Contrarian Investment, Extrapolation and Risk
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Background

Value and Glamour

Value stocks are generally identified with high ratios of book value to market value (**b/m**), earnings and cash flow to price (**e/p and c/p**), dividends to price (**d/p**, yield), and by low (recent past) rates of growth in sales (**gs**) and earnings. Anticipated growth rates are thought to be relatively low as well. Securities characterized as value stocks generally exhibit less volatility than the market as a whole.

Glamour (or growth stocks) are characterized by complementary features (high growth rates and low ratios of accounting variables to market value). High future rates of growth are considered to be embedded in current market valuations. Securities characterized as glamour stocks generally exhibit greater than average market volatility.

Using these, or similar, distinctions, various researchers (LSV cite, among others, Basu, 1977, DeBondt and Thaler, 1985, 1987, and Fama and French, 1992, 1993) have observed that post-categorization returns to value stocks are significantly greater than those to glamour stocks. When market risk is measured by solely volatility, these results are considered to be anomalous: higher returns without commensurate risk.

That this pattern is in the data is not in dispute. At issue are two connected questions: (1) what may have caused the results found in the data, and (2) should we anticipate similar results in the future.

Three views of the observed patterns enter into the argument to explain their genesis:

- Irrational - naïve strategies tend to extrapolate trends in sales growth, earnings growth and recent stock market performance into the future to a degree not justified by historical data. As early as 1962, I. M. D. Little, in an article entitled "*Higgledy Piggledy Growth*" observed that those British companies that exhibited relatively high earnings growth in one five year period did not have a particularly better chance to do so in the following five year period. In 1966, Little returned to the question in an article "*Higgledy Piggledy Growth Again*" with co-author A. C. Rayner. This time they controlled for industry differences and found again that earnings growth leaders within an industry from 1952 to 1956 did not have a better chance than other industry participants to be leaders in growth from 1957 to 1961. In 1967, Lintner and Glauber presented "*Higgledy Piggledy Growth in America*" which echoed the British observations using U.S. stocks.

  In spite of evidence that growth is mean reverting, naïve investors continue to value highly those companies with above average recent trends. LSV posit that institutional money managers (potentially less naïve than individuals) are drawn into the glamour sector as well. This may be an example of agency error wherein the manager buys "good companies" because he will not be blamed for buying such a company even if the future unfolds unfavorably. Buying a value stock that subsequently performs poorly is more open to criticism. It is also suggested that glamour stocks may successfully ride a short term projection -- winners win (Jegadeesh and Titman,1993) before a later reversal (DeBondt and Thaler, 1985, Rouwenhorst, 1996). Investors horizons may be too short to buy and hold value stocks.

- Risk not captured by volatility - Fama and French (1993) observe results similar to others but argue for a rational explanation of investor behavior. In their view, value stocks carry with them risks that are not captured by traditional volatility measures. This argument is clearly opposed by Lakonishok, Shleifer and Vishny (LSV).

  Any researchers who discount the Fama and French explanation must be extremely diligent in their avoidance of survivorship and look ahead bias. If the risks borne by value stocks are realized in delistings, takeunders and bankruptcy, then these failing value stocks must not be allowed to fall out of the data base (thus the necessity of including the appropriate Compustat Research data files in my replication). Nor can successful value stocks be allowed to “drop into” the data. This latter point is addressed by LSV in their discussion of the wholesale 1978 Compustat drop in. They argue that this affected smaller and NASDAQ listed securities to a much greater degree than it did on large NYSE/AMEX listed companies. They add some support to their view by reproducing their Table II results using the upper 50% of the stock population. These results are shown in their Table III (which I have not replicated).

- Data snooping - In the physical sciences experiments are endlessly repeatable (whether or not affordable). In financial research there is only one realized path available in any market and time period. Some out of sample experiments may be performed by looking to multiple markets (e.g., “*Higgledy Piggledy Growth in America*”, “*International Momentum Strategies*“) and to multiple time periods (all the graduate students replicating and updating earlier works). Lo and MacKinlay, 1990, observe that this one path limitation, combined with an inclination of researchers to look for what they expect to find, opens the door to the dangers of data snooping. With only one realized path, it must be the case that either glamour outperformed value or value outperformed glamour or they are indistinguishable. If the ex-post data had not revealed the superiority of value investments, researchers might well be looking at some other ex-post phenomena instead.

