SOCIALLY RESPONSIBLE INVESTMENT SCREENING: STRONG EVIDENCE OF NO SIGNIFICANT COST FOR ACTIVELY MANAGED PORTFOLIOS
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1. INTRODUCTION AND OVERVIEW

In **Investing for Good**, Kinder, Lydenberg, and Domini [1994, p.3] identify three main types of social investors: 1) social guideline investors, 2) shareholder activists, and 3) community-development investors. This article treats social guideline investing.

Social guideline investing (SGI) includes two types: 1) social screens and 2) positive social tilts. **Social Screening** is prohibiting investment in the securities of companies/industries that the investor perceives to be engaged in socially negative behavior such as defense, alcohol, tobacco, gambling, pollution, etc. **Positive social tilting** is proactively investing in the securities of companies that the investor perceives to be engaged in socially positive business activities and/or to be exhibiting socially proactive management practices such as affirmative hiring/promotion, progressive child care, employee education, etc.. This paper concerns the performance cost of social screening. It does not treat positive social tilting.

Background

Religious investors such as Catholics, Mormons, and Quakers have a long history of social screening. A broadened, active interest in social screening arose from exclusions of companies doing business in South Africa (see Grossman and Sharpe [1986]). Social screening then moved on to other social exclusions including alcohol, defense, gambling, guns, nuclear, pollution, pornography, and tobacco. In the 1990s SGI expanded to include positive social tilting as well as social screening. By 2000, nearly two trillion, more than 20% of institutional funds, are socially focused.

There is now an infrastructure including not only investment management per se but also support organizations (such as the Interfaith Center on Corporate Responsibility and the Social Investment Forum), newsletters, annual conferences, introductory literature including books/monographs such as ***Ethical Investing*** by Domini and Kinder [1984]**,** ***Making Money While Being Socially Responsible*** by Kinder, Lydenberg, and Domini [1993]**,** ***The Social Investment Almanac*** by Kinder, Lydenberg, and Domini [1995], and ***Investing With Your Values*** by Brill, Brill, and Feigenbaum [1999]. A growing number of investment management organizations specialize in SGI, can implement client-customized social screens, and/or can implement positive social tilts.

2. PERFORMANCE ASSESSMENT

In addition to the extensive information and management support infrastructure, an emerging literature on SGI investment performance exists. An important SGI performance milestone was the creation of the Domini 400 index in 1991. The Domini 400 was created by first applying social screens to the S&P 500 index to exclude approximately 250 companies and then adding back 150 companies not in the S&P 500: 100 large companies selected for size and industry and 50 smaller companies selected for positive social attributes. The net result was an index of 400 socially responsible companies. The performance of this index compared to the S&P 500 has supported two emerging views. The milder is that SGI involves no significant risk-adjusted cost. The stronger is that SGI produces superior risk-adjusted performance.

An important interdependency exists between the growth in socially responsible investing and the perception of low cost, of no significant cost, or even of positive performance value. The emerging view that socially responsible investing involves no significant cost (see Guerard [1997a, 1997b]) and the stronger contention that socially responsible investing can actually improve performance (see for instance Waddock and Graves [1997a, 1997b]) makes it relatively easy for an organization to impose their social values in their investment activities. No cost in risk-adjusted return means that an organization can affirm its social values without foregoing return. However, if socially responsible investing provides better risk-adjusted returns, then socially responsible investing is not just a question of costlessly affirming organizational values but rather a question of prudent investment management. If socially responsible investing can consistently provide superior risk-adjusted returns, then it pays to be socially responsible even if there is no issue of affirming social values.

Grossman and Sharpe [1986] consider South Africa's screens and set a framework of SGI performance assessments. Kurtz [1997] provides an excellent overview of the SGI performance assessment literature through 1996 including detailed commentary on many of the studies. In terms of framework, there are two dimensions to SGI performance assessment: 1) passive, index-matching versus active portfolio management and 2) social screening verses positive social tilting.

The crux of performance assessment for an SGI index or fund is comparison with a pertinent stock index, e.g., comparing the Domini 400 index (or the Domini 400 fund) with the S&P 400 or the S&P 500 from which the Domini 400 was derived. As developed in Kurtz [1996], **comparison** means adjusting one index to reflect known differences in factor exposure and factor performance over a pertinent time period and comparing the two factor-adjusted return series. The consensus view summarized in Kurtz [1997] is that the return for the Domini 400 before adjusting for factor differences is attributable to higher beta (systemic market volatility exposure), higher growth, and smaller size outweighing any return cost associated with the relatively higher price-earnings ratio on the Domini 400. However, even after making corrections for these factor differences, there is yet some positive return that could be attributable: 1) to the positive social tilt, 2) to omitted factor corrections such as not correcting for dividend yield differences, and/or 3) to luck of index construction and time period.

Given that the strong up-market of the 1990s was favorable to higher beta, high growth, and small size, one can question the robustness of the favorable SGI performance. Is the conclusion of no significant cost and the stronger contention of positive performance value an artifact of the 1990s market? Will SGI indexing perform as well in down markets or markets that are less favorable to growth and smaller market capitalization?

For actively managed SGI portfolios/funds, one can either compare their factor-adjusted performance with pertinent indices or see how their factor-adjusted performance ranks vis-à-vis non-SGI funds. To eliminate management judgment/skill, one can compare SGI funds with comparable non-SGI funds from the same investment management organization, e.g. the CREF socially responsible stock fund versus other CREF stock funds. However, even with a common manager, performance assessments for active SGI portfolios/funds suffer from ambiguity, especially when there is both screening and positive social tilting. Concluding there is superior factor-adjusted performance is a joint conclusion about SGI and portfolio management and the factor adjustments. Was superior performance from SGI, from good portfolio management, or from "luck" with respect to style and SGI exclusion/inclusions being good for the time period in question? Given uncertainty in factor measurements, how confident are we about these factor-corrected comparisons? Most importantly, how robust are these results and how likely are they to hold in future periods?

Guerard [1997a, 1997b] extends SGI performance assessment for active quantitative portfolio management. Rather than looking at the after-the-fact performance for actual SGI portfolios/funds, Guerard used an objectively specific return forecasting model to generate a return for every security in a security universe. Ranking on forecasted returns in each quarter produced a cross-section of forecast-ranked portfolios representing fractiles of the distribution of predicted returns. Applying social screens and then repeating the process produced a second set of socially screened, return-ranked portfolios. By comparing the time series of returns on the forecast-ranked portfolios constructed from the overall security universe with socially screened subsets of the overall universe, Guerard [1996a, 1996b, 1997] concluded that there was no significant cost (no significant return difference) from social screening.

This paper extends Guerard [1997a, 1997b]. Once again, a quantitative security return forecasting model is used to generate a forecasted return for each security in each quarter of our 1984-1997 study period. However, rather than just using the return forecast to produce fractile portfolios, a mathematical assignment program produces a cross-section of return-ranked portfolios matched on four pertinent return factors: 1) beta, 2) growth, 3) size (market capitalization), and 4) dividend yield. The net result is a robust assessment of active SGI that eliminates any distortion from beta, growth, size or dividend yield. Thus, this study greatly strengthens the conclusion of no significant cost to social screening. Moreover, contrary to consensus views in much of the social screening literature, it establishes the conclusion of no significant cost to social screening in a value-focused, growth-suppressed fundamental return-forecasting framework for a relatively long time period (1984-1997).

For objectivity, we employ each of the Kinder, Lydenberg and Domini social screens individually and in combination. We test 54 quarters (starting with Q3 in 1984 to the end of 1997). By using a long test period, a wide range of screens, and suppressing beta, growth, size, and dividend yield, we believe we significantly expand the breadth, time period, and robustness of the evidence for no significant performance cost to social screening.

The rest of this paper is organized as follows. The next section provides an overview of the value-focused security return-forecasting model. Then we introduce the idea of performance assessment using a set of matched portfolios, describe how we construct the matched portfolios, and summarize the study process. We then present empirical results in the KLD screens, test for robustness, and finally draw conclusions as well as the usual noting of limitations and need for still more research.

3. A RETURN PREDICTION MODEL

Factor assessments of socially responsible portfolio performance have concluded that most socially responsible portfolios (e.q. the Domini 400 Fund vs. the S&P 500 Index) generally differ from the security universe in the following ways namely: 1) more systematic risk (higher beta), 2) smaller size (market capitalization), 3) higher growth (including a technology tilt), and 4) a higher price-earnings ratio. Realizations of superior returns are attributed to the favorable impact of higher risk (in the net up market of the 1980s and 1990s), higher growth, and smaller size outweighing any negative impact of the higher price-earnings ratio.

To our knowledge, factor assessments of socially responsible investment performance have not been concerned with correcting for differences in dividend yield. However, the fact that there is a known dividend yield tilt requires that this factor also be included in assessing performance.[1]

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[1]For a review of the massive literature on dividends and valuation with emphasis on tax effects, see the recent monograph Dividend Policy: Its impact on Firm Value by Lease et al [2000]. For early

This paper uses the return prediction model of Guerard, Gultekin, and Stone [1997], hereafter GGS, as an illustrative active portfolio management strategy. Readers interested in details of the return prediction model are referred to GGS [1997].

The point here is not to advocate the GGS model but rather to use it as an illustrative value-focused active portfolio strategy in comparing socially screened and unscreened performance. Reasons for using a quantitative security return forecasting model include: 1) the ability to create of a return forecast for every stock in the security universe; 2) the ability of other researchers to replicate our results by using a rule-based forecast system operating on past publicly available data that removes judgment from active portfolio management. We selected a value-focused forecast so that we could exclude growth and size (capitalization), two of the return factors generally used to explain SGI performance and two factor reasons for suspecting brittleness in SGI performance in the 1990s.

The GGS regression equation and variable definitions are summarized in Exhibit 1. The GGS forecast model can be viewed as an extension of return momentum modeling. However, rather than simply ranking on past returns, a fundamental regression model is first estimated to determine recent return generation structure. By return **generation structure**, we refer to the relative importance of each of the model variables in explaining recent return cross-sections. An indication of the relative importance of the eight fundamental variables is given by the time average value of the regression coefficients estimated for each year in our 1984-97 study period. These time average values are tabulated at the bottom of Exhibit 1. They support the low P-E (high earnings yield) approach to value investing advocated by Graham and Dodd [1962] and validated as a cross-sectional return anomaly by Basu [1977]. They also support the Fama and French [1992, 1995, 1996] finding that the book-to-market ratio is an important variable for explaining the cross-section of security returns. However, while both these variables are significant in explaining returns, the majority of the forecast performance is attributable to other

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work on the impact of dividend yield on stock returns, see for instance Brennen [1970], Rosenberg and Maratha [1978], Blume [1980], Miller and Scholes [1978,1982], and Peterson, Peterson, and Ang [1985]. For a work showing the cross-section of returns with varying dividend yield but the same beta see Stone and Bartter [1985], Blin and Douglas [1987], and Stone [1994].

model variables, namely the cash-to-price, sales-to-price, and earnings forecast revisions. This fact is established in Section 9, where the impact of both the earnings yield and the book to market ratio are suppressed. See especially Exhibit 23.

In addition to determining a relative weight for each of the eight fundamental value measures, the model also incorporates analysts' earnings forecasts. After each annual re-estimation of regression coefficients, new forecast coefficients are determined using the significance-based smoothing process given in GGS [1997]. These adaptively smoothed forecast coefficients are then combined with start-of-quarter values of each model variable to obtain a predicted return score for every stock in the security universe.

The GGS forecast model does not include any explicit security risk variable such as beta. Beta is our control variable for systematic risk. In addition to using beta to control for systematic market risk, there are known return performance factors that are not an explicit part of the forecast model. In addition to beta (systematic market risk), we identify three non-model cross-sectional return factors as control variables, namely: 1) firm size (capitalization), 2) growth, and 3) dividend yield (tax effects for gains vs. dividends). We define and discuss the role of non-model performance control factors in the next two sections.

4. PERFORMANCE ASSESSMENTS: THE MATCHED PORTFOLIO FRAMEWORK

Implicit in the preceding discussion has been a standard framework for explaining the difference in the performance of two portfolios. First, one identifies pertinent performance factors (such as beta, size, growth, and dividend yield). Then, one assesses a fair adjustment return for each factor. Differences in return for two portfolios are explained by differences in their factor loadings (factor exposure). Any remaining difference is then attributable to "non-factor performance," i.e., superior security selection, luck, or possibly omitted factors.

In this article, we present an alternative framework for assessing performance and isolating factor impacts. This framework is designed both to assess portfolio-level forecast value and to identify the relative value of various forecast variables in a multivariate forecast model. Here, we adapt the ability to do portfolio-level forecast performance experiments to assess the cost of social screening in the context of active portfolio management using explicit forecasts of security returns.

We shall refer to this portfolio-level forecast performance assessment framework as a **matched portfolio assessment.** The crux of the matched portfolio assessment is constructing a set of portfolios that vary systematically in one attribute (forecasted return) but that are matched for a set of control variables (control factors) such as beta, size, growth, and dividend yield. **Matched** means that each portfolio in the cross-section has the same portfolio average value of each control variable. For the set of matched portfolios, there is no cross-sectional variation in the portfolio-average value of any of the control variables.[2]

Using a cross-section of factor-matched portfolios to evaluate social exclusions is an alternative to the conventional procedure of correcting portfolios for differences in factor exposures. The cross-sectional approach has three benefits. The first benefit is generality. We see an entire cross-section for how realized return depends on forecasted return rather than focusing on a limited number of specific portfolios. Moreover, we can evaluate a time-series of comparable cross-sections across time so that assessing both the time performance and cross-time consistency is straight forward compared to having to impose numerically different factor corrections in different time periods.

The second benefit is robustness in the way non-forecast return factors are reflected in performance assessments. Rather than measuring factor performance in a particular time period and correcting for measured factor differences, all portfolios in the matched cross-section have the same average values of all control factors, in this case beta, growth, size, and dividend yield. Thus, rather than making a linear correction to a measured factor value, we suppress cross-

[2]This definition of matched portfolio uses the portfolio mean value of each control variable as the basis for defining a matched set. A more general definition would require not only the same mean but also the same distribution about each portfolio mean as developed in Stone [2001]. Two points are pertinent. First, the implicit assumption of a well-defined linear factor price correction is sufficient to justify the portfolio mean as well-defined match. Second, as we note in reporting average within-portfolio standard deviations in Exhibit 21, there is not significant cross-sectional variation in the within-portfolio standard deviations of any of the four control factors. However the size control has small nonsystematic fluctuations. The growth control exhibits a small systematic (but not significant) reduction in within-portfolio standard deviations in going from low return to high return portfolios.

sectional variation in the control factors. Thus, no measured factor correction is necessary since there is no difference in the values of controlled factors in the set of matched portfolios. Along with not having to deal with factor measurement error and factor correction error, a particularly important part of the robustness argument for the matched portfolio comparison is avoiding the linearity assumption implicit in factor corrections.

The third benefit of the matched cross-section approach is understandability to the non-technical reader not familiar with the statistical issues in first measuring factor prices and then dealing with questions of statistical confidence in applying these measured factor prices. In contrast, with the matched portfolio approach, we simply compare cross-sectional plots for an overall universe and a screened universe. While we cannot avoid performance measures (such as comparative Sharpe ratios), the non-technical reader can visually assess the comparative performance of the overall universe and the screened subset by looking at a plot showing realized return versus predicted return for the two cross-sections. The visual assessment is meaningful because the two matched cross sections have suppressed cross-portfolio variation in the pertinent control factors.

5. CONSTRUCTING OTHERWISE MATCHED PORTFOLIOS

This section first motivates the need to construct a set of matched portfolios and then outlines the logic for the algorithm used to generate the matched set. We acknowledge that the benefits of generality and visual simplicity for the matched set framework do involve a cost, namely considerable computational effort to construct cross-sections of matched portfolios in every time period, which in this study consists of 54 quarters in the 1984-1997 study period.

Let us focus on a point in time for which we have a predicted return for each security. We can rank these securities into fractiles on the basis of predicted return. For concreteness, assume that we divide the universe of these forecast-ranked securities into twenty range-based fractiles. We can think of each fractile as a portfolio. We can compute the beta, market capitalization, growth, and dividend yield as the average of individual security values for each of these 20 fractile portfolios. If it should turn out that each of these 20 fractile portfolios had the same average beta, market cap, growth, and dividend yield, we would have a set of twenty fractile portfolios that are matched on our four control variables (beta, market capitalization, growth, and dividend yield). However, they would differ significantly in forecasted return since the portfolios are fractiles of the forecasted return distribution. We can now observe realized portfolio returns and see how well realized portfolio returns rank-order correlate with predicted portfolio returns. In fact, we can plot realized return as a function of predicted return for these otherwise matched portfolios. Since these fractile portfolios are identical on risk and all other control factors, this plot is a cross-sectional summary of performance possibilities from information in the return forecast.

