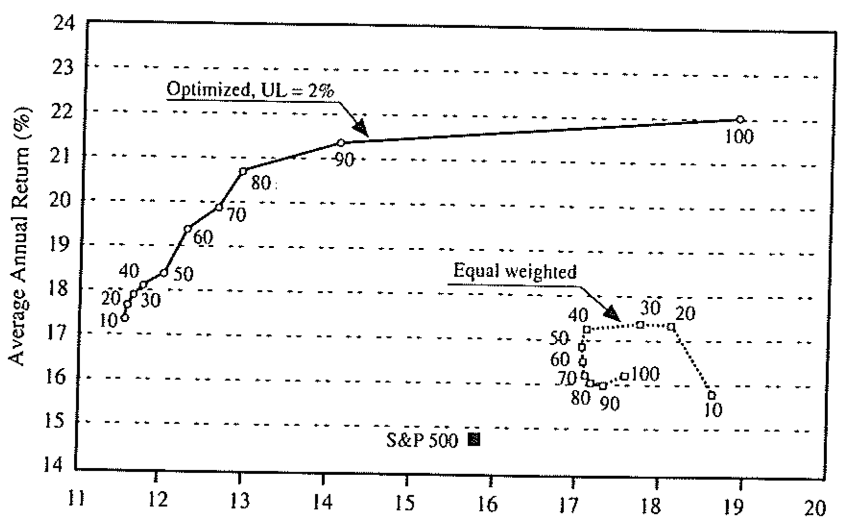

Fig. 5. Observed risk-return tradeoff, U.S. Model REGR(WLRR,4Q,4). TCR 2%.

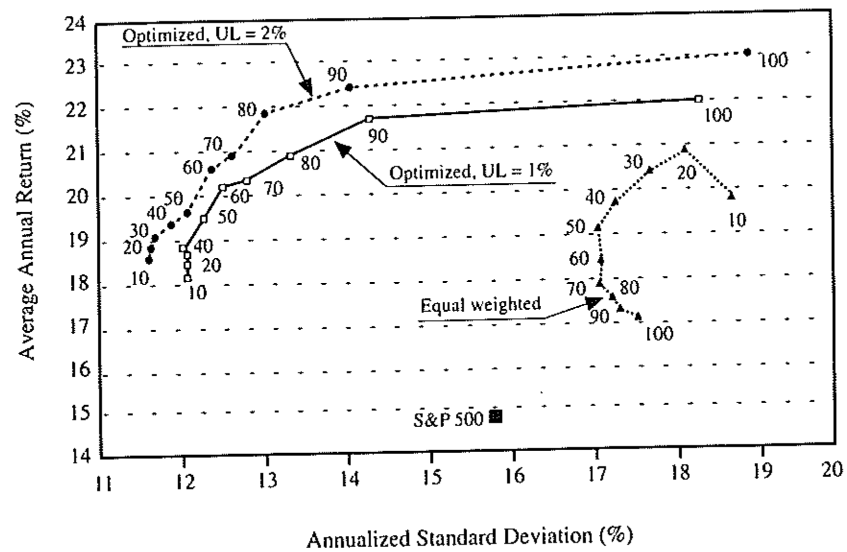

Fig. 6. Observed risk-return tradeoff, U.S. Model REGR(WLRR,4Q,4). TCR 1%.

tions costs assumptions. The REGR(WLRR,4Q,4) estimation technique produces the highest GM in the U.S. The two percent transactions cost figure is included for comparison purposes with Japan and the one percent assumption is probably more realistic. [5] The U.S. REGR(WLRR,4Q,4) with one percent transactions costs looks quite similar to the Japanese curve. Realized average returns are higher and realized standard deviations are higher in Japan than in the United States. It is very interesting to note the higher Sharpe ratios in the United States than in the Japan. We show the respective GMs and Sharpe ratios in Table 3.

4. Effects of survivor bias

For reasons noted in the introduction, we analyzed the effect of survivor bias in Japan and the U.S. The differences between the effect in the U.S. and that in Japan is illustrated in Table 4 and some following figures and table. The results in Table 4 are from the simulations in Table 1, and similar ones for the U.S., with OP = 3, TOV = 10.00, RP = Rtri = 0 and for 16 methods

[5] If one pursued the equally-weighted strategy described in footnote 4 in the United States (purchasing of the upper quintile selling of the securities once they fall into the lower quintile and quarterly rebalancing to produce equally-weighted portfolios), one finds that the equally-weighted portfolios produce average annual returns of 19.92 and 20.90 percent for the two and one percent transactions costs, respectively. The corresponding Sharpe ratios are 0.63 and 0.68, respectively, for the October 1975–December 1990 period.