The three views have clear differences. Nonetheless the implications for future stock market performance are not so clearly separable and testable:

- Suppose, with twenty years more data, that value stocks have continued to outperform glamour stocks. The irrationalists may say: “still crazy after all these years”, the risk-based argument: could be “still risky after all these years.” The data snoopers will lose some ground under this scenario but twenty years may be too short a time to refute their arguments entirely.

- Alternatively, with twenty years more data, value stock may have underperformed. While this would bolster the data snooper argument, it may not distinguish the other two. The irrationalists might claim that the naïve investors have been educated. The risk-based argument might be carried forward with new risk proxies and/or with the observation that the risks associated with high b/m companies have been mitigated by accounting changes or other environmental differences.

Methodology

LSV describe the economic methodology and I will repeat some of what they have said. Because much of my attention was on the computer systems aspects of the methodology, I provide more detail in this area.

Appendix A contains a flow chart showing the flow of data from Compustat, and CRSP through the system I developed. The incoming files include ina.bin and ina5877 (industrial annual data from Compustat) containing accounting data from 1958 through 1996 for those companies surviving to the last data date, res.bin and res5978.bin (research data from Compustat) containing the corresponding data (from 1959) for those companies that have disappeared (merger, bankruptcy, other delisting causes) from the ina data base over time, msf.bin (monthly stock data from CRSP from 1926 through 1996).

Researchers who argue (as LSV do) against the Fama and French risk-based view of the value story must be particularly careful not to omit those companies that have left the data base through failure. Similarly they must guard against the selection of companies who have succeeded their way into the data base (leaving less successful companies behind). Fama and French argue that value stocks incorporate a risk that volatility measures (e.g., beta) do not capture. At any date, the list of value stocks is likely to include “fallen angels” (formerly successful companies) with high book/market ratios, low (or negative) sales growth, etc. For these companies the risk of business failure (bankruptcy, other reorganization, takeunder) is high. If these stocks were to be omitted from the study, the Fama and French “distress” argument would not be fully represented. This necessitates the inclusion of the “res” data sets. Similarly biased results may derive from a success-favoring entry process. The large influx of companies into the Compustat data base in 1978 poses this potential threat. LSV argue that such bias potential is mitigated:

- Most of the entering companies were NASDAQ listed and this study uses NYSE/AMEX stocks only.
- Many of the results of this study require five years past data. I note that about as many of the results, however, do not require more than one previous fiscal year.
- Table III repeats the results of table II using those companies in the largest half (market capitalization) of the data base. My concerns about these two-dimensional tables are noted below.

Much of my work is done by two programs msfmerge.f and msfcount.f (Appendix E contains all my code). Msfmerge merges Compustat and CRSP data. It qualifies companies for inclusion (primarily by excluding companies never listed on the NYSE or AMEX, companies with no accounting data between 1961 and 1996, or shares other than ordinary common). Msfmerge then prepares the ratios necessary to differentiate value-to-glamour deciles in one and two dimensions at any portfolio formation date (4/30/j). In general, I try to include companies that can contribute to the study even when their data is incomplete or occasionally discontinuous. Thus, for example, when some months of return data are omitted, I substitute size decile returns. This procedure is also used in the months following delisting as described by LSV. Further, I include a company in one categorical (e.g. b/m) decile portfolio in any year it which it has appropriate categorizing data regardless of whether I have sufficient data to assign it to another categorical (e.g., e/p) decile portfolio. For each included company and for each year I compute:

- size (market capitalization) = price 4/30/j * number of shares at latest date < 5/1/j.
- b/m = book value (end of fiscal year < 1/1/j) / size.
- e/p = income (fiscal year ending < 1/1/j) / size.
- c/p = cash flow (income plus amortization and depreciation fiscal year ending < 1/1/j) / size.
- d/p = dividends with ex-date in (j-1) / size.
- s/p = sales (fiscal year ending < 1/1/j) / size.
- gs = sales (fiscal year ending < 1/1/j) / sales (fiscal year ending < 1/1/j-1) - 1.
- an_ret = annual return computed as:

$$\{\prod_{5/31/j}^{4/30/j+1}(1+monthly\_return_t)\}(1+delist\_return_t)-1$$

Where monthly_return is replaced by size decile return if missing (or after delisting); no company had more than one delisting; delisting return <> 0 iff (4/30/j)<delisting date<(5/31/j+1).