The typical reader is probably thinking: "Nice, but fractile rankings will never provide a match for every fractile on every control variable. Absolutely impossible! There will be variation in both risk and other performance factors. Thus, I can never really see the pure cross-sectional dependence of realized portfolio return on predicted portfolio return from just grouping securities into forecasted return fractiles."

We agree. In fact, the situation is much worse than not having a match on the controls. When control variables such as beta and growth are correlated with variables in the forecast model such as the earnings yield (earning-price ratio), the cross-section of fractile portfolios will have a strong cross-sectional dependence on both beta and growth.

Since we cannot expect a partitioning into fractiles to produce portfolios matched on our control factors, let us see what it takes to construct an otherwise matched set starting with a set of fractile-based portfolios. Consider fractiles five and six (assuming a rank ordering from 1 to 20). If fractile #5 and fractile #6 did not match on some of the four controls, we could shift some securities between portfolios to move toward a match. For instance, if the beta for fractile #5 were below the beta for fractile #6, we could move a high beta security from fractile #6 to fractile #5 and vice versa. Such trial-and-error adjustments to the composition of the fractile portfolios might ultimately produce a matched cross section. However, it is computationally horrendous and lacks objectivity.

It is computationally horrendous because trial-and error shifting could involve 1000s of shift trials to obtain even a near match for 20 portfolios subject to just four controls. It lacks objectivity because each trial-and-error solution would be different. If we are going to use a matched cross-section to assess forecast performance (or comparative forecast performance in the case of assessing social exclusions), then we clearly need a systematic procedure that another researcher using the same security universe and same measures can replicate.

The task of modifying fractile-based portfolios to produce a set of otherwise matched portfolios can be solved systematically as a mathematical programming problem using standard solution algorithms. The objective is not just to reassign securities to produce a match but to find the assignment of securities to portfolios that produces the best match. The **best match** (best assignment of securities to portfolios) involves optimizing two complementary objectives. First, we seek to preserve a wide range of well-ordered return forecasts like those associated with the starting set of range-based fractiles. We say "preserve" here because the shifting of securities to other fractiles necessarily involves some loss of range. Second, we want to preserve within-portfolio forecast homogeneity. For instance, if we were considering a shift in and out of portfolio #5, we would prefer shifts between either #4 and #5 or #6 and #5 over a shift between #20 and #5. The shift between #20 and #5 would involve very different return forecasts.

Fortunately, preserving a well-ordered forecast range and preserving within-portfolio forecast homogeneity are complementary objectives. Minimizing the number and portfolio-rank distance of matching shifts (preserving forecast homogeneity) also tends to preserve forecast range and visa versa.

Exhibit 3 verbally summarizes the objective function and constraints that define the **mathematical assignment program (MAP).** The **MAP** can be viewed as a computer algorithm for transforming an unmatched set of fractile portfolios into a corresponding set of fractile-based control-matched portfolios that have the same average value of each control variable. The critical constraints in the mathematical assignment program are the equal value constraints. These require that every portfolio in the matched set have the same portfolio average value of beta, size, growth, and dividend yield. Thus when realized portfolio return is plotted as a function of predicted return in Exhibits 6 and 7, this cross-sectional dependency of realized return on predicted return involves no cross-sectional variation in the portfolio average value of beta, size, growth, and dividend yield at the time the portfolios were formed. Differences in performance cannot be attributed to differences in beta, size, past growth, or dividend yield at the time of portfolio formation. Eliminating the impact of beta, size, and growth is particularly pertinent to assessing the impact of social screening because favorable differences in these performance factors have been suggested as explanations for the good performance of socially screened indices and portfolios.

The mathematical assignment program is an optimization algorithm[3]. The objective function involves a trade-off between preserving a wide range of predicted returns and minimizing the shifting of securities to meet the equal restrictions. The preceding sentence used the phrase "preserving a wide range of predicted returns" because the predicted return fractiles start with the widest possible range in predicted return. As securities are shifted to other portfolios to satisfy the equal value constraints, some range is lost. The optimization algorithm finds those portfolio changes that jointly minimize reduced range and the amount of security shifting. In effect, the algorithm preserves as much as possible the composition and range of the original fractile portfolios while producing a matched cross-section of fractile-based portfolios that satisfy the equal value restrictions on the control factors.

The other constraints are technical restrictions to make sure the algorithm functions well. The data usage constraints require that: 1) each matched portfolio has the same number of securities as its corresponding fractile portfolio in the original set of range-based fractiles, and 2) all securities are assigned to some portfolio. The equal increment constraint ensures that there are equal changes in predicted return for adjacent fractiles. This restriction makes exact the tendency

[3] While the idea of using an optimization algorithm to organize portfolio-level assessment of the information in a quantative security return forecasting model is an innovation in forecast performance assessment, the underlying idea can be viewed as a multi-factor (multi-control) extension of the general linear programming formations of Sharpe [1971] and Stone [1973]. The general algorithm for grouping observations to create matched cross-sections is developed in Stone, Adolphson, and Miller [1993]. The special case of constructing matched portfolios from return forecast fractiles is developed in depth in Stone, Guerard, and Gultekin [2001]. An algorithm for an exact distributional match for each control rather than the mean-only match is developed in Stone [2001]. Readers interested in a detailed formulation of the mathematical assignment program and its use for portfolio-level experiments on any security-level return forecasting model are referred to the more technical treatments in Stone, Guerard, and Gultekin [2001] and Stone [2001].

of the initial fractile portfolios to have approximately equal increments in predicted portfolio return.

To synthesize, the mathematical assignment program summarized in Exhibit 3 describes a computer-based algorithm that transforms an initial set of range-based fractile portfolios into a matched set of fractile-based portfolios in an objective way. By plotting realized portfolio return on each portfolio as a function of predicted portfolio return, we can isolate the dependence of realized return on predicted return with all distortion from variation in the control factors removed.[4]

6. DESIGN LOGIC

This section summarizes the security universe, the performance assessment time periods, and logic for converting security data into cross-sections of matched portfolios in each time period.

The **security universe** is all the securities used to form portfolios. For this study, the security universe is defined by securities that are common to the three databases (CRSP, COMPUSTAT, and I/B/E/S) that also have all necessary security data required to generate a forecast and to estimate the control factors. In particular, the security universe at a point in time consists of all securities in the I/B/E/S database for which at least three prior years of monthly return data are contained in CRSP and at least five prior years of sales, earnings, dividends, and total assets are contained in COMPUSTAT along with the following quarter's return data. The security universe changes each quarter.

The performance assessment period is the quarter 3 of 1984 through the end of 1997. Portfolios are formed at the start of each quarter and held for one quarter. The forecast model is updated annually. "**Updating**" means re-estimating the weights applied to the eight fundamental

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[4] The phrase "all distortion" might be too strong. As already noted in footnote 2, the algorithm for constructing the matched portfolios uses the portfolio average value of each control variable. Without functional form or distributional assumptions, a perfect match would have not only the same average value of each control across all portfolios but would also have the exact same distribution about the mean in each portfolio. While we have not ensured exactly the same distribution across the set of matched portfolios, an after-the-fact assessment of the set of matched portfolios (summarized in Exhibit 21) indicates that there is no significant systematic cross-sectional variation in within-portfolio variance for any of the four controls used in this study.

forecast variables and the one I/B/E/S forecast measure in accord with logic summarized in Exhibit 2. The forecast variables do not change but their weighting is updated annually on the basis of most recent predictive power.

Exhibit 4 summarizes the logic for creating a forecast cross-section of otherwise matched portfolios from a universe of available securities. At the start of each year, the universe of securities is determined. The forecast model is updated (variable weightings re-estimated). At the start of each quarter, a return forecast score is generated for every security from the most recently available historical data. Likewise, the pertinent start-of-quarter values of each control factor (beta, size, growth, and dividend yield) are determined for each security.

The return forecast score and control factor values for each security are input to the MAP to create the optimal set of matched portfolios each quarter. First, securities are assigned to fractiles of the distribution of forecasted return. Then, the MAP determines the optimal reassignment to preserve range and otherwise minimize cross-fractile shifting while producing a match on each control factor.

Once the MAP determines the security membership in each of the twenty matched portfolios, values of both forecasted return and realized return for each portfolio are computed as weighted averages of the forecasted and realized return for each security assigned to each of the matched portfolios.

The predicted returns score and realized returns for the set of twenty matched portfolios summarizes a portfolio-level cross-section of how portfolio return relates to predicted portfolio return score with no cross-sectional variation in the starting values of any of the four control factors.

Exhibit 5 is a matrix that summarizes the cross-sectional dependence of realized portfolio return on predicted return score for all 54 quarters in the 1984-1997 timeframe. Each line in the matrix of Exhibit 5 corresponds to one quarter and twenty forecast ranked portfolios. Each line was generated using the MAP for constructing matched portfolios summarized in Exhibit 4. Each line provides a portfolio-level summary of a quarterly return prediction and the actual realized return for the set of twenty matched portfolios constructed at the start of each quarter.

A matrix of return cross-sections over time is difficult to interpret. Plots summarizing cross-sections, averages and other pertinent performance statistics are necessary to make the data intelligible. Exhibit 6 gives a simple time average of the cross-sections. Each of the twenty points plotted in Exhibit 6 is the arithmetic (uncompounded) time average of realized return and predicted return score for a given portfolio rank. Thus, to get the time average for realized portfolio return and predicted portfolio return score for portfolio rank #10, one sums down the two columns under label #10 in Exhibit 5 and divides the total by 54 (the number of quarters) to obtain the arithmetic average return. Thus, the plot in Exhibit 6 is constructed by plotting the annualized values of bottom-line time averages in Exhibit 5. The vertical axis is the annualized average value of realized quarterly return. The horizontal axis is the predicted return score for each fractile-based portfolio. The cross-section is a visual summary of how well predicted return score results in portfolio-level realized returns that rank-order correlate with prediction. The spread between the low-ranked portfolios and top-ranked portfolios gives the average annual return value in the forecast.

7. IMPACT OF SOCIAL SCREENS

Our source for social screens is Kinder, Lydenberg, and Domini (**KLD**). Exhibit 8 summarizes their social screens and gives the average number of securities excluded by each screen.

The logic for comparing performance possibilities for the screened subset of the security universe with the overall universe is straightforward. First we exclude the screened securities to create the screened universe. Then we apply the logic of Exhibit 4 to the screened universe to create another set of matched portfolios that exclude the screened securities. The crux of assessing impact is to compare performance possibility cross-sections for the overall and screened universe for each social screen. Initially we present the 1984-97 summary results by showing graphically: 1) realized portfolio return versus forecasted portfolio return score for the overall universe and each socially screened universe, and 2) realized Sharpe ratios versus forecasted return scores (portfolio forecast rank) for the overall universe and each socially screened universe. We then assess the significance of any differences and consider sub-periods with emphasis on the segment of the cross-section having the highest forecasted portfolio returns, namely the five portfolios in the upper quartile.

Alcohol, Tobacco, and Gambling Screen

The KLD screen for alcohol, tobacco, and gambling involves a primary screen and a secondary screen. Exhibit 9 plots long-run performance possibility cross-sections for the overall universe and three screened universes, namely: 1) the KLD primary exclusion only, 2) the KLD secondary exclusion, and 3) the combination of the primary and secondary exclusions.

In each case, the overall and screened cross-sections are almost identical. The only clear visual difference in realized portfolio return is for the portfolio having the lowest forecasted return for the combination of both alcohol, tobacco, and gambling screens (bottom plot in Exhibit 9).

For the top end of the three return cross-sections, the 1984-97 average quarterly return differences are never more than 0.1%. There is very little difference in return performance possibilities from screening for alcohol, tobacco, and firearms.

Does excluding securities from these three industries significantly reduce diversification? Exhibit 10 plots the cross-section of realized Sharpe ratios versus forecasted return. Again, the overall security universe is virtually identical to the screened cross section. There is no significant loss in attainable diversification from the alcohol-tobacco-gambling screen.

Defense Screen

Exhibits 11 and 12 plot average realized return and Sharpe ratios, respectively, for the KLD defense screens. Results are similar to those for screening on alcohol, tobacco, and gambling. Visually, there is no significant impact on realized returns or Sharpe ratios for any of the three defense screens.

Environmental and Nuclear Screens

Exhibits 13 and 14 plot average realized returns and Sharpe ratios for the KLD environmental screens. Exhibits 15 and 16 are for the KLD nuclear screens.

Except for the portfolio with the lowest forecasted return, there is again no significant visual difference in the cross-section for the overall universe and these screened universes.

Combination of All Screens

Exhibits 17 and 18 plot average realized returns and Sharpe ratios for the combination of all screens. Even with the very large number of excluded securities, there are not significant costs from social screening. Likewise, there are not significant return benefits. The plots suggest no significant difference in either the return or the Sharpe ratio cross-sections. In the context of the GGS forecast model, the two performance possibility cross-sections (realized returns and realized Sharpe ratios) indicate no significant return cost from applying the KLD screens for the 1984-1997 time period. Likewise, there is not significant benefit. Screening has no significant long-run impact on either the portfolio return possibility cross-section or the Sharpe ratios.

The results so far are averages for the 1984-1997 study period. We first treat sub-periods. Then we address the question of year-to-year consistency and finally assess robustness of results both to forecast model variations and to the control restrictions.

8. SUBPERIODS AND YEAR-TO-YEAR CONSISTENCY

Is the conclusion of no significant cost or benefit to social screening just a long-run effect? What happens in sub-periods? How consistent is this on a year-to-year or even quarter-to-quarter basis?

Exhibit 19 plots realized return cross-sections for the three major sub-periods. The results persist. The cross-section for the entire universe and the screened universe with all KLD exclusions are very similar in each sub-period. While not plotted here, we obtain the similar results for each individual screen.

9. THE UPPER QUARTILE FUND

For an active long-only investor, the most pertinent part of the cross-section is the upper end. Let us focus on the top quartile (top five portfolios in forecasted return score).

We shall call the combination of the top five portfolios an **upper quartile fund**. Exhibit 20 compares Sharpe ratios for the upper quartile fund from the overall universe and a similar upper quartile fund formed by using all KLD screens. Using all the KLD screens to construct a "socially screened upper-quartile fund" does not cause any change in reward-to-risk. Similar conclusions pertain to the individual screens. For the upper quartile fund, the Sharpe ratios (reward-to-risk ratios) for Q384 through the end of Q497 are identical except for one screen, ALG#2.

10. FORECAST VARIATIONS: SUPPRESSING THE IMPACT OF BOTH THE EARNINGS YIELD AND THE BOOK-TO-MARKET RATIO ON FORECASTED RETURN PERFORMANCE

We have used the GGS [1997] security return forecasting model as an illustrative value-focused forecasting framework. Three questions arise. How sensitive are the results to this particular model? Will they hold for other value-style models? Will they hold for any empirically estimated momentum-structure model including a growth-focused model?

A closely related question pertains to two of the model variables, namely the earnings-price ratio and the book-to-market ratio. Both are well-established anomaly variables. Is this really just a composite anomaly cross-section? Is the substance of the results simply that a composite earnings-price and book-to-market anomaly is insensitive to KLD social screens?

We cannot say how growth-style active forecasts would perform under social exclusions. The fact that we use growth as a control variable means that this question is outside the scope of our study. The same pertains to size rotation and other sector capitalization styles. Size is controlled and thus size-based active investing is outside of the scope of this study.

Our results are clearly limited to value style active investing. However, our results are amazingly robust to variations in value variables. To illustrate, we can remove both the earnings-price ratio and the book-to-market ratio by making them additional control variables in the MAP.

The return possibility cross-sections with both of these variables suppressed are plotted in Exhibit 21. This shows a moderate reduction in the range of realized return but otherwise remarkable robustness, especially for the top quartile that is most pertinent to active management. Moreover, this cross-section establishes that the conclusion of no significant performance difference is not an artifact of either the known book-to-market anomaly or the earnings-price anomaly or a combination of the two.

While not shown here, one-at-a-time suppression of the other model variables shows that our results hold for many variations to the GGS [1997] model and thus for most empirically estimated value-style forecasting models. Our results are extremely robust to any empirically estimated value-focused forecasting approach for this sample in this time period.