Table 3
Simulation results: D-POS JP, US. Let End = 9012 TOV = 10 TCR = 2 UL = 2 NOBS = 60. UNID = 131 survivor-biased-free universe, US, Strt = 7510 UNID = 150 survivor-biased-free universe, JP, Strt = 7509.

SID	ERET	UNID	PM	PPar	GM	Shrp
901370	REGR(WLRR,4Q,4)	150	−1.0	1.00	24.55	0.81
901371	REGR(WLRR,4Q,4)	150	−1.0	0.90	22.60	0.78
901372	REGR(WLRR,4Q,4)	150	−1.0	0.80	20.75	0.71
901373	REGR(WLRR,4Q,4)	150	−1.0	0.70	19.21	0.66
901374	REGR(WLRR,4Q,4)	150	−1.0	0.60	18.12	0.62
901375	REGR(WLRR,4Q,4)	150	−1.0	0.50	16.72	0.58
901376	REGR(WLRR,4Q,4)	150	−1.0	0.40	15.89	0.55
901377	REGR(WLRR,4Q,4)	150	−1.0	0.30	15.18	0.53
901378	REGR(WLRR,4Q,4)	150	−1.0	0.20	14.92	0.51
901379	REGR(WLRR,4Q,4)	150	−1.0	0.10	14.24	0.48
50701	REGR(WLRR,4Q,4)	131	−1.0	1.00	20.61	0.89
50702	REGR(WLRR,4Q,4)	131	−1.0	0.90	20.52	1.07
50703	REGR(WLRR,4Q,4)	131	−1.0	0.80	20.03	1.11
50704	REGR(WLRR,4Q,4)	131	−1.0	0.70	19.23	1.09
50705	REGR(WLRR,4Q,4)	131	−1.0	0.60	18.80	1.09
50706	REGR(WLRR,4Q,4)	131	−1.0	0.50	17.86	1.02
50707	REGR(WLRR,4Q,4)	131	−1.0	0.40	17.60	0.98
50708	REGR(WLRR,4Q,4)	131	−1.0	0.30	17.35	0.97
50709	REGR(WLRR,4Q,4)	131	−1.0	0.20	17.11	0.95
50710	REGR(WLRR,4Q,4)	131	−1.0	0.10	16.82	0.92

SID = simulation identification number; ERET = expected return method; UL = upper limit; TCR = transactions costs percentage; TOV = turnover constraint; GM = geometric mean; Shrp = sharpe ratio.

Table 4
Differences of returns between unbiased and biased.

Models	U.S. (75.10–90.12)	Japan (75.10–90.12)
EPR	0.81	−0.47
BPR	0.33	−0.18
CPR	−0.18	−0.08
SPR	−0.21	−0.73
(OLS,4Q)	1.05	−0.29
(ROB,4Q)	0.36	0.14
(LRR,4Q)	0.60	−0.49
(WLRR,4Q)	0.72	−0.38
(OLS,2S)	1.22	0.03
(ROB,2S)	0.92	0.27
(LRR,2S)	0.86	−0.35
(WLRR,2S)	0.96	−0.23
(OLS,3S)	1.08	−0.31
(ROB,3S)	0.42	0.04
(LRR,3S)	0.00	0.33
(WLRR,3S)	0.90	−0.05
Benchmark	1.04	−0.84

U.S. average difference: 0.64; Japan average difference: −0.20; probability (that they are equal): 0.00.