- pet = annual return computed as compound of monthly size decile returns.

- for each of b/m, e/p, c/p, d/p, s/p, gs, the number of companies with existing data; this data is presented as a table in Appendix C.

The output format for this information organizes each company's data (one record per company) into:

- Indicative information (e.g., cusip)
- Ratios (6 x 36) representing types of ratios and years 1961 through 1996;
- Retsiz (3 x 36) for years 1961 through 1996, an_ret, pet and size;
- Ranks (6 x 36) initially set to zero (filled in by msfcount program).

The idea is that each company may be represented as a bundle of ratios, returns, size and ranks. The development of the ranks matrix, within the data for each security, allows all portfolio statistics to be computed in one pass of the company data without ever forming files for the 2400 portfolios followed in this study. The output file containing this information is msfmerge.out.

The msfcount program is executed repeatedly with alternating sorts of the msfmerge.out data set (which is also designated msfmerge.oop as necessary). For example, I sort the data based on the first ratio (b/m) for the year 1980. Since msfmerge.f has counted the number of companies with meaningful 1980 b/m ratios (say, 2000), I then assign the rank of 1 to the first 200 companies, the rank of 2 to the companies 201 through 400 and so on. Through a process that permutes ratio types and years, the ranks matrix may be filled in for each security with values in each matrix cell equal to 0 (not included) or 1 through 10. A sample ranks matrix is shown in Appendix D for General Electric Corporation.

Special treatment is necessary to compute the LSV growth in sales rank. Here a trailing weighted average rank is developed. First LSV sort on the gs ratio for a given year and assign a raw gs rank (e.g. 1 to 2000) to each valid company. In another pass of the data through the program, a weighted average trailing rank (1 times t-4 rank plus 2 times t-3 rank, etc.) is computed and divided by 15. The result is a weighted average rank, e.g., 1000 out of 2000. This value, "gswa", is saved in a ratio field. The data is then sorted on gswa for each year and, with a third program pass, a decile rank is developed and kept as the gs rank.

The paragraph above describes what I believe LSV say they have done. I found that the regression of returns on gswa requires additional scaling in order to reproduce the LSV results. I chose to do my scaling by normalizing the raw gs ranks to percentages just before computing the gswa. Thus, for each company in each year, the raw gs rank is divided by the number of ranked securities. A company that ranked 900 out of 2000 in a year has a scaled rank of 45%. The gswa is then a weighted average of such scaled raw ranks. As a result the gswa used in the regression has been mapped into [0,1].

The rank matrix thus contains yearly decile ranks (or portfolio indicators) for b/m, e/p, c/p, d/p and gs. Using this information, the returns on portfolios defined by these five variables may be computed for each of the five years following portfolio formation. The return on any such portfolio is simply the average of the annual returns for the members of the portfolio. In year one following formation this is an average of all the valid securities used in the ranking process. In the second through fifth years, it is the average of the surviving companies. Note that the process above has defined annual returns for years running from 5/1/t to 4/30/t+1 where t = the formation year plus 0, 1, 2, 3, 4. These annual returns include delisting returns and size decile replacements as needed.

In addition to portfolios formed on the basis of these five ranks, an additional five portfolios per year are defined in two dimensions: c/p + gs, e/p + gs, b/m + gs, e/p + b/m, and b/m + c/p. Ranks of 1-3,4-7, and 8-10 are for one variable are crossed with the same groupings for the second variable. Thus there are nine portfolios such as c/p rank 4-7 combined with gs rank 8-10.