11. CONTROL IMPACT ASSESSMENT

We have used the portfolio mean of each control to define control-matched portfolios. How similar are the distributions of each control variable within each of the twenty portfolios in the cross-section?

Exhibit 22 plots the long-run average of each control and the average standard deviation about the mean. These values are for the overall sample. These plots show very little variation in the standard deviation of any control. There is, however, some tendency for growth to be less disperse in upper the quartiles. There is also some cross-sectional variation in the standard deviation of size but no systematic increase or decrease.

Exhibit 23 plots the long-run average return plus a one standard deviation confidence band above and below the predicted return. While the standard deviation is somewhat smaller for the low and high return predictions (unlike many rank-ordering forecasts that tend to show greater dispersion for the extremes), there is again no dramatic cross-sectional variation in the realized standard deviations.

The almost constant standard deviation across the twenty-portfolio cross-section is the reason that the comparative return and comparative Sharpe ratios have very similar cross-sections.

12. CONTROL VALUES AFTER SCREENING

The cross-sections for the screened subsamples have securities excluded. The MAP matches controls to the population mean. Thus, it is pertinent to ask how much the mean of each control shifted for each KLD exclusion and the overall combination of all KLD exclusions.

Exhibit 24 shows the average value of each control variable for the overall sample and each KLD exclusion. Beta does not change. There is no significant shift in dividend yield or growth. However, size does decrease some for each KLD exclusion. In combination, there is a significant drop in size. To the extent that there is a small positive return to the size factor, the variation in size between samples gives a bias toward higher return for the screened cross-sections, especially the one with all KLD screens in combination. It is for this reason that we conclude, "no significant performance cost" rather than "slight performance advantage" in characterizing our results. Clearly, size is the control variable that merits further refinement in future work.

13. SYNTHESIS: SOCIAL SCREENING IMPACT

This study has used an illustrative security return forecast and the construction of a forecast-based cross-section of otherwise matched portfolios to study (in the sense of systematic back testing) how social screening impacts active portfolio management, where "active" here means based on a value-focused statistical prediction of security returns.

We believe that this paper greatly expands the generality and robustness of our major conclusion: no significant cost to social screening. "**No significant cost**" means no statistically significant difference in risk-adjusted return for the performance possibility cross-section and especially for the upper quartile on which an active long-only manager would focus. This result also means no significant benefit to social screening.

The time period has been expanded to 1984-1997. This includes the market break of October 1987 and the down market of 1989-90. The conclusion of no significant cost holds for major subperiods: 1984-88, 1989-93, and 1994-97. Most importantly for a long-only fund manager, results for the screened and unscreened upper quartile funds are remarkably consistent on a quarter-to-quarter and year-to-year basis. The conclusion of no significant cost/benefit is not just a long-run average. It has remarkable short-run consistency!

Previous studies of actively managed socially responsible funds have focused on explaining differences within a factor adjustment framework. As noted in our review of previous research, the consensus view seemed to be that superior returns were attributable to greater risk, higher growth, and smaller size outweighing any negative impact of a higher price-earnings ratio. Dividend yield (tax effects) have generally not been given serious attention as a performance adjustment factor in these analyses.

These results raise the possibility that performance from social screening could be "**brittle,**" i.e., very sensitive to market environment. The 1990s markets have rewarded both risk bearing and a growth-focused investment style. Moreover both size and price-earnings factors have exhibited high quarter-to-quarter and year-to-year variation in performance impact. Thus, in a market adverse to risk bearing, growth, size, and/or high price-earning's ratios, socially responsible portfolios could do worse because of their factor exposures.

It is important to separate assessments of socially responsible investment performance from particular factor exposures. By constructing forecast cross-sections of portfolios matched over the entire cross-sections on risk (beta), growth, size, and dividend yield, we have eliminated most cross-sectional impact from these particular performance factors. Thus, our conclusion of "no significant cost/benefit from social screens" is robust to these factor exposures although there is enough size-shift in combined screens that some caution about size here is pertinent.

This study has only considered social screens and not positive social tilts. For social screens similar to the KLD screens used in this study, the conclusion of no significant cost is not dependent on favorable factor exposures. Moreover, our conclusion of no significant cost seems remarkably robust on a number of dimensions. First, the cross-time, both quarter-to-quarter and year-to-year consistency is remarkably strong, especially for the upper quartile pertinent to active long-only management. Second, while not studied in depth here, the results are robust to variations in the value-focused forecast model including especially suppression of the earnings-price and book-to-market variables. Third, the results seem to hold for both individual KLD screens and all combinations. Thus, industry-level performance factors associated with some screens do not cause significant performance differences <u>when</u> one controls for factor exposures. Finally, given the previous view that growth, size and/or risk-bearing were possibly sources of performance for socially screened portfolios, our extension here to value style active management greatly broadens the set of investment styles for which we can argue strong evidence of no significant performance cost once one controls for systematic market risk and other priced factors.

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EXHIBIT 1

SUMMARY: THE FUNDAMENTAL VALUE-FOCUSED REGRESSION-ESTIMATED SECURITY RETURN FORECASTING MODEL

<u>FUNDAMENTAL VARIABLES: CURRENT</u>

EP	=	[earnings per share]/[price per share]	=	earnings-price ratio
BP	=	[book value per share]/[price per share]	=	book-price ratio
CP	=	[cash flow per share]/[price per share]	=	cash flow-price ratio
SP	=	[net sales per share]/[price per share]	=	sales-price ratio
EF	=	consensus earnings-per-share forecast in I/B/E/S		

<u>FUNDAMENTAL VARIABLES: SMOOTHED</u>

REP	=	[current EP ratio]/[average EP ratio over the past five years]
RBP	=	[current BP ratio]/[average BP ratio over the past five years]
RCP	=	[current CP ratio]/[average CP ratio over the past five years]
RSP	=	[current SP ratio]/[average SP ratio over the past five years]

<u>FUNDAMENTAL REGRESSION MODEL</u>

$$TR_s = a_o + a_1EP_s + a_2BP_s + a_3CP_s + a_4SP_s + a_5REP_s + a_6RBP_s + a_7BCP_s + a_8RSP_s + a_9EF_s + E_s$$

<u>TIME-AVERAGE VALUE OF ESTIMATED COEFFICIENTS</u>

a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
.115	.034	.081	.071	.047	.055	.036	.085	.441

<u>REFERENCE:</u> Guerard, Gultekin, & Stone, <u>Research in Finance</u> [1997].

EXHIBIT 2
LOGIC: GENERATION OF RETURN FORECASTS

First Pass Regression Estimation

Use fundamental data and I/B/E/S forecasts to estimate regression coefficients that best explain returns in past year.

↓

Prediction Model Paramaterization

1. Adjust most recently estimated model to zero out wrong sign and insignificant coefficients.
2. Smooth by averaging current coefficients and previously estimated values.

Result: Updated coefficients for return prediction model.

↓

Quarterly Return Forecast Generation

1. Obtain most recent value of EP, BP, CP, SP.
2. Obtain most recent earnings forecasts from I/B/E/S.
3. Use updated coefficients and data in steps 1 and 2 above to forecast quarterly return for each security.

↓

Portfolio Formation

1. Use predicted security returns to form twenty range-based fractiles.
2. Input into mathematical assignment program (MAP) to create a cross-section of twenty forecast-ordered, control-matched portfolios.

EXHIBIT 3
VERBAL SUMMARY: MATHEMATICAL ASSIGNMENT PROGRAM (MAP) THAT TRANSFORMS TWENTY RANGE-BASED FRACTILE PORTFOLIOS INTO TWENTY FORECAST-ORDERED CONTROL-MATCHED PORTFOLIOS

OBJECTIVE FUNCTION

Maximize the range of forecasted returns while minimizing the cross-fractile security shifting required to produce otherwise matched portfolios.

PORTFOLIO SIZE: FULL ASSIGNMENT

1. The number of securities in each portfolio are the same as the number of securities in the corresponding fractile of the forecasted return distribution.

2. All securities are assigned to at least one portfolio but fractional assignment is allowed to meet constant value or equal increment constraints exactly.

CONTROL CONSTRAINTS

Make the portfolio average value of each of the twenty fractile-based portfolios identical for the following control variables:

1. beta
2. market capitalization
3. growth
4. dividend yield

EQUAL INCREMENT CONSTRAINT

Provide for well-ordered cross-sectional variation in the forecasted return variable by having the same increment in the value of forecasted portfolio return between each pair of rank-ordered portfolios.

COMMENTS

1. The starting range-based fractiles have approximately equal increments in forecasted portfolio return. The equal-increment constraint preserves the well-ordered spacing in the starting fractiles.

2. See Stone, Guerard, and Gultekin [2001] for a detailed, step-by-step formulation of the MAP summarized verbally here. See Stone [2001] for an algorithm that produces an exact distributional match.