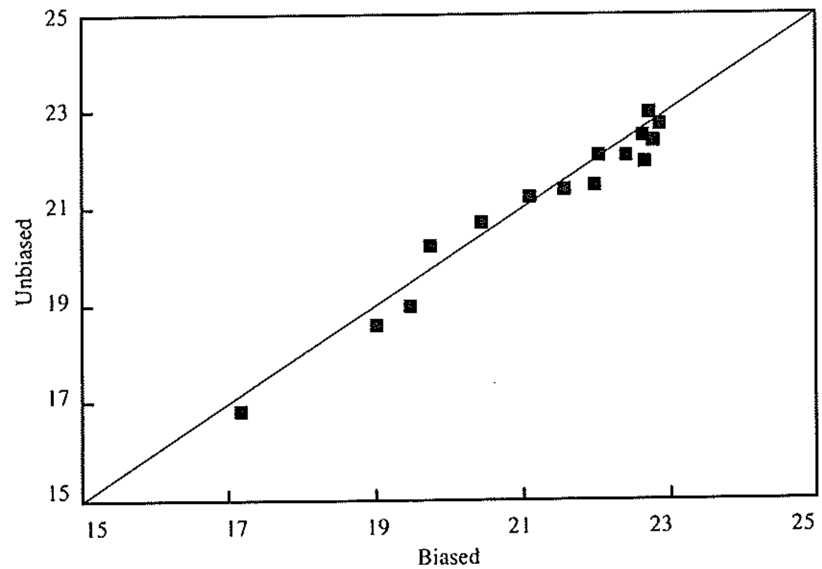

Fig. 7. Japanese survivor bias – geometric means (7412–9012).

of estimating expected return. The methods are indicated in the first column of the table. BPR, EPR, CPR and SPR are as defined in Table 1c. The others are estimation procedures denoted as REGR(x, y, z) in Table 1, with $z = 4$ and with x and y as indicated.

On the average the unbiased (including survivors) geometric means in the U.S. exceeded those of the biased (excluding survivors) GMs by 64 basis points. For the same period, the Japanese unbiased GMs were less than the biased ones by 20 basis points. The probability that the U.S and Japanese observations came from the same (normal) population is less than 0.0001. Since the U.S. unbiased average exceeds the biased average, a greater dollar's worth of non-survivors disappeared for 'profitable reasons', e.g., because of mergers and acquisitions. Since the Japanese unbiased average is less than the biased average, a greater yen's worth of non-survivors disappeared for 'unprofitable reasons', e.g., bankruptcies. It seems plausible that the difference is due to greater merger and acquisition activity in the U.S.

Figures 7 through 10, and Table 4, address the following question: if an investment policy does well (or poorly) when evaluated in terms of a biased database will it also do well (poorly) when evaluated in terms of the unbiased database. Figure 7 plots GM for the unbiased Japanese simulation, for each of the sixteen estimation techniques, against the GM for the Japanese simulation with the biased database, for the period 7412–9012. We see that in the Japanese case, at least for the 16 methods considered, if a policy did

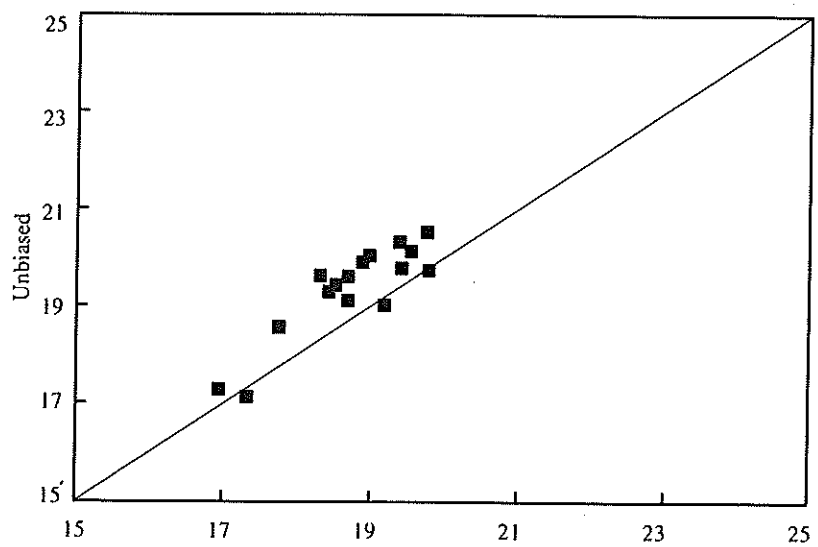

Fig. 8. U.S. survivor bias – geometric means (7510–9012).

well in a database without survivors it would do about as well with a database with survivors. The unbiased GM exceed the 45° line in the U.S., shown in Figure 8, although the correlation coefficient between the biased and unbiased GM in the U.S. is 0.885.