In all there are ten portfolio categories, nine or ten portfolio rankings, twenty-four portfolio formation dates (1968 through 1991) and five years worth of post-formation portfolio returns computed on actual data and on a size-proxy basis. Thus there are 22,800 ((5x10 + 5x9)x5x24x2) average annual returns which are formed in one pass into an array measuring (10,10,5,24,k=3). The last dimension (k=1,2 or 3) leaves room for security returns (k=1), size proxy returns (k=2) and a counter of the number of such pairs (k=3) to permit averaging of the annual returns for each portfolio. The program port_ret.f is responsible for this calculation. Port_ret also boils this information down by averaging over the 24 portfolio formation years resulting in a (10, 9 or 10, 5, 2) array which constitutes the data displayed in Tables I and II. Port_ret also computes the Table V values using a subset of the incoming data. Appendix B develops and discusses this calculation.

Using the same input as port_ret, parse.f computes the information shown in Table VI. Using the same information in a somewhat modified format, matest.m computes the regression displayed in Table IV.

Results

Simple Glamour and Value Strategies

My Table I results are similar in all significant respects to the Table I results computed by LSV. I have added Panel E:D/P (dividends to price). The left to right differential for this ratio, with or without size adjustment, is smaller than that developed for the other variables. Despite having identified D/P as one of the value defining ratios, LSV omit this panel. The extreme value and growth portfolio returns, with and without size adjustment are:

Average Annual Percentage Returns - First Five Years after Portfolio Formation

Definition	Value	Glamour	Excess
B/M	18.7	9.3	9.4
B/M - Size Adjusted	4.3	-3.6	7.9
C/P	20.5	9.4	11.1
C/P - Size Adjusted	5.7	-3.7	9.4
E/P	19.1	11.2	7.9
E/P - Size Adjusted	4.2	-2.4	6.4
GS	17.9	11.9	6.0
GS - Size Adjusted	3.3	-1.8	5.1
D/P	15.9	13.2	2.7
D/P - Size Adjusted	1.8	-1.1	2.9

LSV discuss their very similar results. Their comments purport to explain why the greatest differences occur for C/P and why lesser differentials are developed for B/M (less “clean”), E/P (a temporary depression in earnings may cause a stock to migrate towards the low end, i.e., glamour) of the E/P spectrum, GS (“not as dramatic ... nevertheless ... sizable”).

Contrarian Strategies

My Table II results are similar in all significant respects to the Table II results computed by LSV. The results for the value and glamour portfolios are summarized below:

Average Annual Percentage Returns - First Five Years after Portfolio Formation

Definition	Value	Glamour	Excess
C/P X GS	21.3	10.5	10.8
C/P X GS - Size Adjusted	6.3	-2.8	9.1
E/P X GS	21.2	10.8	10.4
E/P X GS - Size Adjusted	6.0	-2.4	8.4
B/M X GS	19.8	11.5	8.3
B/M X GS - Size Adjusted	5.1	-1.9	7.0
E/P X B/M	19.5	10.3	9.2
E/P X B/M - Size Adjusted	4.7	-2.9	7.6
B/M X C/P	20.0	10.5	9.5
B/M X C/P - Size Adjusted	5.2	-2.7	7.9

LSV comment “Because the classifications are done independently, extreme glamour ... and value portfolios ... contain greater than the average numbers of stocks, …[due to correlation].”

As above, LSV comment on these numbers and provide explanations of why some of the differences may be larger or smaller than the others.

LSV follow this with a subsection addressing the glamour/value story using the largest fifty percent of the data base. I have not reproduced Table III. LSV’s results are similar to those of Table II. The potential selection and survivor bias discussed in the methodology section, if it exists, should be less pronounced among the largest stocks. This group of stocks is also more closely followed by analysts and institutional investors. If the irrational view explains overall results, then it appears that the professionals must be irrational as well.

Regression Analysis

Table IV contains my regression results in the same format as those developed by LSV. Although the results differ in every particular, the overall picture that one gets is similar. Each of the individual explanatory variables (including the d/p variable that I added) has the predicted sign and all except size are, or are close to, significant at the 5% level. As noted by LSV, on a standalone basis, the most significant variable is C/P and not B/M (favored by Fama and French). As with LSV, my E/P variable is also more significant than is the B/M variable.