EXHIBIT 4
LOGIC: GENERATION OF MATCHED PORTFOLIOS AND THE PERFORMANCE POSSIBILITY CROSS-SECTION

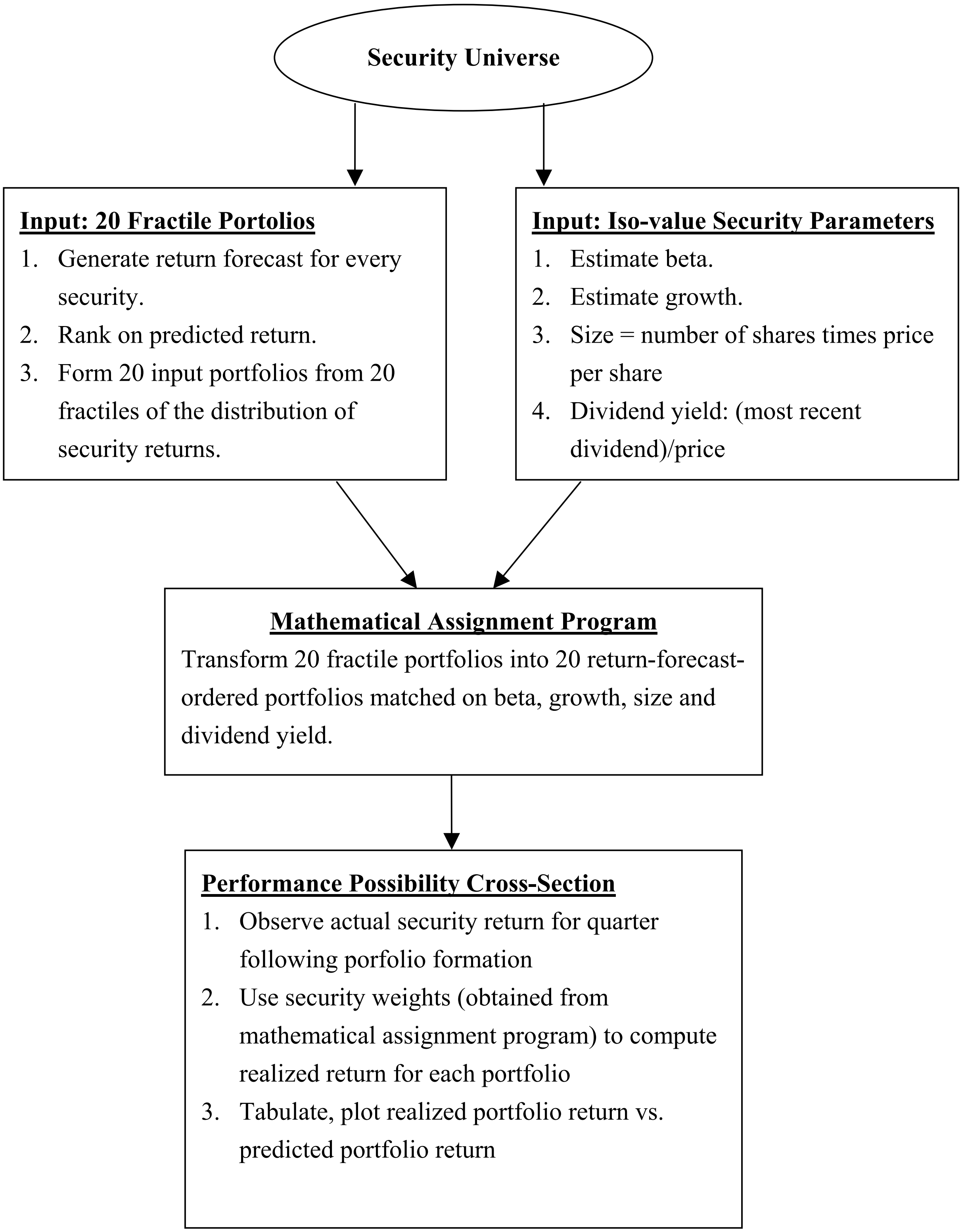


EXHIBIT 5
EX-ANTE RANK, REALIZED RETURN
BY QUARTER AND PORTFOLIO

TIME	PORTFOLIO NUMBER																			
	1		2		3		4		5		6		7		8		9		10	
Q384	5.4	0.03	10.0	0.02	14.6	0.06	19.2	0.04	23.8	0.08	28.4	0.06	33.0	0.06	37.6	0.08	42.3	0.07	46.9	0.09
Q484	4.7	-0.05	9.4	-0.04	14.1	-0.01	18.7	-0.03	23.4	-0.02	28.1	-0.03	32.8	-0.00	37.5	-0.02	42.1	0.02	46.8	0.00
Q185	4.9	0.12	9.5	0.08	14.2	0.11	18.8	0.07	23.5	0.09	28.1	0.09	32.8	0.12	37.4	0.13	42.1	0.12	46.7	0.12
Q285	4.7	-0.04	9.3	0.03	14.0	0.01	18.7	0.00	23.3	0.01	28.0	0.04	32.6	0.04	37.3	0.03	41.9	0.05	46.6	0.02
Q385	3.5	-0.02	8.3	-0.06	13.1	-0.05	17.9	-0.02	22.7	-0.06	27.5	-0.04	32.3	-0.06	37.1	-0.03	41.9	-0.03	46.7	-0.02
Q485	3.9	0.10	8.6	0.10	13.4	0.08	18.1	0.14	22.9	0.15	27.6	0.12	32.4	0.16	37.1	0.13	41.9	0.16	46.6	0.14
Q186	3.3	0.22	8.1	0.10	12.9	0.08	17.7	0.10	22.5	0.10	27.3	0.07	32.2	0.14	37.0	0.18	41.8	0.13	46.6	0.15
Q286	3.8	0.02	8.5	-0.02	13.3	0.02	18.0	0.00	22.8	-0.01	27.6	0.02	32.3	0.02	37.1	0.02	41.8	0.02	46.6	0.03
Q386	3.7	-0.11	8.5	-0.11	13.3	-0.13	18.0	-0.08	22.8	-0.06	27.5	-0.10	32.3	-0.06	37.0	-0.08	41.8	-0.11	46.6	-0.06
Q486	4.2	0.05	8.9	0.03	13.6	0.03	18.3	0.02	23.0	0.02	27.8	0.02	32.5	0.05	37.2	0.04	41.9	0.07	46.7	-0.01
Q187	3.5	0.22	8.3	0.26	13.1	0.18	17.9	0.25	22.6	0.23	27.4	0.20	32.2	0.20	37.0	0.25	41.8	0.22	46.6	0.22
Q287	3.5	-0.03	8.3	0.02	13.0	0.06	17.8	0.04	22.6	-0.01	27.4	0.02	32.2	0.02	37.0	0.03	41.8	0.05	46.6	0.01
Q387	5.4	0.00	10.0	0.03	14.6	0.07	19.2	0.04	23.8	0.06	28.4	0.09	33.0	0.04	37.6	0.04	42.2	0.07	46.8	0.08
Q487	3.3	-0.28	8.2	-0.32	13.0	-0.29	17.8	-0.28	22.6	-0.26	27.4	-0.28	32.2	-0.26	37.0	-0.27	41.9	-0.26	46.7	-0.24
Q188	4.0	0.18	8.8	0.19	13.5	0.13	18.3	0.15	23.0	0.13	27.7	0.20	32.5	0.19	37.2	0.20	42.0	0.14	46.7	0.16
Q288	3.2	0.06	8.0	0.07	12.8	0.08	17.7	0.03	22.5	0.03	27.3	0.01	32.1	0.05	37.0	0.01	41.8	0.07	46.6	0.07
Q388	3.6	-0.01	8.4	0.02	13.2	-0.01	18.0	0.01	22.8	-0.00	27.6	-0.03	32.4	-0.04	37.1	-0.01	41.9	-0.06	46.7	-0.02
Q488	4.2	0.01	9.0	0.03	13.7	0.01	18.4	-0.02	23.1	0.01	27.8	-0.03	32.6	-0.02	37.3	-0.04	42.0	0.00	46.7	0.04
Q189	4.3	0.08	9.0	0.09	13.7	0.06	18.4	0.06	23.1	0.09	27.8	0.06	32.5	0.07	37.3	0.12	42.0	0.08	46.7	0.08
Q289	3.2	0.04	8.0	0.03	12.8	0.04	17.7	0.05	22.5	0.08	27.3	0.09	32.2	0.06	37.0	0.04	41.8	0.08	46.6	0.08
Q389	3.1	-0.03	7.9	0.05	12.7	0.05	17.6	0.05	22.4	0.05	27.2	0.07	32.1	0.09	36.9	0.05	41.8	0.11	46.6	0.04
Q489	3.6	-0.05	8.4	-0.09	13.2	-0.05	18.0	-0.04	22.7	-0.04	27.5	0.00	32.3	-0.05	37.1	-0.04	41.9	-0.05	46.6	-0.00
Q190	3.2	-0.01	8.0	-0.07	12.8	-0.00	17.6	-0.05	22.5	-0.03	27.3	-0.01	32.1	-0.03	36.9	-0.02	41.8	-0.02	46.6	-0.01
Q290	3.6	0.05	8.4	0.06	13.2	0.06	17.9	0.03	22.7	0.05	27.5	0.03	32.3	0.08	37.1	0.04	41.9	0.03	46.7	0.03
Q390	3.6	-0.21	8.4	-0.21	13.1	-0.19	17.9	-0.23	22.7	-0.22	27.5	-0.21	32.3	-0.24	37.0	-0.19	41.8	-0.19	46.6	-0.22
Q490	3.3	-0.03	8.1	-0.01	12.9	0.04	17.7	0.05	22.5	0.09	27.3	0.07	32.1	0.10	36.9	0.05	41.8	0.06	46.6	0.06
Q191	3.5	0.28	8.2	0.23	13.0	0.29	17.8	0.28	22.6	0.24	27.4	0.31	32.2	0.24	37.0	0.20	41.8	0.23	46.6	0.22
Q291	4.5	0.00	9.1	0.03	13.8	-0.00	18.5	0.00	23.2	0.01	27.9	0.02	32.5	0.01	37.2	0.02	41.9	0.01	46.6	0.02
Q391	3.2	0.04	8.0	0.02	12.9	0.01	17.7	0.05	22.5	0.03	27.3	0.02	32.2	0.05	37.0	0.07	41.8	0.12	46.6	0.12
Q491	2.8	0.03	7.7	0.03	12.5	0.04	17.4	0.03	22.2	0.06	27.1	0.08	32.0	0.07	36.8	0.11	41.7	0.08	46.5	0.10
Q192	3.5	0.10	8.3	0.04	13.1	0.07	17.9	0.02	22.6	0.08	27.4	0.01	32.2	0.10	37.0	0.02	41.8	0.08	46.6	0.06
Q292	4.0	-0.10	8.7	-0.07	13.4	-0.08	18.2	-0.05	22.9	-0.09	27.6	-0.07	32.4	-0.10	37.1	-0.04	41.9	-0.05	46.6	-0.05
Q392	4.6	-0.02	9.3	0.01	14.0	-0.00	18.6	-0.01	23.3	0.03	28.0	0.02	32.6	0.03	37.3	0.06	42.0	0.05	46.6	0.05
Q492	4.6	0.10	9.3	0.12	13.9	0.12	18.6	0.17	23.3	0.17	27.9	0.15	32.6	0.17	37.3	0.13	42.0	0.16	46.6	0.13
Q193	4.7	-0.01	9.3	0.05	14.0	0.03	18.7	-0.01	23.3	-0.02	28.0	0.05	32.6	0.08	37.3	0.06	42.0	0.04	46.6	0.07
Q293	3.0	-0.01	7.8	-0.01	12.7	0.01	17.5	-0.02	22.4	0.02	27.2	0.00	32.0	-0.02	36.9	-0.02	41.7	0.04	46.6	0.03
Q393	2.6	0.01	7.5	0.04	12.4	0.01	17.3	0.06	22.2	0.05	27.0	0.01	31.9	0.08	36.8	0.06	41.7	0.05	46.6	0.07
Q493	2.9	0.05	7.8	0.04	12.6	0.05	17.5	0.02	22.3	0.06	27.2	0.07	32.0	0.05	36.9	0.04	41.7	0.02	46.6	0.01
Q194	2.7	-0.00	7.6	-0.01	12.4	-0.02	17.3	-0.02	22.2	-0.04	27.1	-0.01	31.9	-0.01	36.8	-0.03	41.7	-0.02	46.6	-0.00
Q294	2.8	-0.05	7.6	-0.04	12.5	-0.01	17.4	-0.05	22.2	-0.06	27.1	-0.03	32.0	-0.05	36.8	-0.05	41.7	-0.01	46.6	-0.03
Q394	2.9	0.05	7.7	0.03	12.6	0.08	17.4	0.09	22.3	0.07	27.2	0.10	32.0	0.06	36.9	0.04	41.7	0.08	46.6	0.05
Q494	2.8	-0.06	7.7	-0.05	12.6	-0.02	17.4	-0.06	22.3	-0.03	27.2	-0.00	32.0	-0.00	36.9	0.01	41.7	0.01	46.6	0.00
Q195	2.8	0.06	7.7	0.08	12.6	0.07	17.4	0.04	22.3	0.07	27.2	0.10	32.0	0.06	36.9	0.06	41.8	0.04	46.6	0.06
Q295	3.4	0.12	8.2	0.10	13.0	0.10	17.8	0.07	22.6	0.12	27.4	0.10	32.2	0.07	37.0	0.15	41.8	0.14	46.6	0.09
Q395	2.8	0.09	7.7	0.03	12.5	0.06	17.4	0.08	22.2	0.06	27.1	0.10	32.0	0.10	36.8	0.11	41.7	0.09	46.5	0.07
Q495	3.6	-0.04	8.4	-0.03	13.1	0.00	17.9	-0.02	22.7	-0.05	27.5	0.03	32.3	-0.02	37.0	0.02	41.8	0.05	46.6	0.07
Q196	3.0	0.07	7.9	0.04	12.7	0.06	17.6	0.04	22.4	0.09	27.2	0.06	32.1	0.03	36.9	0.00	41.8	0.03	46.6	0.05
Q296	3.5	0.04	8.3	0.07	13.1	0.05	17.9	0.06	22.7	0.01	27.4	0.08	32.2	0.06	37.0	0.06	41.8	0.06	46.6	0.05
Q396	3.2	-0.01	8.0	-0.01	12.8	-0.02	17.6	-0.02	22.4	0.00	27.3	-0.03	32.1	-0.01	36.9	-0.03	41.7	0.01	46.5	-0.03
Q496	3.7	0.05	8.5	0.03	13.2	0.06	18.0	0.03	22.7	0.06	27.5	0.07	32.3	0.06	37.0	0.08	41.8	0.08	46.5	0.04
Q197	2.6	-0.02	7.5	-0.03	12.4	-0.01	17.2	-0.04	22.1	-0.04	27.0	-0.03	31.9	-0.03	36.8	-0.03	41.7	0.00	46.5	-0.04
Q297	2.7	0.13	7.6	0.14	12.4	0.11	17.3	0.12	22.2	0.13	27.1	0.12	31.9	0.13	36.8	0.15	41.7	0.13	46.6	0.19
Q397	3.1	0.14	7.9	0.20	12.6	0.16	17.6	0.16	22.4	0.14	27.3	0.16	32.1	0.12	36.9	0.19	41.8	0.14	46.6	0.19
Q497	2.7	-0.09	7.6	-0.06	12.5	-0.07	17.3	-0.06	22.2	-0.07	27.1	-0.05	31.9	-0.05	36.8	-0.06	41.7	-0.05	46.5	0.02

EXHIBIT 5
EX-ANTE RANK, REALIZED RETURN
BY QUARTER AND PORTFOLIO

TIME	PORTFOLIO NUMBER																			
	11		12		13		14		15		16		17		18		19		20	
Q384	51.5	0.08	56.1	0.09	60.7	0.10	65.3	0.08	69.9	0.06	74.5	0.07	79.2	0.08	83.8	0.10	88.4	0.05	93.0	0.09
Q484	51.5	-0.00	56.2	-0.02	60.9	0.01	65.5	0.04	70.2	0.02	74.9	0.05	79.6	0.02	84.3	0.01	88.9	0.05	93.6	-0.00
Q185	51.4	0.15	56.0	0.11	60.7	0.12	65.3	0.10	70.0	0.15	74.6	0.13	79.3	0.09	83.9	0.11	88.6	0.16	93.2	0.19
Q285	51.2	0.04	55.9	0.07	60.6	0.09	65.2	0.08	69.9	0.05	74.5	0.04	79.2	0.07	83.8	0.07	88.5	0.06	93.1	0.05
Q385	51.4	-0.04	56.2	-0.03	61.0	-0.07	65.8	-0.03	70.6	0.01	75.4	-0.01	80.2	-0.02	85.0	-0.01	89.8	-0.04	94.6	-0.00
Q485	51.4	0.12	56.1	0.18	60.9	0.19	65.6	0.14	70.4	0.13	75.1	0.16	79.9	0.15	84.6	0.18	89.4	0.19	94.1	0.20
Q186	51.4	0.06	56.2	0.11	61.0	0.14	65.8	0.15	70.6	0.13	75.5	0.14	80.3	0.18	85.1	0.15	89.9	0.21	94.7	0.20
Q286	51.3	0.08	56.1	0.02	60.9	0.07	65.6	0.05	70.4	0.06	75.1	0.03	79.9	0.07	84.6	0.08	89.4	0.07	94.2	0.06
Q386	51.3	-0.10	56.1	-0.08	60.8	-0.12	65.6	-0.07	70.3	-0.09	75.1	-0.11	79.9	-0.09	84.6	-0.11	89.4	-0.07	94.1	-0.10
Q486	51.4	0.02	56.1	0.03	60.8	0.01	65.5	0.03	70.3	0.01	75.0	0.03	79.7	0.08	84.4	0.07	89.1	0.06	93.9	0.04
Q187	51.4	0.23	56.2	0.23	61.0	0.27	65.7	0.28	70.5	0.24	75.3	0.25	80.1	0.24	84.9	0.23	89.7	0.23	94.5	0.32
Q287	51.4	-0.01	56.2	0.00	61.0	0.02	65.8	0.01	70.6	0.04	75.4	0.03	80.1	0.05	84.9	0.05	89.7	0.06	94.5	0.08
Q387	51.4	0.04	55.9	0.06	60.5	0.08	65.1	0.07	69.7	0.07	74.3	0.09	78.9	0.10	83.5	0.06	88.1	0.06	92.7	0.08
Q487	51.5	-0.27	56.3	-0.27	61.1	-0.26	65.9	-0.27	70.7	-0.29	75.6	-0.25	80.4	-0.25	85.2	-0.21	90.0	-0.21	94.8	-0.24
Q188	51.5	0.20	56.2	0.15	60.9	0.18	65.7	0.22	70.4	0.21	75.2	0.29	79.9	0.14	84.6	0.15	89.4	0.13	94.1	0.15
Q288	51.5	0.08	56.3	0.04	61.1	0.11	65.9	0.08	70.8	0.06	75.6	0.06	80.4	0.09	85.3	0.09	90.1	0.08	94.9	0.15
Q388	51.5	0.01	56.3	-0.01	61.1	0.04	65.9	-0.01	70.7	-0.01	75.5	-0.01	80.3	0.00	85.1	-0.02	89.8	-0.04	94.6	0.01
Q488	51.5	-0.01	56.2	0.01	60.9	-0.02	65.6	-0.00	70.4	0.03	75.1	0.02	79.8	0.02	84.5	0.01	89.2	0.06	94.0	0.04
Q189	51.4	0.07	56.1	0.09	60.8	0.10	65.5	0.06	70.2	0.09	74.9	0.03	79.7	0.07	84.4	0.10	89.1	0.06	93.8	0.10
Q289	51.5	0.05	56.3	0.06	61.1	0.07	65.9	0.08	70.8	0.07	75.6	0.06	80.4	0.08	85.2	0.10	90.1	0.04	94.9	0.09
Q389	51.4	0.08	56.3	0.07	61.1	0.09	65.9	0.06	70.8	0.09	75.6	0.11	80.5	0.08	85.3	0.12	90.1	0.08	95.0	0.10
Q489	51.4	0.03	56.2	-0.03	61.0	-0.02	65.8	-0.04	70.5	0.00	75.3	-0.02	80.1	-0.03	84.9	-0.02	89.7	-0.03	94.4	-0.03
Q190	51.4	-0.04	56.2	-0.04	61.1	-0.02	65.9	-0.03	70.7	0.04	75.5	-0.03	80.4	-0.03	85.2	0.00	90.0	0.01	94.8	-0.00
Q290	51.4	0.07	56.2	0.05	61.0	0.07	65.8	0.08	70.6	0.06	75.4	0.07	80.2	0.05	84.9	0.06	89.7	0.07	94.5	0.10
Q390	51.4	-0.20	56.2	-0.17	60.9	-0.18	65.7	-0.21	70.5	-0.22	75.3	-0.22	80.1	-0.18	84.8	-0.17	89.6	-0.21	94.4	-0.18
Q490	51.4	0.04	56.2	0.08	61.0	0.08	65.8	0.05	70.6	-0.01	75.4	0.11	80.3	0.10	85.1	0.06	89.9	0.12	94.7	0.07
Q191	51.4	0.28	56.2	0.23	61.0	0.27	65.8	0.28	70.6	0.31	75.4	0.32	80.2	0.24	85.0	0.24	89.8	0.28	94.6	0.31
Q291	51.3	-0.01	56.0	-0.01	60.6	-0.01	65.3	0.04	70.0	0.00	74.7	0.04	79.4	-0.02	84.0	-0.00	88.7	-0.01	93.4	0.02
Q391	51.5	0.10	56.3	0.04	61.1	0.09	65.9	0.07	70.8	0.03	75.6	0.07	80.4	0.05	85.2	0.09	90.1	0.09	94.9	0.07
Q491	51.4	0.18	56.3	0.01	61.1	0.04	66.0	0.03	70.8	0.08	75.7	0.04	80.5	0.06	85.4	0.02	90.3	0.04	95.1	0.09
Q192	51.4	0.09	56.2	0.09	61.0	0.10	65.7	0.05	70.5	0.11	75.3	0.15	80.1	0.08	84.9	0.12	89.7	0.14	94.5	0.09
Q292	51.3	-0.05	56.1	0.00	60.8	-0.05	65.5	-0.04	70.3	-0.06	75.0	-0.01	79.8	-0.06	84.5	-0.04	89.2	-0.05	94.0	-0.02
Q392	51.3	0.01	56.0	0.04	60.6	0.07	65.3	0.03	70.0	0.06	74.6	0.06	79.3	0.03	83.9	0.00	88.6	0.03	93.3	0.00
Q492	51.3	0.10	56.0	0.09	60.7	0.12	65.3	0.12	70.0	0.12	74.7	0.15	79.4	0.12	84.0	0.16	88.7	0.19	93.4	0.17
Q193	51.3	0.07	55.9	0.05	60.6	0.03	65.3	0.04	69.9	0.04	74.6	0.07	79.2	0.09	83.9	0.06	88.6	0.09	93.2	0.06
Q293	51.4	0.01	56.2	0.00	61.1	0.04	65.9	0.03	70.8	0.05	75.6	0.04	80.4	0.03	85.3	0.02	90.1	0.04	95.0	0.07
Q393	51.5	0.09	56.3	0.09	61.2	0.05	66.1	0.06	71.0	0.11	75.9	0.08	80.8	0.08	85.6	0.11	90.5	0.09	95.4	0.09
Q493	51.4	0.06	56.3	0.03	61.1	0.06	66.0	0.09	70.8	0.03	75.7	0.06	80.5	0.05	85.4	0.04	90.2	0.04	95.1	0.09
Q194	51.4	-0.02	56.3	-0.02	61.2	-0.01	66.1	0.01	71.0	0.01	75.8	-0.01	80.7	-0.02	85.6	-0.03	90.5	-0.01	95.3	-0.02
Q294	51.4	-0.02	56.3	-0.04	61.2	-0.04	66.1	-0.02	70.9	0.00	75.8	-0.02	80.7	-0.04	85.5	-0.04	90.4	-0.07	95.3	-0.03
Q394	51.5	0.10	56.3	0.06	61.2	0.04	66.0	0.11	70.9	0.10	75.8	0.08	80.6	0.11	85.5	0.08	90.3	0.08	95.2	0.09
Q494	51.5	0.02	56.3	-0.01	61.2	-0.03	66.1	-0.04	70.9	-0.03	75.8	-0.01	80.7	0.01	85.5	0.01	90.4	0.03	95.2	-0.01
Q195	51.5	0.01	56.4	0.07	61.2	0.08	66.1	0.09	71.0	0.12	75.8	0.08	80.7	0.09	85.6	0.09	90.4	0.11	95.3	0.11
Q295	51.4	0.07	56.3	0.08	61.1	0.07	65.9	0.09	70.7	0.10	75.5	0.11	80.3	0.09	85.1	0.12	89.9	0.10	94.7	0.12
Q395	51.4	0.09	56.3	0.07	61.1	0.09	66.0	0.09	70.8	0.05	75.7	0.06	80.6	0.09	85.4	0.11	90.3	0.13	95.1	0.08
Q495	51.4	-0.02	56.2	0.04	60.9	-0.01	65.7	0.01	70.5	0.04	75.3	-0.02	80.0	0.01	84.8	-0.02	89.6	0.00	94.4	-0.00
Q196	51.5	0.03	56.3	0.06	61.1	0.08	66.0	0.07	70.8	0.08	75.7	0.08	80.5	0.09	85.4	0.08	90.2	0.05	95.1	0.08
Q296	51.3	0.06	56.1	0.10	60.9	0.09	65.7	0.12	70.5	0.05	75.2	0.06	80.0	0.06	84.8	0.08	89.6	0.09	94.4	0.11
Q396	51.4	0.03	56.2	0.01	61.0	0.01	65.8	-0.01	70.6	0.03	75.4	0.02	80.3	-0.01	85.1	-0.02	89.9	-0.03	94.7	-0.00
Q496	51.3	0.00	56.0	0.04	60.8	0.02	65.6	0.05	70.3	0.08	75.1	0.03	79.8	0.02	84.6	0.07	89.3	0.03	94.1	0.08
Q197	51.4	-0.02	56.3	-0.01	61.2	0.02	66.1	-0.03	71.0	-0.02	75.9	0.00	80.7	-0.02	85.6	-0.03	90.5	-0.03	95.4	0.01
Q297	51.4	0.15	56.3	0.12	61.2	0.16	66.0	0.15	70.9	0.15	75.8	0.12	80.7	0.17	85.5	0.16	90.4	0.14	95.3	0.16
Q397	51.5	0.17	56.3	0.11	61.1	0.17	66.0	0.14	70.8	0.15	75.6	0.15	80.5	0.17	85.3	0.14	90.2	0.20	95.0	0.21
Q497	51.4	0.01	56.3	-0.08	61.2	-0.03	66.0	-0.05	70.9	-0.04	75.0	-0.06	80.6	-0.05	85.5	-0.06	90.4	-0.07	95.2	-0.06