Figures 9 and 10, again with Japanese and U.S. biased and unbiased results, show the rankings of the 16 methods. '1' is assigned to the policy with lowest geometric mean and '16' to the policy with highest GM. We see from Figure 9, for example, that the estimation methods with the first through sixth worst GMs with the biased universe also had the first through sixth worst GMs, respectively, in the unbiased universe. In general, rank in the biased universe is highly correlated with rank in the unbiased universe. Figure 10 shows somewhat less correlation between rankings with and without survivors in the U.S. but, again, the correlation appears to be positive and substantial. [6]

5. Optimal turnover constraints and rebalancing trigger analysis

In the Japanese analysis we found that performance could be substantially improved by tightly constraining turnover when reoptimizing. Is the same

[6] There is little correlation differences between the Japanese biased and unbiased GMs when one examines the 7412–9012 period or a 7510–9012 period that would correspond to the U.S. analysis. Thus, we do not report the 'matched' figures.

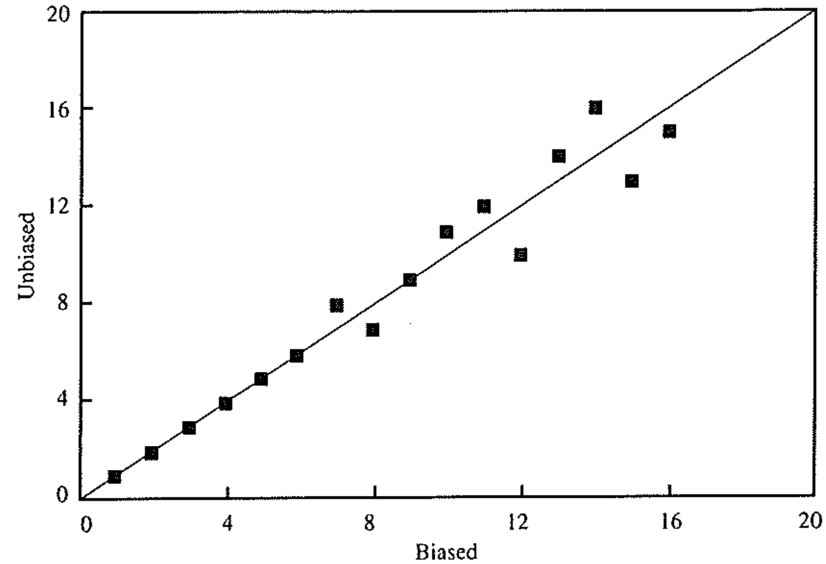

Fig. 9. Japanese survivor bias – GM ranking (7412–9012).

true in the U.S.? Is the same level of turnover constraint optimal in the U.S. as was optimal in Japan? The simulation runs reported in Table 5 indicate that, rather surprisingly to us, perhaps the answer to both questions is 'yes'. Not only does the turnover constraint make a difference in both countries,

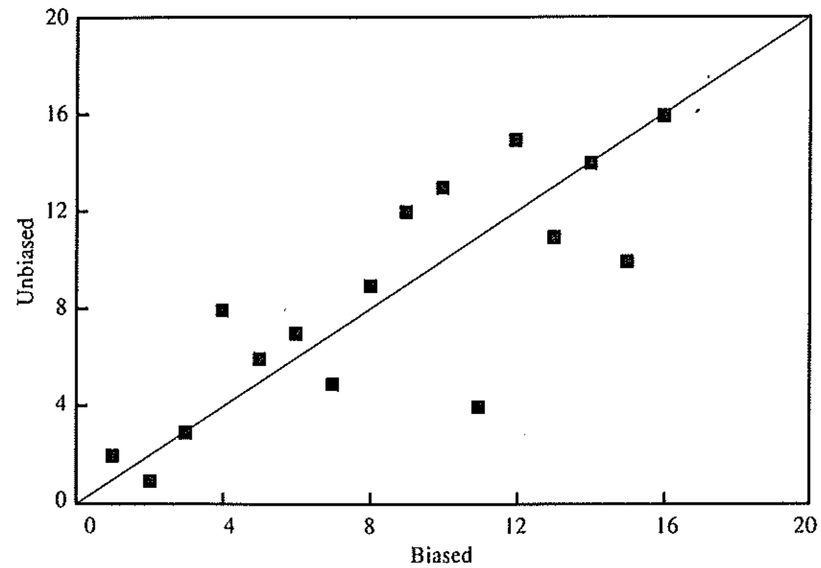

Fig. 10. U.S. survivor bias – GM ranking (7510–9012).