As in the LSV study, I get insignificant results in the cases with multiple explanatory variables for both the (log) size and b/m variables. I also get significant results for the dc/p (cash flow negative dummy) variable where their results are not so. In the next to the last regression, the significance of the c/p+ and dc/p variables appear to have reduced the importance of the GS variable. Further, my e/p+ and de/p (earnings negative dummy) appear to be more significant. LSV note that, in the multiple regressions, the standout variables are GS and C/P. Relative to their work, I find less significance for GS and somewhat more for the negative dummies.

As described above, I rescaled the gswa variable used as the sales growth regressor. Using the absolute weighted average rank (e.g., 1000 our of 2000) results in a minuscule slope parameter. When I remapped gswa into [0,1], the slope was increased about 2000 fold. A reasonableness check may be done by multiplying the slope (-.071) by the average gswa (.5) and adding the intercept (.158) to get a rough average return (.123) which is on the same order as parallel calculations on other explanatory variables

The Extrapolation Model

My Table V has some marked differences from that shown by LSV. The issues I encountered in the preparation of Table V are reviewed in Appendix B.

The Riskiness of Contrarian Strategies

In *The Cross Section of Expected Stock Returns* (1992a), Fama and French outline the debate with respect to the irrational versus riskiness explanation for superior returns to value:

> "If assets are priced rationally, our results suggest that stock risks are multidimensional. One dimension of risk is proxied by size, ME. Another dimension is proxied by BE/ME, the ratio of book value of common equity to its market value.
>
> "It is possible that the risk captured by BE/ME is the relative distress factor of Chan and Chen (1991). They postulate that the earning prospects of firms are associated with a risk factor in returns. Firms that the market judges to have poor prospects, signaled here by low stock prices and high ratios of book-to-market equity, have higher expected returns (they are penalized with higher costs of capital) than are firms with strong prospects. It is also possible, however, that BE/ME just captures the unraveling (regression toward the mean) of irrational market whims about the prospects of firms."

Despite the agnostic claim embedded in the last sentence above, Fama and French are associated with the distress risk point of view. They dismiss the overreaction story of DeBondt and Thaler:

> "Simple tests do not confirm that the size and book-to-market effects in average returns are due to market overreaction, at least of the type posited by DeBondt and Thaler (1985). One overreaction measure used by DeBondt and Thaler is a stock's most recent 3-year return. Their overreaction story predicts that 3-year losers have strong post-ranking returns relative to 3-year winners. … [T]he 3-year lagged return shows no power even when used alone to explain average returns. The univariate average for the lagged return is negative, -6 basis points per month, but less than .5 standard errors from 0."

Looking backward in 1996 and responding to LSV among others, Fama and French (1996) say:

> "Our aggressive interpretation of tests of [the three factor model] has produced reasonable skepticism, much of it centered on the premium for distress (the average HML return). Kothari, Shanken, and Sloan (1995) argue that a substantial part of the premium is due to survivor bias; the data source for book equity (COMPUSTAT) contains a disproportionate number of high-BE/ME firms that survived distress, so the average return for high-BE/ME firms is overstated. Another view is that the distress premium is just data snooping; researchers tend to search for and fixate on variables that are related to average return, but only in the sample used to identify them (Black, 1993 and MacKinlay, 1995). A third view is that the distress premium is real but irrational, the result of investor over-reaction that leads to underpricing of distressed stocks and overpricing of growth stocks (LSV, 1994 and Haugen, 1995)."

LSV argue that the superior returns on value stocks do not represent an increment for distress risk related to B/M or other value discerning variables. Instead these returns represent an opportunity to profit at the expense of the irrational behavior of naïve investors who extrapolate recent results unreasonably into the future.

Their first approach is reflected in Table VI and Figure 2 derived therefrom. My replications of this table and figure again differ in detail but not in general direction and magnitude. The statistical significance of the 3- and 5-year differential returns to value shown in my Table VI differ from those presented by LSV. In Table VI returns are shown for three pairs of strategies (or three zero investment strategies each representing value minus glamour) one year at a time. The one year returns contain no overlap and LSV and I use a simple t-stat derived from the 22 (24 for me) one-year returns.