Exhibit 6
PERFORMANCE POSSIBILITY CROSS-SECTION: AVERAGE TOTAL RETURN VS PREDICTED RETURN SCORE
Overall Sample: Q31984-Q41997

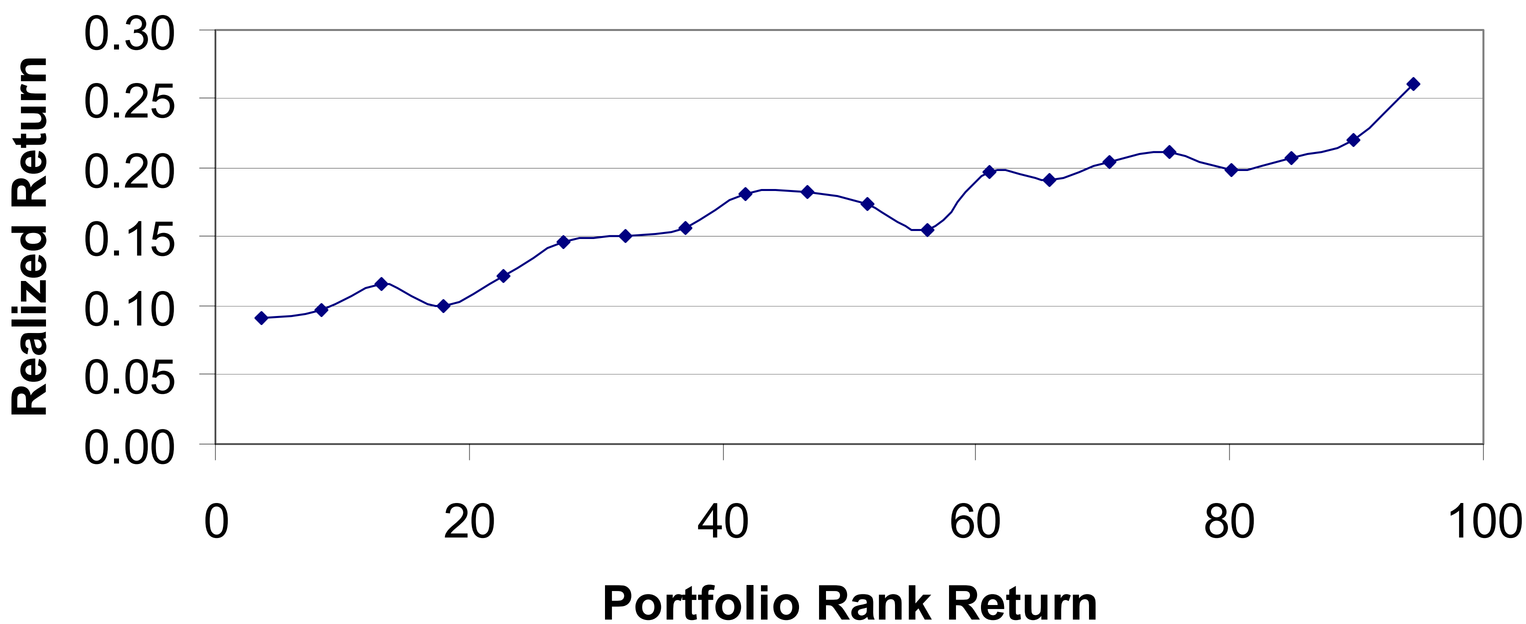
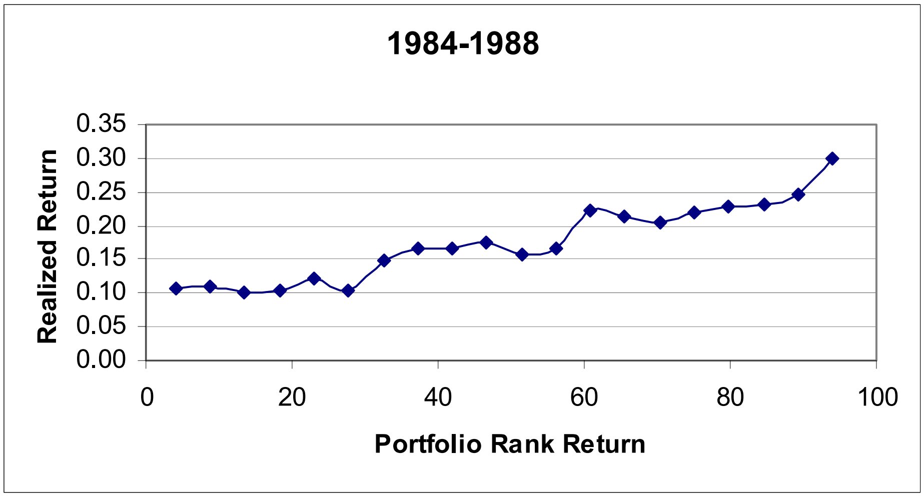
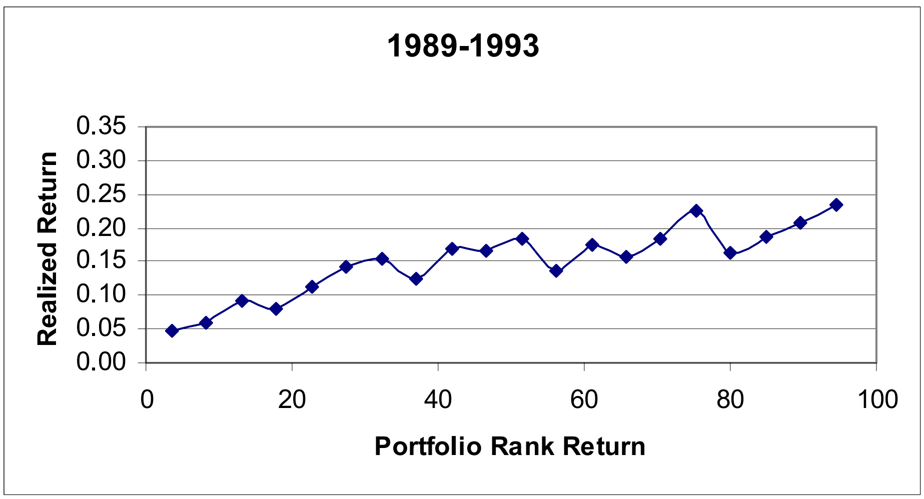


EXHIBIT 7
SUBPERIOD PERFORMANCE OF THE CROSS-SECTION OF COMPARATIVE RETURNS: AVERAGE TOTAL RETURN VS PREDICTED RETURN SCORE





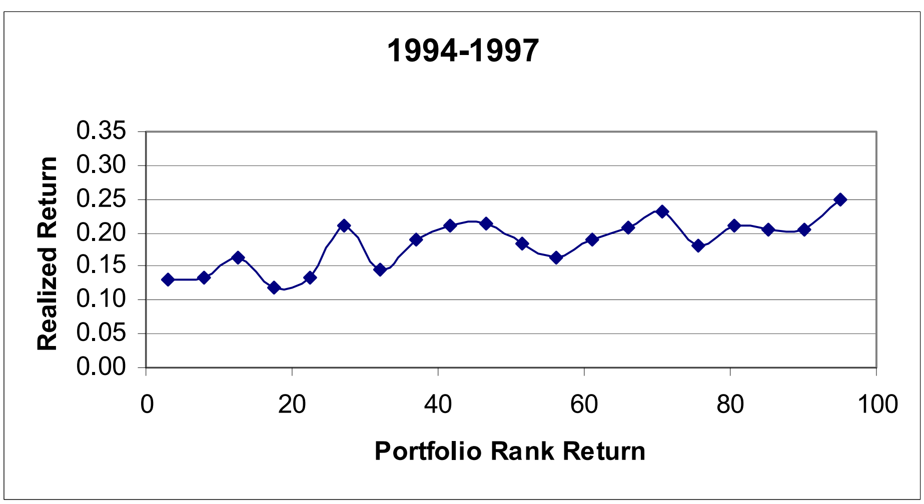
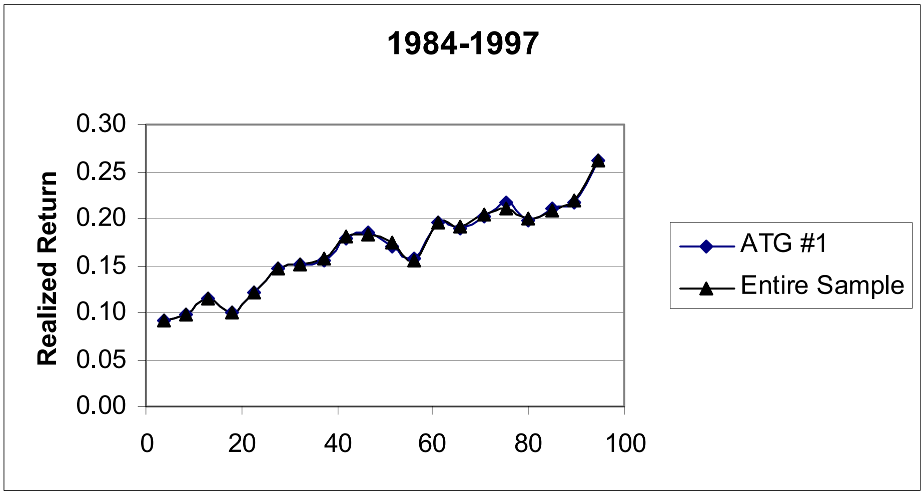
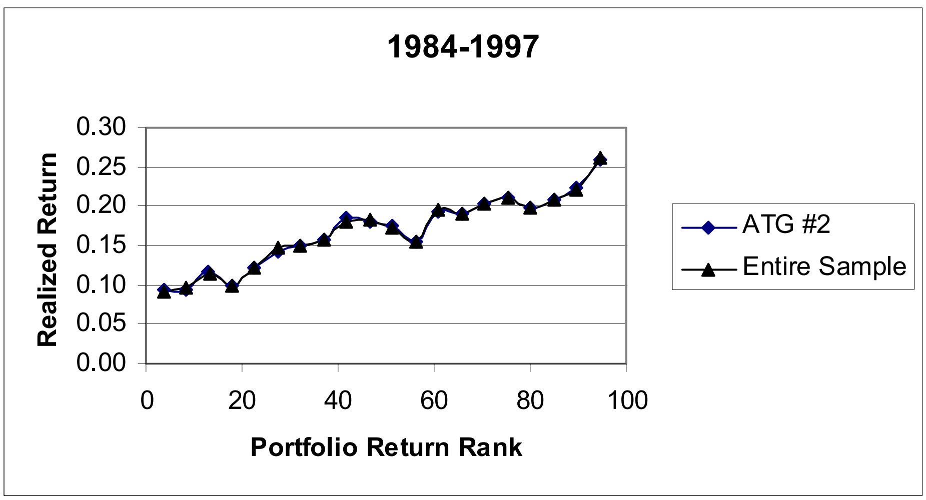


EXHIBIT 8
AVERAGE NUMBER OF STOCKS/QUARTER:
OVERALL SAMPLE AND SCREENED SUBSAMPLES

All matched stocks	**1334**
Alcohol, tobacco, and Gambling #1 screen	1286
Alcohol, tobacco, and Gambling #2 screen	1275
Alcohol, tobacco, and Gambling #3 screens	1227
Defense1 screen	1330
Defense2 screen	1326
Defense1&2 screens	1323
Environment1 screen	1308
Environment2 screen	1307
Environment1&2 screens	1281
Nuclear 1&2 screens	1320
All Screens	**1191**