Table 5
Simulation results: D-POS US. Let Strt = 7510 TCR = 2 UL = 2 End = 9012.
UNID = 131 survivor-biased-free universe, US.

SID	ERET	TOV	Rtri	Nobs	GM	Shrp
50539	REGR(WLRR,4Q,4)	10.0	0.0	60	20.52	1.07
50607	REGR(WLRR,4Q,4)	25.0	0.0	60	18.54	0.89
50608	REGR(WLRR,4Q,4)	20.0	0.0	60	18.99	0.96
50609	REGR(WLRR,4Q,4)	15.0	0.0	60	19.61	1.01
50610	REGR(WLRR,4Q,4)	5.0	0.0	60	20.33	1.03
50611	REGR(WLRR,4Q,4)	10.0	15.0	60	20.31	1.04
50612	REGR(WLRR,4Q,4)	10.0	20.0	60	20.52	1.05
50613	REGR(WLRR,4Q,4)	10.0	30.0	60	20.52	1.06
50614	REGR(WLRR,4Q,4)	10.0	10.0	60	20.16	1.04
50615	REGR(WLRR,4Q,4)	10.0	25.0	60	20.63	1.07
50616	REGR(WLRR,4Q,4)	10.0	0.0	48	19.93	1.05
50617	REGR(WLRR,4Q,4)	10.0	0.0	36	20.04	1.06
50618	REGR(WLRR,4Q,4)	10.0	0.0	24	19.87	1.00
50721	Benchmark	10.0	0.0	60	15.13	0.63

but the optimal level of constraint seems about the same in each, which we had not expected. We find that a 10 percent quarterly turnover constraint and 25 percent rebalancing trigger maximizes the GM in the U.S.

6. Estimation methods

Figure 11 and Table 6 consider the following question: do methods of expected return estimation which perform well (poorly) in one country

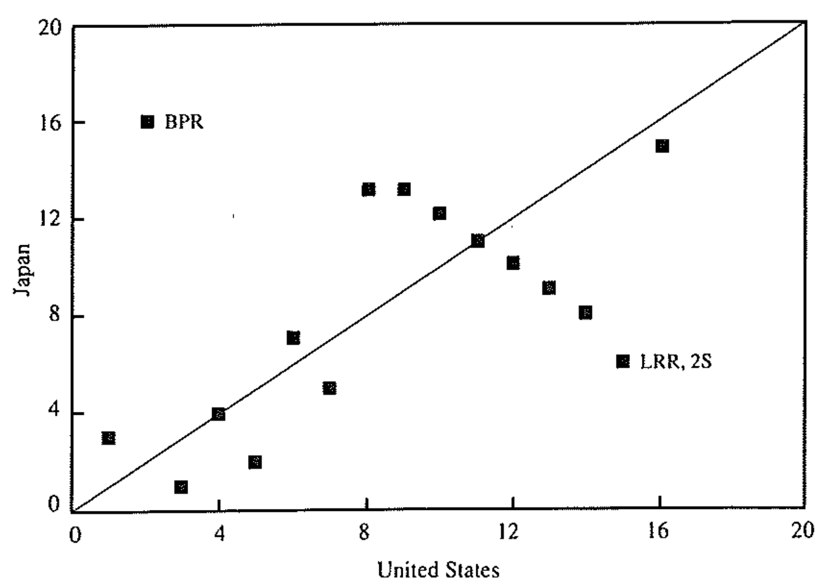

Fig. 11. U.S. vs. Japanese ER methods – unbiased GM rankings (7510–9012).

Table 6
Simulation results: D-POS JP, US. Let End = 9012 UL = 2 NOBS = 60. UNID = 131 survivor-biased-free universe, US. UNID = 150 survivor-biased-free universe, Japan.