For the 3- and 5-year returns, the inherent overlap requires an adjustment to the standard errors. The adjustment used by LSV references Hansen and Hodrick (1980). This paper applies an econometric adjustment to correct for serial correlations in regressions related to a forecast model for foreign exchange forward contracts. With the tutelage of Prof. MacKinlay, I have understood this adjustment to apply to the LSV problem as follows:

Assuming that each year's returns are independent and that the annual variance (σ^2) of these returns is constant over time, the variance of 3-year independent returns is merely $3\sigma^2$. But the one year at a time series of 3-year returns contains overlaps. The 1971:1973 return shares two years with the 1970:1972 and 1972:1974 returns and shares one year with the 1969:1971 and 1973:1975 returns. This coincidence of returns leads to additional off-diagonal terms in the total variance matrix for the 22-year series. For LSV, who report 20 3-year returns, this means that in addition to a diagonal of $20X3\sigma^2$, they have $19X2X2\sigma^2$ coming from the primary off-diagonals and $18X2X1\sigma^2$ coming from the next off-diagonals. Instead, therefore, of a total variance equal to $60\sigma^2$, they have $172\sigma^2$. In my 24-year version, I have $190\sigma^2$ instead of $66\sigma^2$. The adjustment to the naïvely calculated standard error requires that LSV divide by the square root of (172/60) and that I use the square root of (190/66). Similarly for the 5-year returns, I have divided by the square root of (460/100). The corresponding divisor for LSV would be the square root of (410/90). Because Table VI contains the relevant data, it is easy to determine that LSV have used a smaller adjustment (i.e., they arrive at a larger t-stat). I note that my t-stats do not exhibit the tendency to grow as the holding period lengthens as do the t-stats for LSV.

Figure 2 shows the excess returns to value over time using the middle, two-dimensional strategy from Table VI applied on a 1-year basis. The negative years are 1971, 1979 and 1985 for LSV. My extension shows a very small negative for 1990 as well. LSV argue that, if value is a proxy for an unspecified but financially important risk, then the risk should manifest itself in times that are "bad" for capital markets returns generally. This argument flows from the ideas inherent in CAPM, i.e., that risks that are correlated with market performance merit positive returns to risk. If, therefore, C/P X GS (or B/M, or HML in FF notation) proxies for a compensable risk, then the risk should be exhibited in "bad" stock market times. Alternatively, risks exhibited in "bad" economic times (recessions) may stake claim to compensation. The years 1971, 1979 and 1985 do not provide support for such a risk.

This argument is examined in greater detail in Table VII (unreplicated). LSV "define" 4 states of the world by ex-post sorting of overall market returns. The worst 25 months, the additional 88 months of negative returns in their sample, the 122 second best set of positive return months and the 25 best return months. They observe:

> "Overall the value strategy performed somewhat better than the glamour strategy in all states and significantly better in some states. If anything, the superior performance of the value strategy was skewed toward negative market return months rather than positive return months. The evidence in Table VII, Panel I thus indicates that the value strategy did not expose investors to greater downside risk."

Using states of the world defined by rate of GNP growth, Panel 2 results mirror those of Panel 1. Table VIII (unreplicated) exhibits traditional (volatility based) risk measures for the one and two dimensional decile and nonile portfolios used earlier. Value portfolio betas average about .1

higher than glamour portfolios but, LSV argue, most of this is "up-market" beta. Even if it were uniformly distributed across up and down markets, this beta would only explain 100 bp of the roughly 1000 bp in returns shown.

Critique

I entered this project favorably disposed to the conclusion that irrational behavior better explains the success of value strategies than does some unspecified risk. While I am no better satisfied with the risk story than I was before, I am less persuaded than I was by the behavior story.

Having reproduced the major calculations, I have no doubt that strategies based on the value measures have outperformed those based on glamour for most of the last 25 years.