EXIBIT 9
THE CROSS-SECTION OF COMPARATIVE RETURNS:
KLD ALCHOHOL, TOBACCO, AND GAMBLING SCREENS VS OVERALL SAMPLE





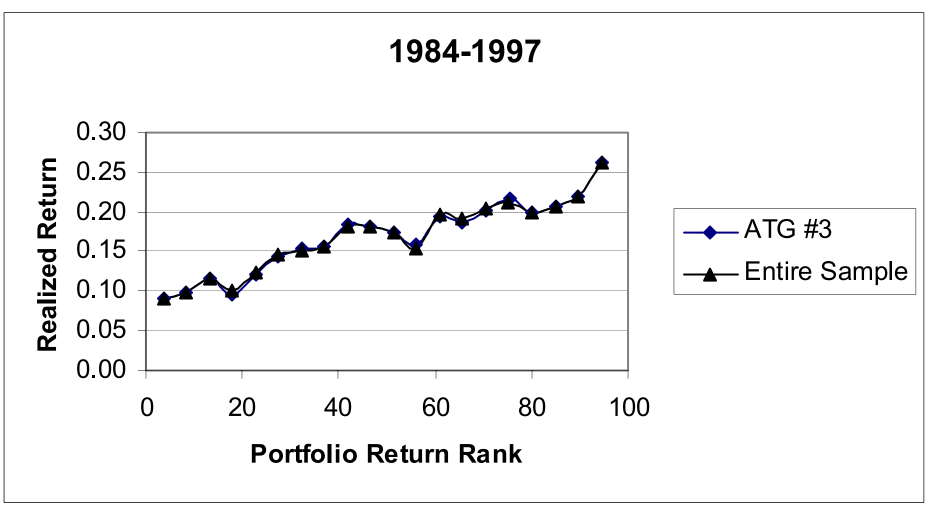
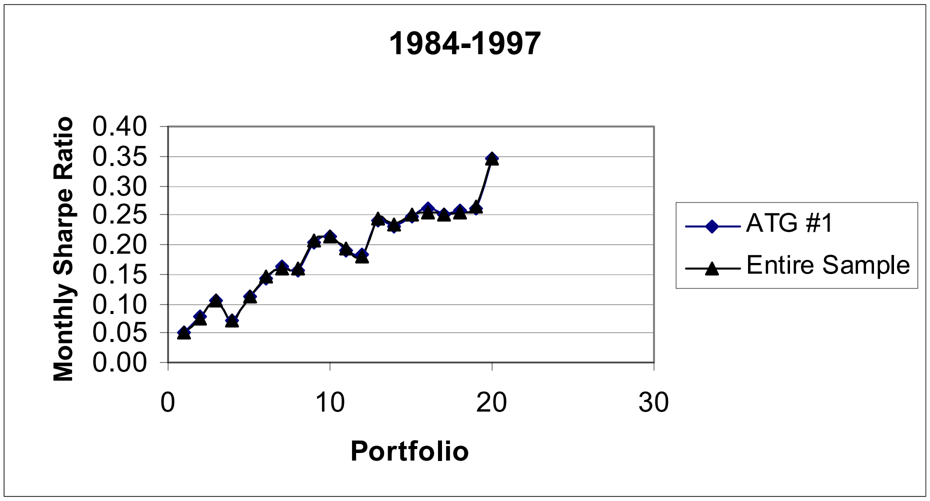
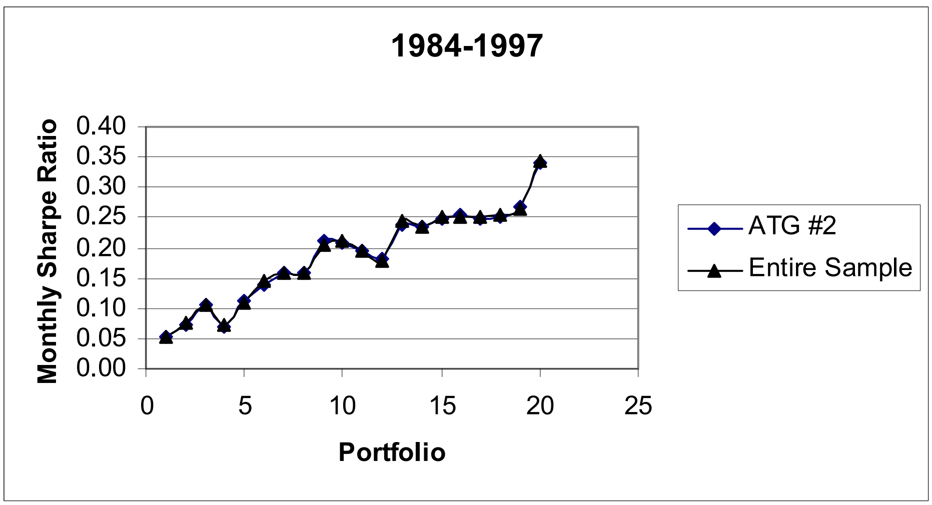


EXHIBIT 10
THE CROSS-SECTION OF COMPARATIVE SHARPE RATIOS:
KLD ALCHOHOL, TOBACCO, AND GAMBLING SCREENS VS OVERALL SAMPLE





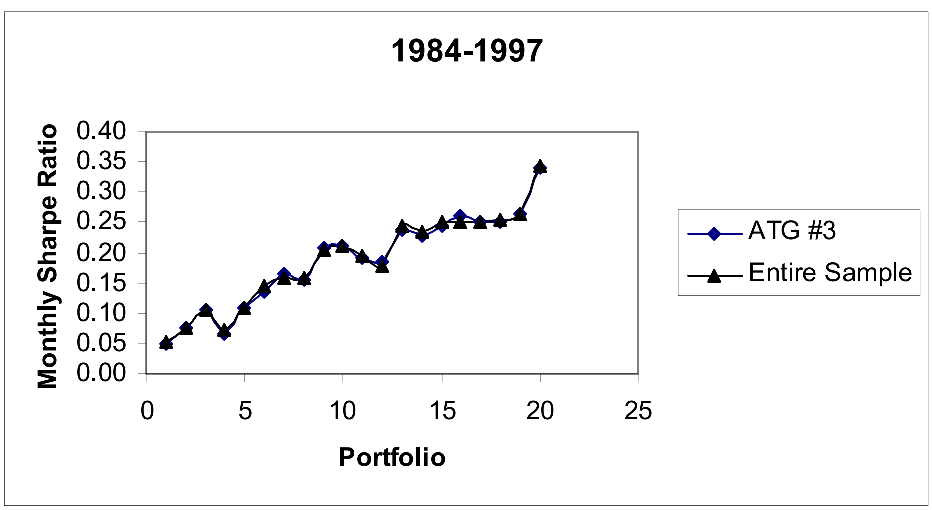
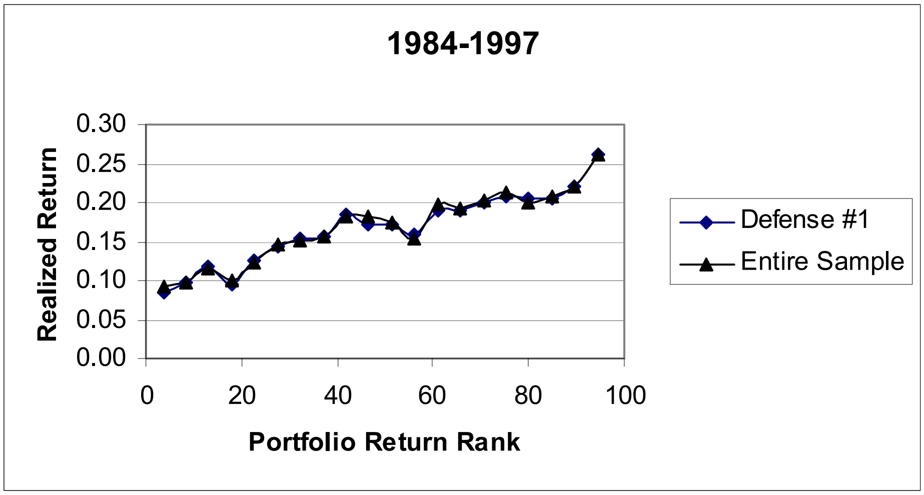
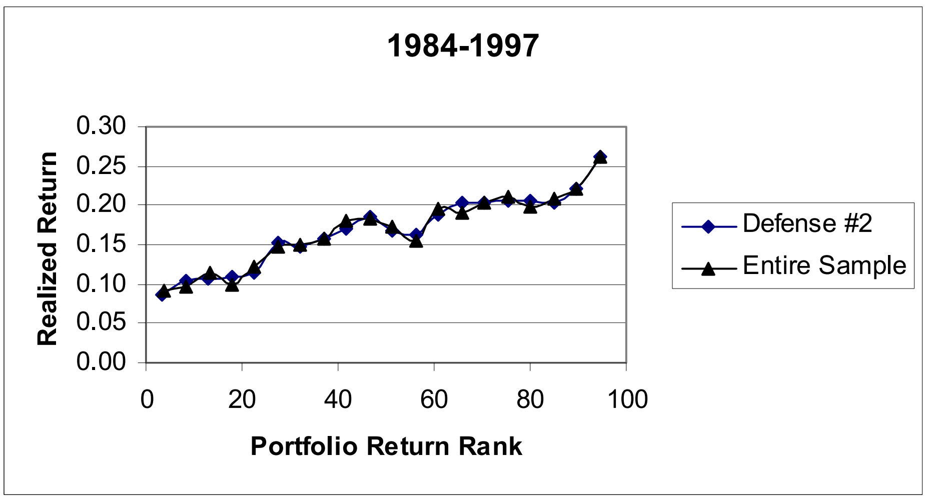


EXHIBIT 11
THE CROSS-SECTION OF COMPARATIVE RETURNS:
KLD DEFENSE SCREENS VS OVERALL SAMPLE





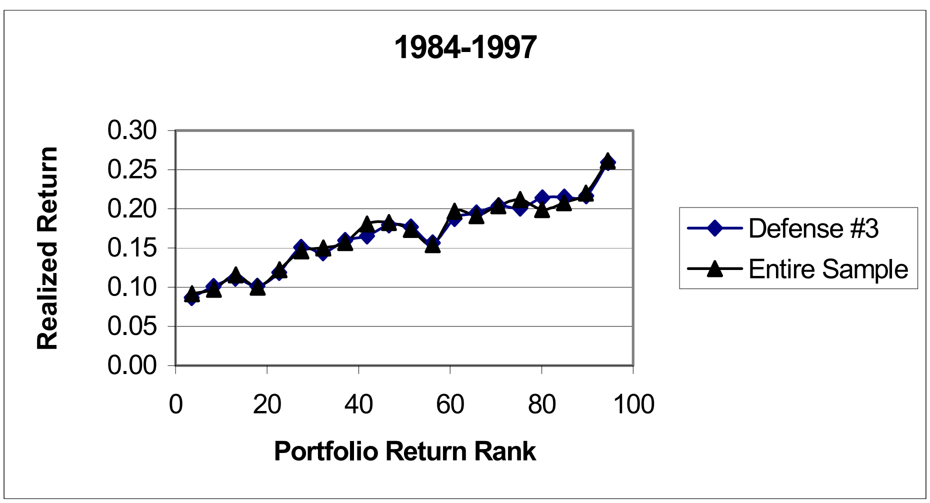
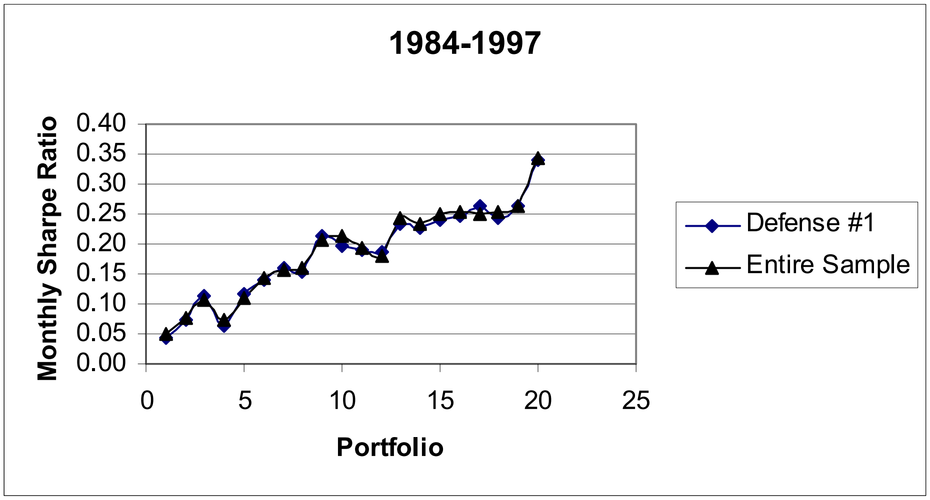
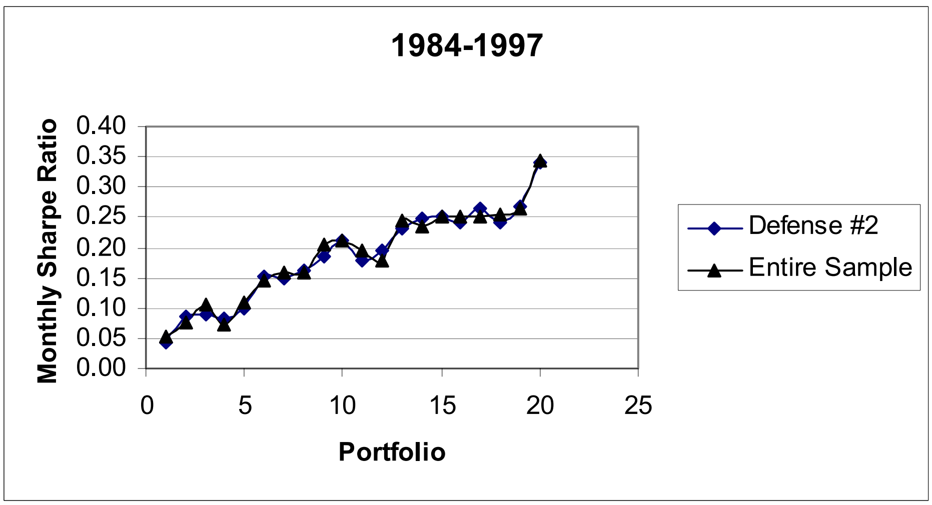


EXHIBIT 12
THE CROSS-SECTION OF COMPARATIVE SHARPE RATIOS: KLD DEFENSE SCREENS VS OVERALL SAMPLE





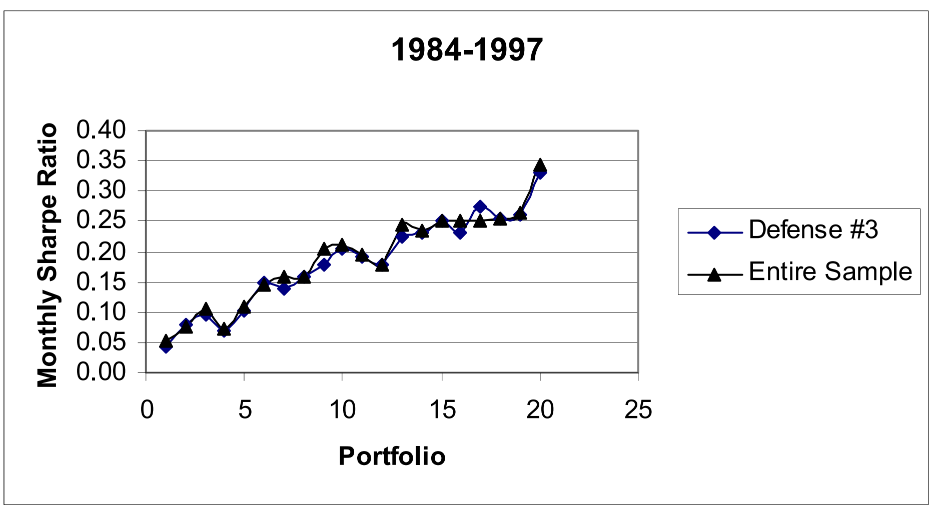
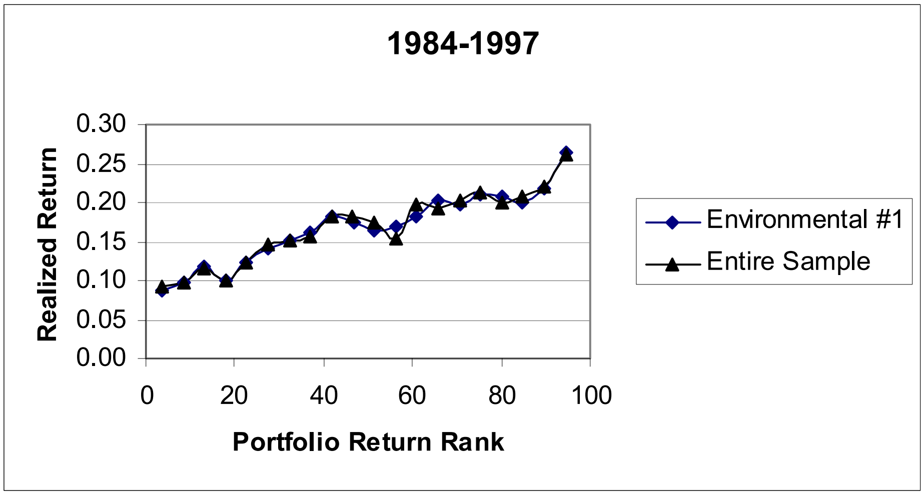
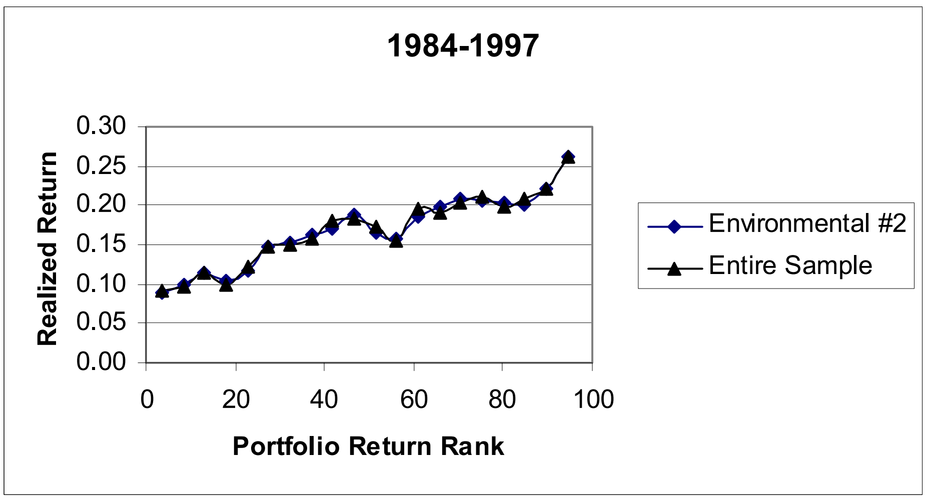