SID	ERET	ERID	UNID	OP	TCR	TOV	GM	Shrp
50532	EPR	8260	131	3	2	10.0	18.59	0.97
50533	BPR	8270	131	3	2	10.0	17.31	0.82
50534	CPR	8280	131	3	2	10.0	19.03	1.00
50535	SPR	8290	131	3	2	10.0	17.15	0.73
50536	REGR(OLS,4Q,4)	8330	131	3	2	10.0	20.00	0.97
50537	REGR(ROB,4Q,4)	8310	131	3	2	10.0	19.81	1.03
50538	REGR(LRR,4Q,4)	8320	131	3	2	10.0	20.14	1.00
50539	REGR(WLRR,4Q,4)	8330	131	3	2	10.0	20.52	1.07
50540	benchmark	8330	131	3	2	10.0	15.13	0.63
50569	REGR(OLS,2S,4)	8380	131	6	2	20.0	19.57	0.90
50570	REGR(ROB,2S,4)	8390	131	6	2	20.0	19.45	0.98
50571	REGR(LRR,2S,4)	8400	131	6	2	20.0	20.28	0.98
50572	REGR(WLRR,2S,4)	8410	131	6	2	20.0	19.43	0.92
50573	REGR(OLS,3S,4)	8340	131	6	2	20.0	19.99	0.92
50574	REGR(ROB,3S,4)	8350	131	6	2	20.0	19.13	0.90
50575	REGR(LRR,3S,4)	8360	131	6	2	20.0	19.80	0.92
50576	REGR(WLRR,3S,4)	8370	131	6	2	20.0	19.62	0.93
901333	REGR(OLS,2S,4)	6130	150	6	2	20.0	21.15	0.73
901334	REGR(ROB,2S,4)	6140	150	6	2	20.0	19.55	0.70
901335	REGR(LRR,2S,4)	6150	150	6	2	20.0	19.77	0.66
901336	REGR(WLRR,2S,4)	6160	150	6	2	20.0	20.49	0.73
901337	REGR(OLS,3S,4)	6210	150	6	2	20.0	20.99	0.72
901338	REGR(LRR,3S,4)	6230	150	6	2	20.0	21.05	0.72
901339	REGR(ROB,3S,4)	6220	150	6	2	20.0	18.98	0.66
901340	REGR(WLRR,3S,4)	6240	150	6	2	20.0	21.15	0.73
901342	REGR(OLS,4Q,4)	6170	150	3	2	10.0	20.90	0.72
901343	REGR(ROB,4Q,4)	6180	150	3	2	10.0	21.03	0.73
901344	REGR(LRR,4Q,4)	6190	150	3	2	10.0	20.84	0.69
901345	REGR(WLRR,4Q,4)	6200	150	3	2	10.0	22.52	0.82
901346	EPR	6380	150	3	2	10.0	16.72	0.56
901347	BPR	6390	150	3	2	10.0	22.68	0.78
901348	CPR	6400	150	3	2	10.0	19.19	0.66
901349	SPR	6410	150	3	2	10.0	19.07	0.61
901341	Benchmark	6200	150	3	2	10.0	17.19	0.59

SID = simulation identification number; ERET = expected return method; TCR = transactions costs percentage; TOV = turnover constraint; GM = geometric mean; Shrp = Sharpe ratio.

perform similarly in the other? The results for this figure and table are for the same unbiased 16 cases reported in Table 4. The x-axis of Figure 11 presents the GM ranking of the method in the U.S.; the y-axis presents that in Japan. The correlation coefficient between unbiased ranked Japnese and U.S. policies is 0.396, statistically significant at the 13 percent level. In particular, the REGR(WLRR,4Q,4) is best in the U.S. and second in Japan. If you ignore two points which we have labelled, the relationship is quite close. We have no explanations for the two outliers. The point labelled BPR is especially puzzling. It reports that the Japanese simulation which estimated expected return using only book to price rankings did quite well; but the same estimation procedure did much less well in our U.S. simulation. One reason this is puzzling is that Fama and French (1992) report that BPR does well in the U.S. There is no necessary contradiction in the two results since the methodologies are different. We hope to develop a more satisfactory explanation by seeing which aspect of the differing methodology explains the differing results.

7. The possible problem of data-mining

When one attempts to identify the 'best' model building technique and strategy, one should be concerned with whether the return in excess of the benchmark could be the result of data-mining, a term normally associated with recommending the best-performing historical model without regard to the possibility that the relative performance might be continued into the future. Markowitz and Xu (1991) recently addressed the data-mining issue and present proposed data mining corrections based on three alternative models of how observations are generated. In particular, the model assumes that y_{it}, the logarithm of one plus the return for portfolio selection model i at year t, can be written as:

$$Y_{it} = \mu_i + z_t + \epsilon_{it}. \tag{2}$$

Let us assume that portfolio selection model i with expected return r_{it} equalling μ_i, is random. [7] The best linear estimate of μ_i, an unknown, given the observed r_i, is:

$$\mu_i^{\text{est}} = \bar{y} + \beta^{\text{est}}(\overline{y_i} - \bar{y}),$$

where:

$$\beta^{\text{est}} = \frac{\text{Var}(\mu)}{\text{Var}(\mu) + \text{Var}(\epsilon)/T} \tag{3}$$

and $\bar{y}$ = overall average of all portfolio selection methods.