My discomfort with the LSV explanation arises from several sources:

- Their presentation of results seems in various places to reflect a desire to offer the most favorable evidence. This includes not presenting a dividend-to-price ratio although their introduction points to high dividend yield as one of the definitions of value.
- Their inclination to explain every relative advantage (when, for example, b/m does not the develop the strongest ex-post differential return, we are told it is not a "clean" variable). Some of these relative advantages are likely to be time and place dependent. An excess return (value over growth) of 1000 bp is impressive but the difference between the excess derived from C/P (11.4%) versus that derived from B/M (9.7%) is less compelling. Finding too much meaning in the data points to a potential weakness for data snooping.
- The way in which LSV treat the issue of negative earnings in footnote 4 is not entirely satisfying. They correctly observe that there is no manifest bias in any strategy that may be clearly defined ex-ante. However, there is nothing inherently unusable about negative earnings or cashflows. The contention that "negative ratios cannot be interpreted in terms of expected growth rates," ignores the fact that earnings and cashflows are the net values derived from income (inflow) and expense (outflow). Analysts are unlikely to admit that they do not or cannot project income and expense separately before netting.
- The use of the two dimensional discriminants through the intersection process leaves some very small cells. In more than a few cases the most populous of the nine resulting cells has more than ten times the number of stocks as does the least populous. While the "thin" cells tend to be ambiguous (value by one measure, glamour by the other), the imbalance suggests that we should be cautious in interpreting anything but the end points. LSV do point out the population unevenness and do tend to focus on the endpoints.
- The statistical tests of Table VI (discussed above) and the lack of precise formulas for Table V calculations do not bring comfort to this replicator.
- I believe it is highly unlikely that the LSV disagreement with the risk-based proponents will be resolved by future out of sample data. LSV have staked out a position that continues in the event that value continues to outperform glamour and that leaves room to claim victory if the trend is reversed. They conclude: "Are the anomalous excess returns on value stocks likely to persist? It is possible that over time more investors will become convinced of the value of being a contrarian with a long horizon and the returns to value strategies will fall."

The above suggests that my priors have been turned around. This is not the case. I have similar difficulties with the Fama and French presentations. The data snooping argument may be most meritorious but in any short run it is always irrefutable and thus unproved.

A last miscellaneous note: LSV's final comment: "The large difference in returns on glamour and value stocks can, at least in principle, explain why money managers have underperformed the market by over 100 basis points per year before accounting for management fees. By looking at the actual portfolios of money managers, one can find out whether they have been overinvested in glamour stocks and underinvested in value stocks." This suggests that there are "money managers" who are losers as a class while somewhere else there must be "non-money-managers" who "overinvest" in value and thus win. A simpler explanation should be considered first: Wall Street extracts this 100 bp from active traders and money managers are active traders. The value and growth index funds are perfectly capable of delivering returns close to their respective bogies because they avoid the extractions associated with transactions.

Basu, S., 1977, Investment performance of common stocks in relation to their price earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, 663-682.

Black, F., 1993, Beta and return, *Journal of Portfolio Management* 20, 8-18.

Chan, K.C., and Nai-fu Chen, 1991, Structural and return characteristics of small and large firms, *Journal of Finance* 46, 1467-1484.

DeBondt, W., and R. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

Fama, E. and J. D. MacBeth, 1973, Risk, return and equilibrium: empirical tests, *The Journal of Political Economy,* 81, 607-436.

Fama, E. and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 46, 427-466.

----------, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

----------, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance,* 51, 55-84.

Hansen, L. P., and R. J. Hodrick, 1980, Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis, Journal of Political Economy, 88, 829-53.

Haugen, Robert A., 1995, The new finance: the case against efficient markets, *Prentice-Hall, Inc.*

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: Implications for market efficiency, *Journal of Finance,* 48, 65-92.

Kothari, S. P., J. Shanken, and R. Sloan, 1992, Another look

Lintner, J. and R. Glauber, 1967, Higgledy piggledy growth in America, *Unpublished paper presented to the Seminar on the Analysis of Security Prices,* University of Chicago, May.

Little, I. M. D., 1962, Higgledy piggledy growth, *Bulletin of the Oxford University Institute of Economics and Statistics* 24, November.

Little, I. M. D., and A. C. Rayner, 1966, Higgledy piggledy growth again, Basil Blackwell, Oxford.

Lo, A. and A. C. MacKinlay, 1990, Data snooping biases in tests of financial asset pricing models, *Review of Financial Studies*, 3, 431-467.

MacKinlay, A. C., 1995, Multifactor models do not explain deviations from the CAPM, *Journal of Financial Economics*, 38, 3-28.

Rouwenhorst, K.G., 1996, International momentum strategies, unpublished, presented at Wharton, November, 1996.