EXHIBIT 13
THE CROSS-SECTION OF COMPARATIVE RETURNS:
KLD ENVIRONMENTAL SCREENS VS OVERALL SAMPLE





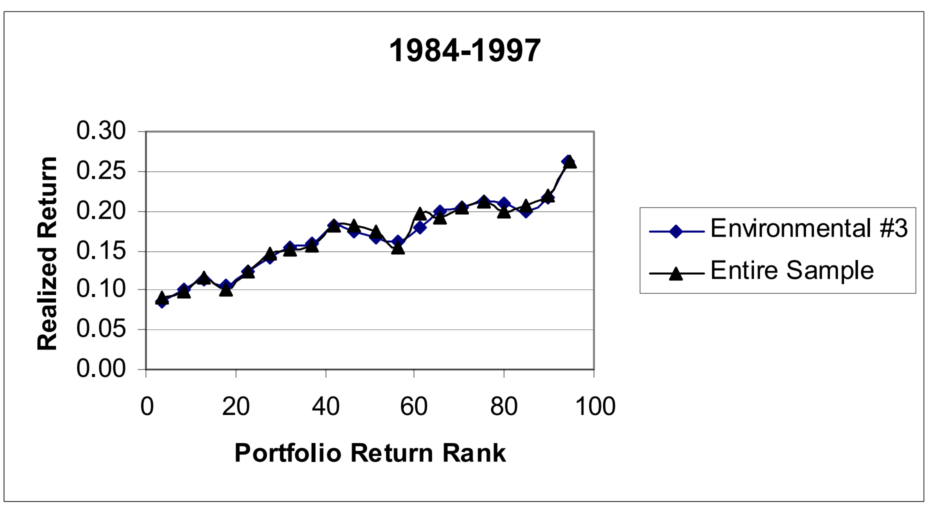
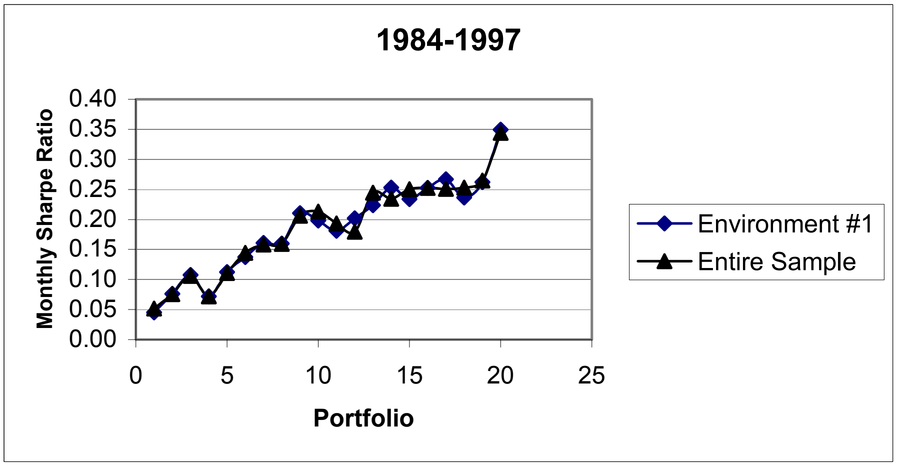
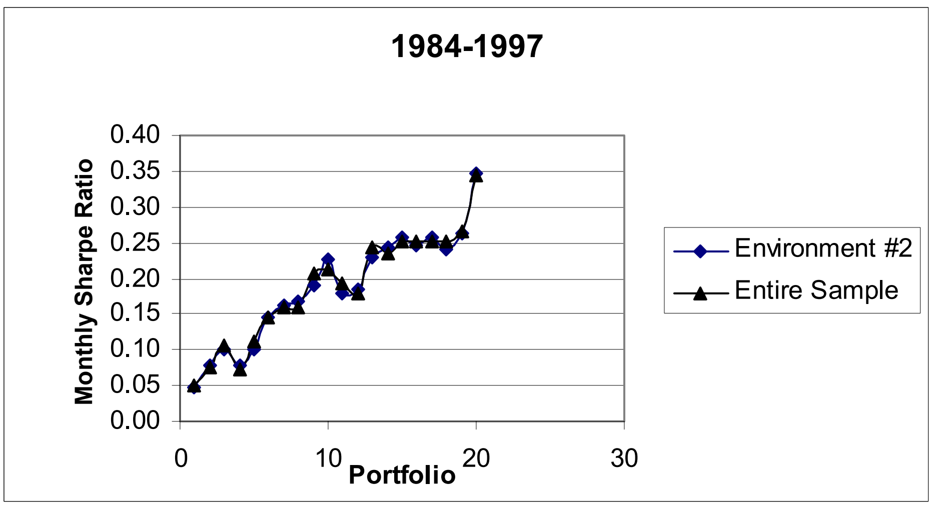