If simulation SID = 900869 had been the only one we tried, then the historical average return would be an unbiased estimate of future expected return, assuming that the future is drawn from the same population as the past. Similarly, actual log(1 + GM) would be an unbiased estimate of its future value. This is not true in the present case, since we simulated many policies and SID = 900869 was selected as the one with maximum GM. A 'data mining correction', as discussed in Markowitz and Xu and illustrated in Figure 2, is required. According to this calculation, in the present case we should 'believe' only 59 percent of the observed difference between the best

[7] Markowitz and Xu (1991) assume $E\epsilon_{it} = 0$, and $\text{cov}(\epsilon_{is}, \epsilon_{jt}) = 0$, $\forall i = j$, $s = t$.

and the average simulated policy. Specifically, we estimate GM = 23.68 rather than 25.60 for SID = 900869, again assuming that the future is drawn from the same population as the past. Simulation results quoted below are without data mining corrections. [8]

8. The effects of shorter backtest periods

In this study, we use a 1975–1990 backtest period in Japan. If one used a subset of this period, 1985–1990 for example, one finds that the 16 basis models plus the universe benchmark, one finds that the Markowitz and Xu data-mining beta is 0.30 ($t = 1.43$) and is not statistically significant. The use of the four univariate models, the REGR(X, 4Q, 4) models, and the universe benchmark provides a data-mining beta of 0,55, which is statistically significant. Thus, the quarterly models are significantly different whereas the semi-annual models add little unique value. The benefit of the shorter period is that one can integrate earnings forecasts into the composite model. The use of the Tokyo Keizai operating income forecasts, available for the 1985–92 period, creates a Japanese trade-off curve that dominates the historical data curve (Guerard et al., 1992). Thus, one may not be as confident in modelling a subset of the period, as with the entire period, that the highest GM is not due to 'luck'. [9]

9. Summary and conjectures

The Japanese equity market has been like the U.S. market in some ways; in some ways it has been different. With respect to the quantitative analysis questions considered here we have seen, for example, that the effects of survivor bias was relatively minor in Japan and substantial in the U.S., and that the realized average return versus standard deviation curve for the period covered in Figure 11 is quite different for the two countries. On the other hand, a tight constraint on turnover produced the highest GM in both countries and, for the most part, the expected return estimation procedures which worked best in one country did best in the other. The REGR(WLRR,4Q,4) estimation procedure produced the highest GM in both

[8] The Markowitz and Xu (1991) data-mining betas were 0.476 ($t = 1.91$) for the 16 models plus the universe benchmark in Japan and 0.567($t = 2.31$) in the U.S. Thus, the 16 basis models are statistically different from the respective averages.

[9] In February 1992, GPRD re-estimated the basis sixteen backtest models (January 1975–December 1991) and found that the REGR(WLRR,4Q,4) again prevailed in the complete backtest period, producing a geometric mean of 22.72 percent (Sharpe ratio of 0.75) in an equally-weighted portfolio strategy and an optimized portfolio GM of 21.27 percent (Sharpe ratio of 0.74). The proprietary model produced an optimized portfolio GM of 24.42 percent (and a Sharpe ratio of 0.83). Thus, despite the problems of the Japanese economy in 1991, the valuation models did well in backtest and real-time (relative) performance.

countries for the complete estimation periods. In particular, the estimation procedures used in the Japanese simulation SID = 900869 outperformed all estimation procedures listed in Table 2 for the U.S. market, as it did for the Japanese.

Any attempt to extrapolate from the past is subject to the unavoidable caveat that the future may be different. This is true for intuitive investment methods as well as for quantitative ones. Despite this sobering thought, we will hazard conjectures on some subjects, and avoid them on others. We have no idea whether realized tradeoff curves will be higher or lower in the future, or whether the tradeoff curve in Japan will look like that in the U.S. But it seems like a favorable bet, if not a certain one, that the constraint levels and estimation procedures that did best in both countries in the past will do fairly well in the future.

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