EXHIBIT 14
THE CROSS-SECTION OF COMPARATIVE SHARPE RATIOS: KLD ENVIRONMENTAL SCREENS VS OVERALL SAMPLE





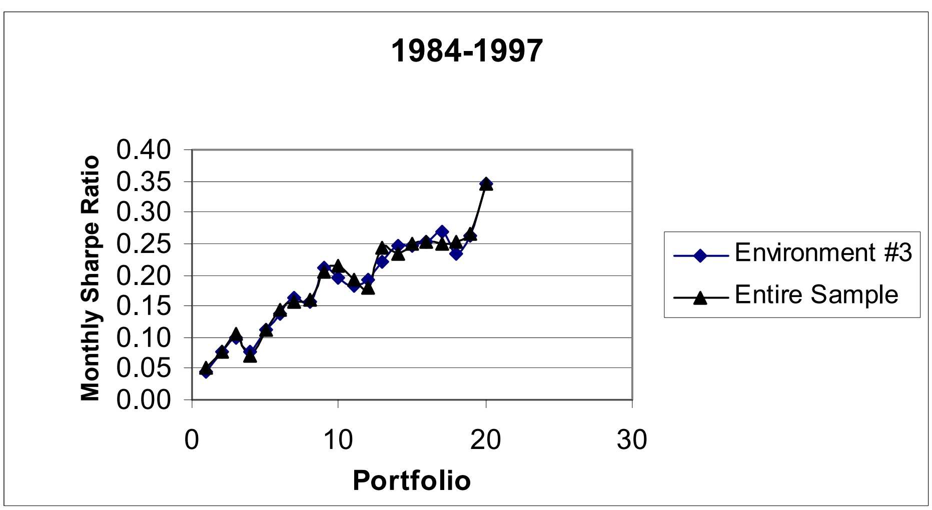


EXHIBIT 15
THE CROSS-SECTION OF COMPARATIVE RETURNS:
KLD NUCLEAR SCREENS VS OVERALL SAMPLE
1984-1997

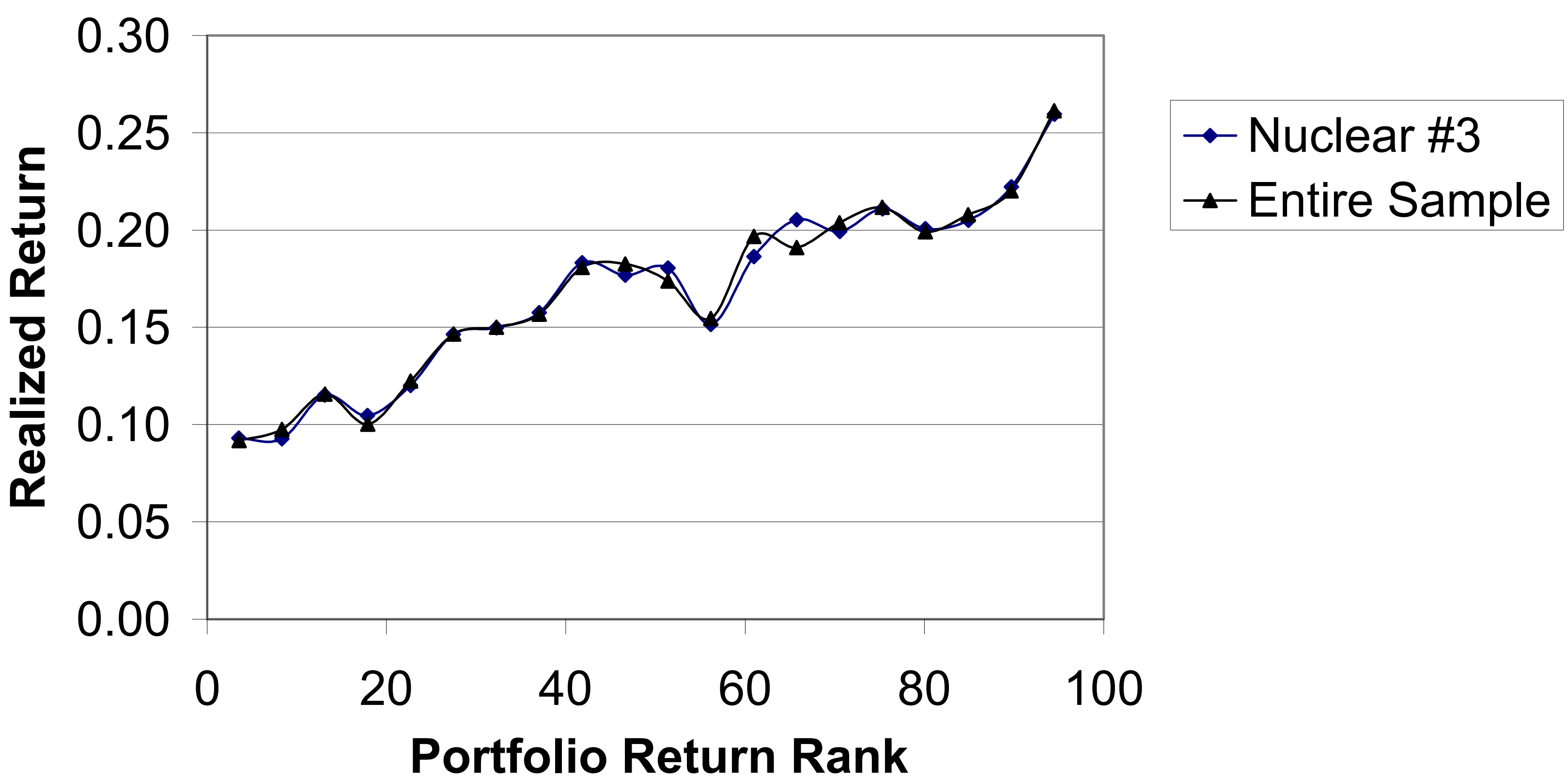


EXHIBIT 16
THE CROSS-SECTION OF COMPARATIVE SHARPE RATIOS:
KLD NUCLEAR SCREENS VS OVERALL SAMPLE
1984-1997

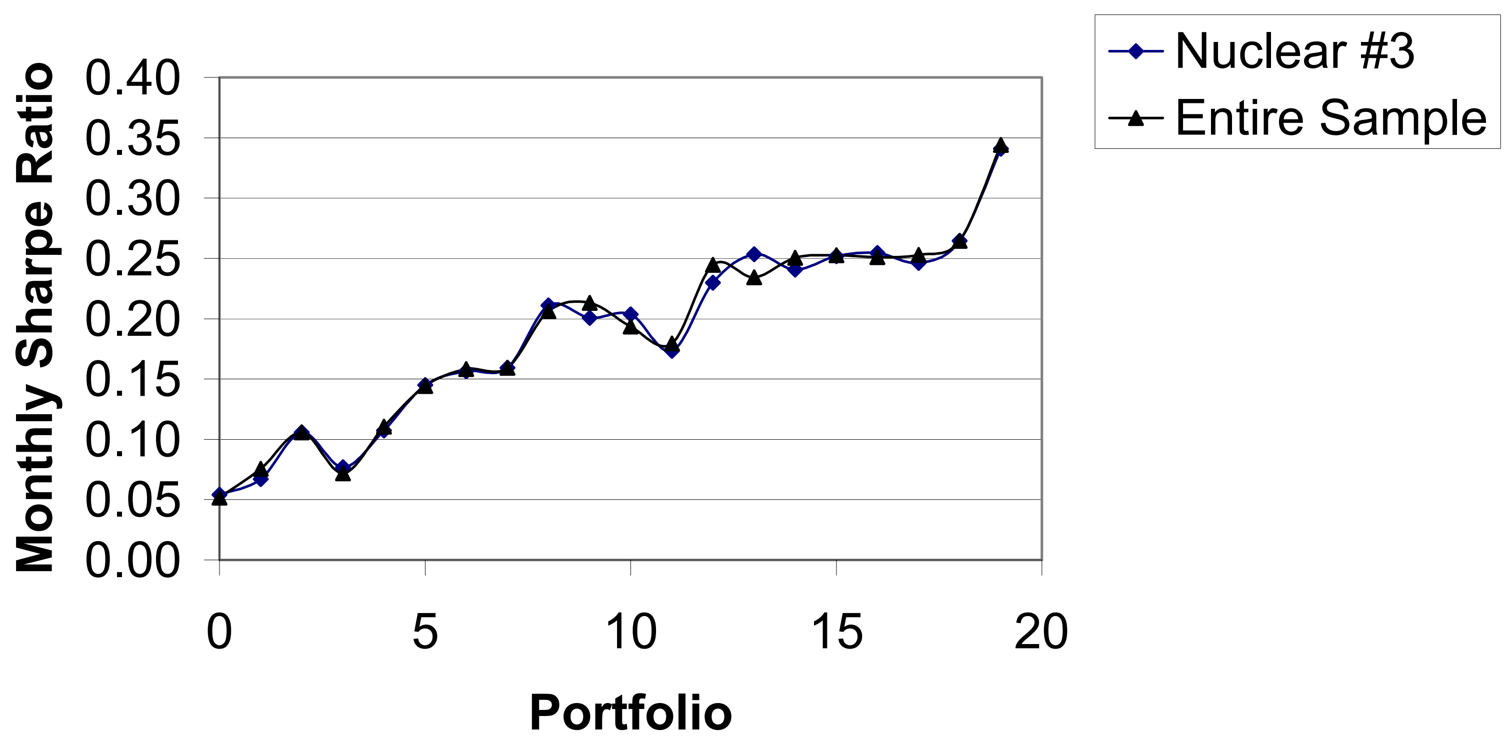


EXHIBIT 17
THE CROSS-SECTION OF COMPARATIVE RETURNS: ALL KLD SCREENS VS OVERALL SAMPLE
1984-1997

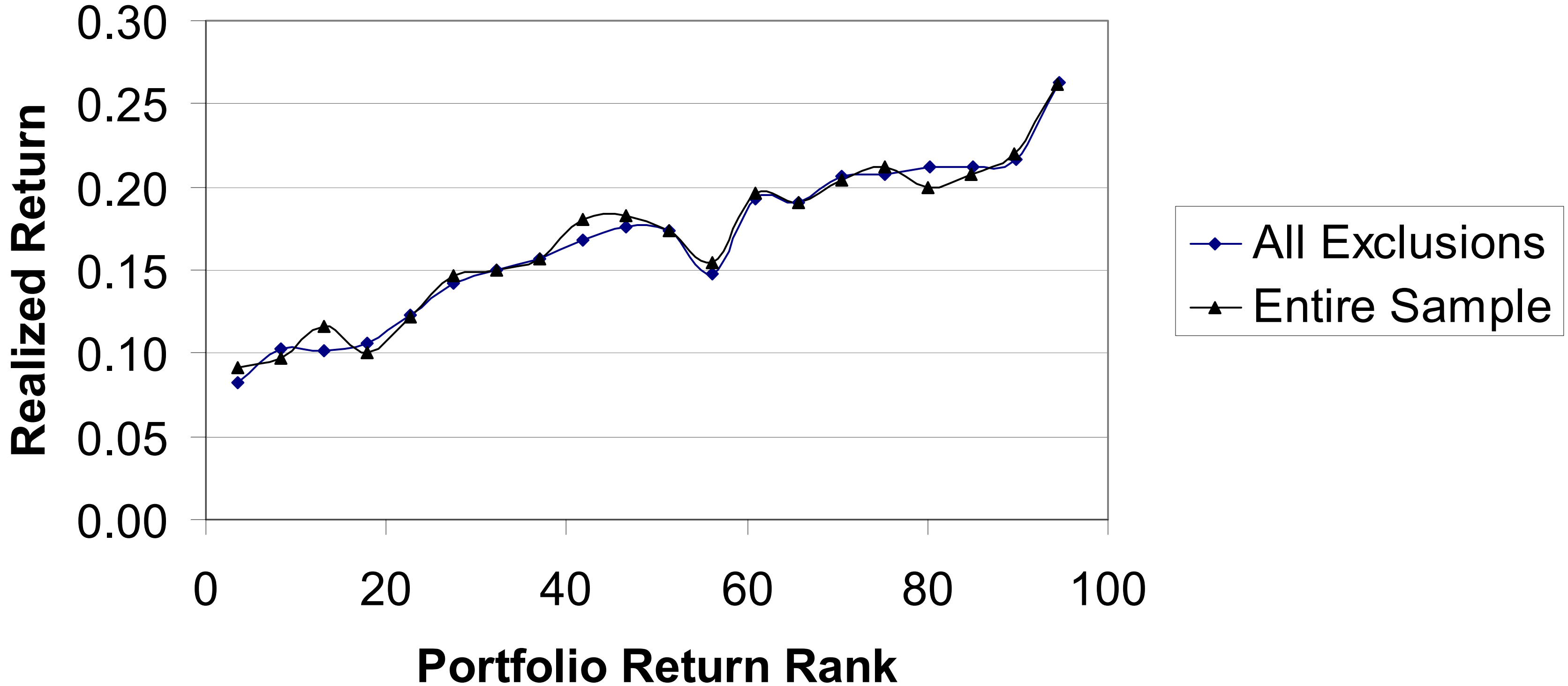


EXHIBIT 18
THE CROSS-SECTION OF COMPARATIVE SHARPE RATIOS:
ALL KLD SCREENS VS OVERALL SAMPLE

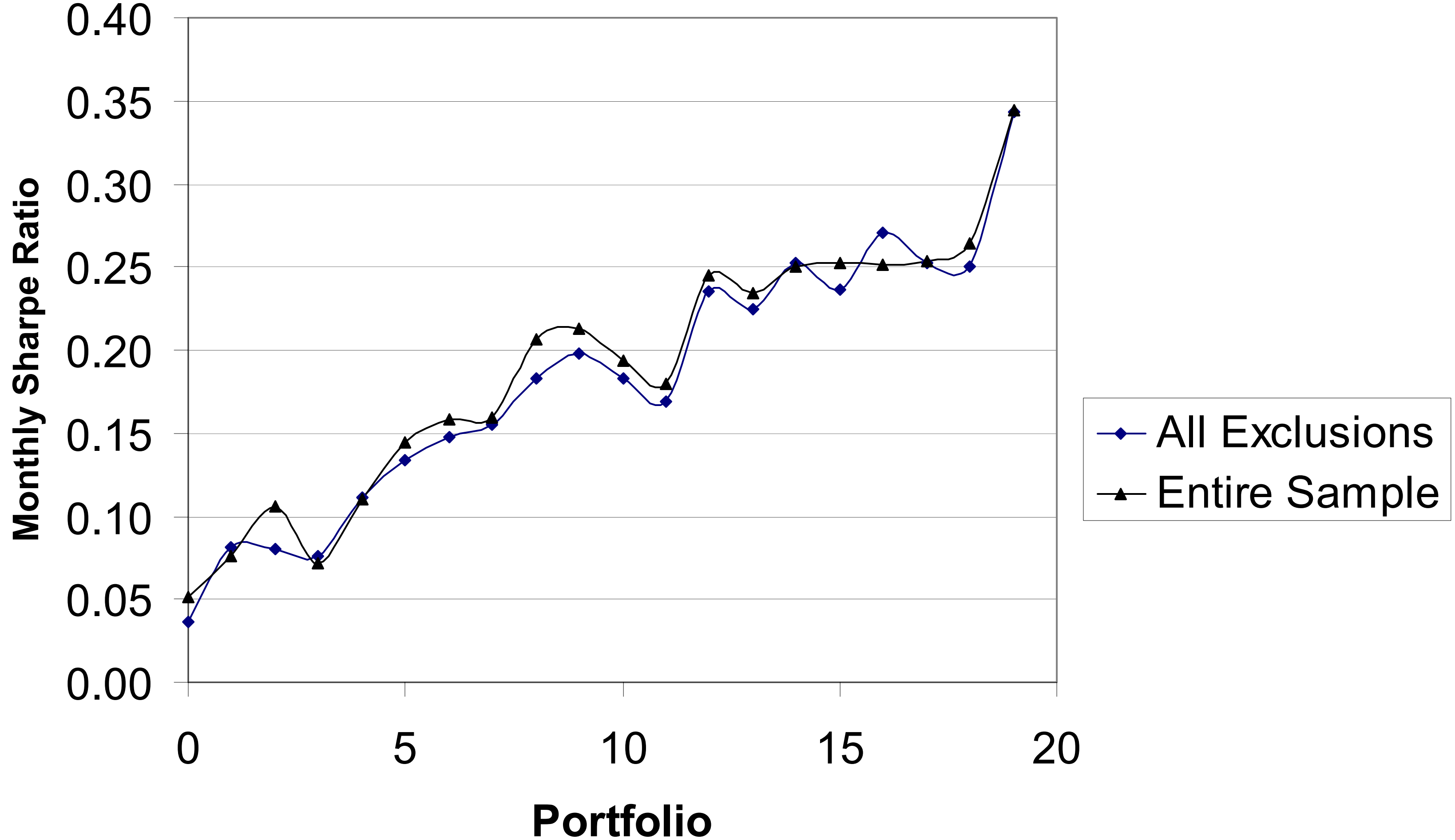
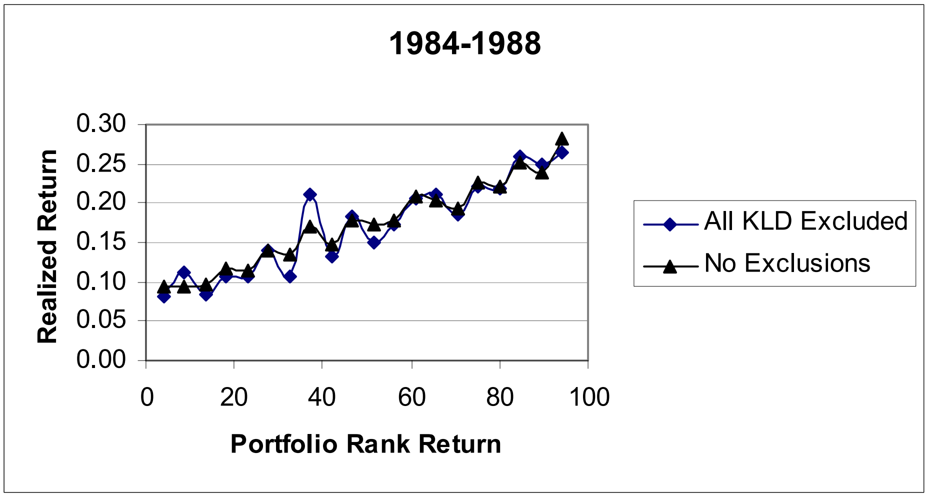
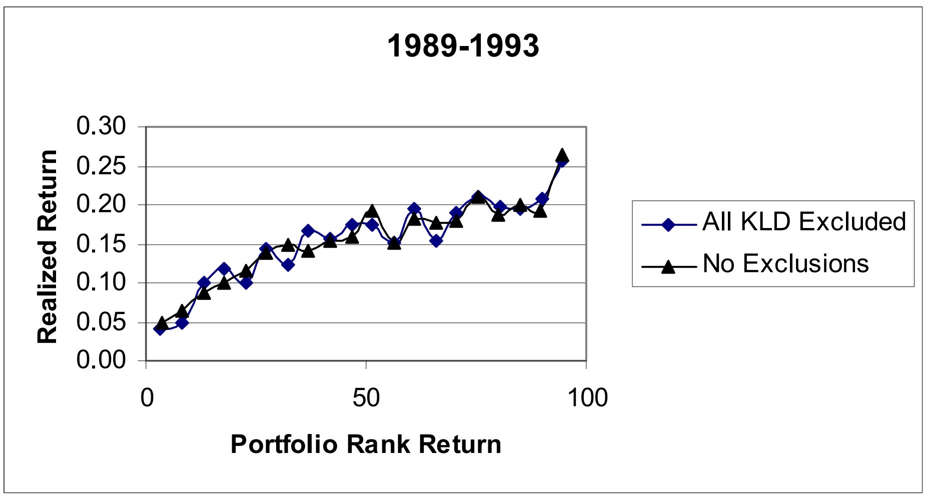


EXHIBIT 19
THE CROSS-SECTION OF SUBPERIOD RETURNS:
ALL KLD SCREENS VS OVERALL SAMPLE





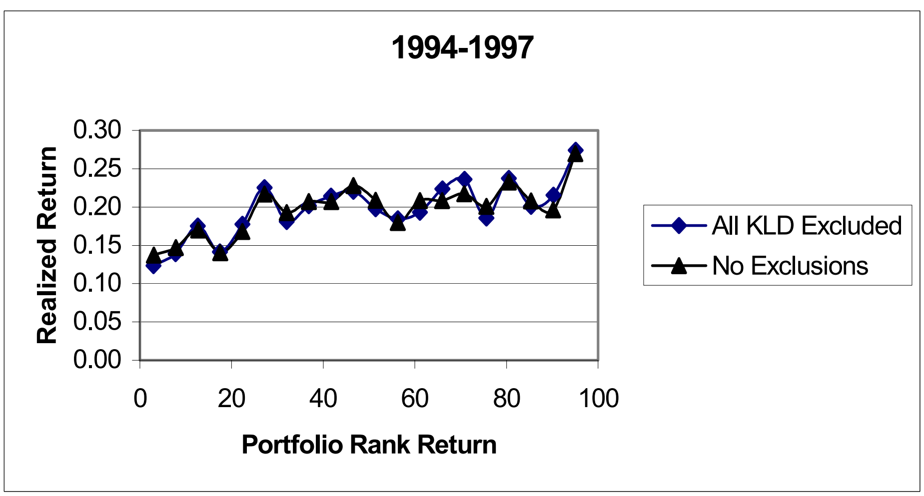


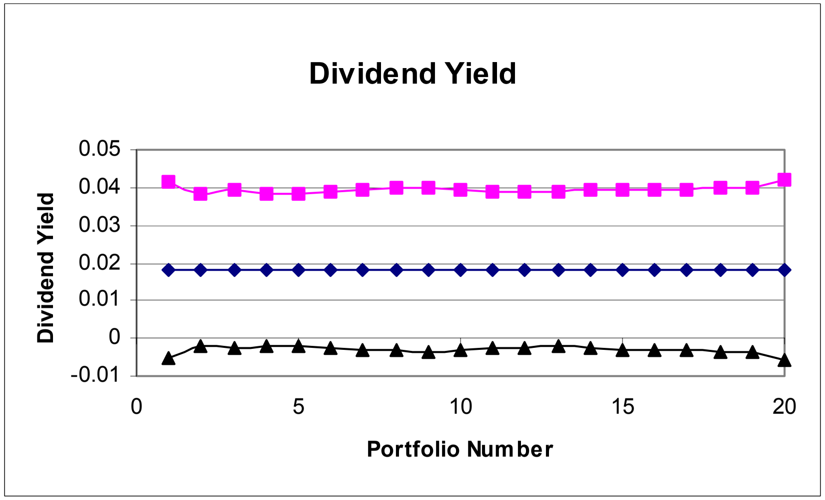
EXHIBIT 20
REALIZED SHARPE RATIOS FOR THE UPPER QUARTILE: SCREENED AND UNSCREENED SAMPLES
Q384-Q497

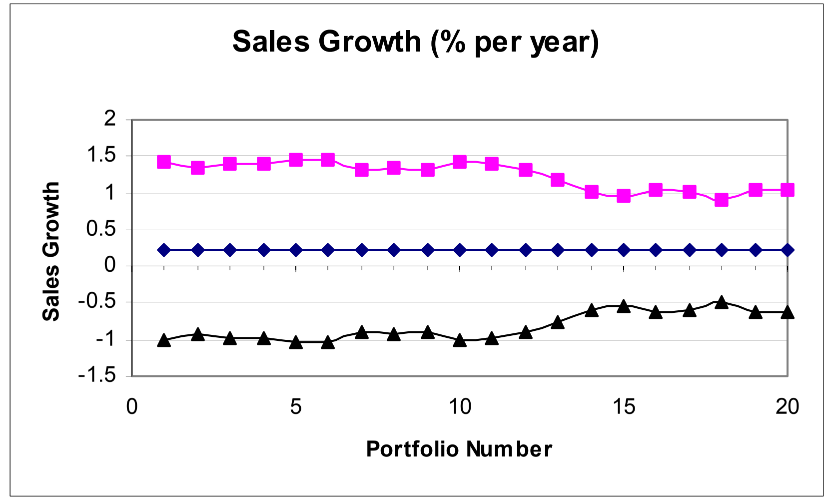
Security Set	Quartile 4
Universe: No Screening	0.28
Defense 1	0.28
Defense 2	0.28
Defense 1&2	0.28
ATG 1	0.28
ATG 2	0.26
ATG 1&2	0.28
Environment 1	0.28
Environment 2	0.28
Environment 1&2	0.28
Nuclear	0.28
All Screens	0.28

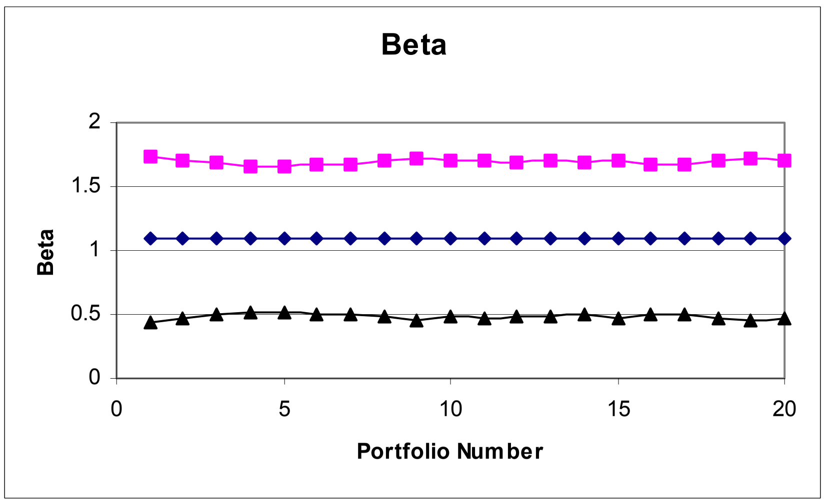
Comments:

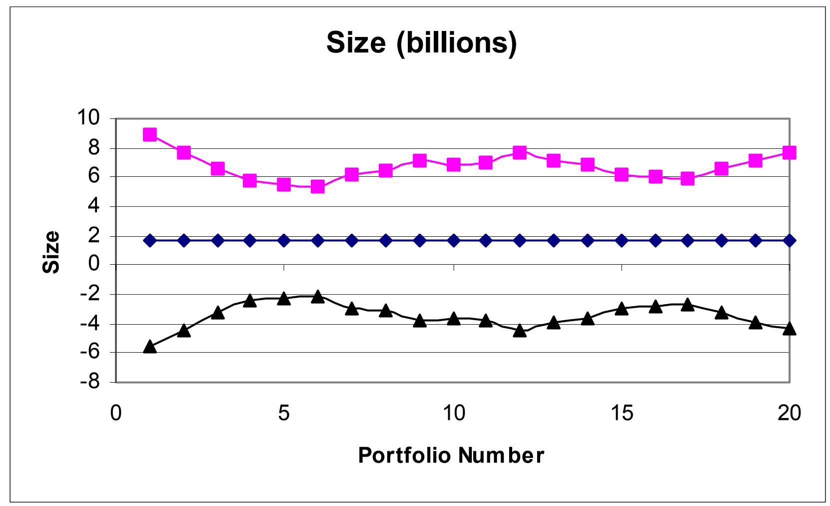
1. The upper quartile portfolio is formed by combining the top five portfolios in each time period.
2. Each annualized Sharpe ratio was computed using realized monthly returns on the respective upper quartile portfolio.
3. The only screened universe not having a realized Sharpe ratio of .28 is ATG2.

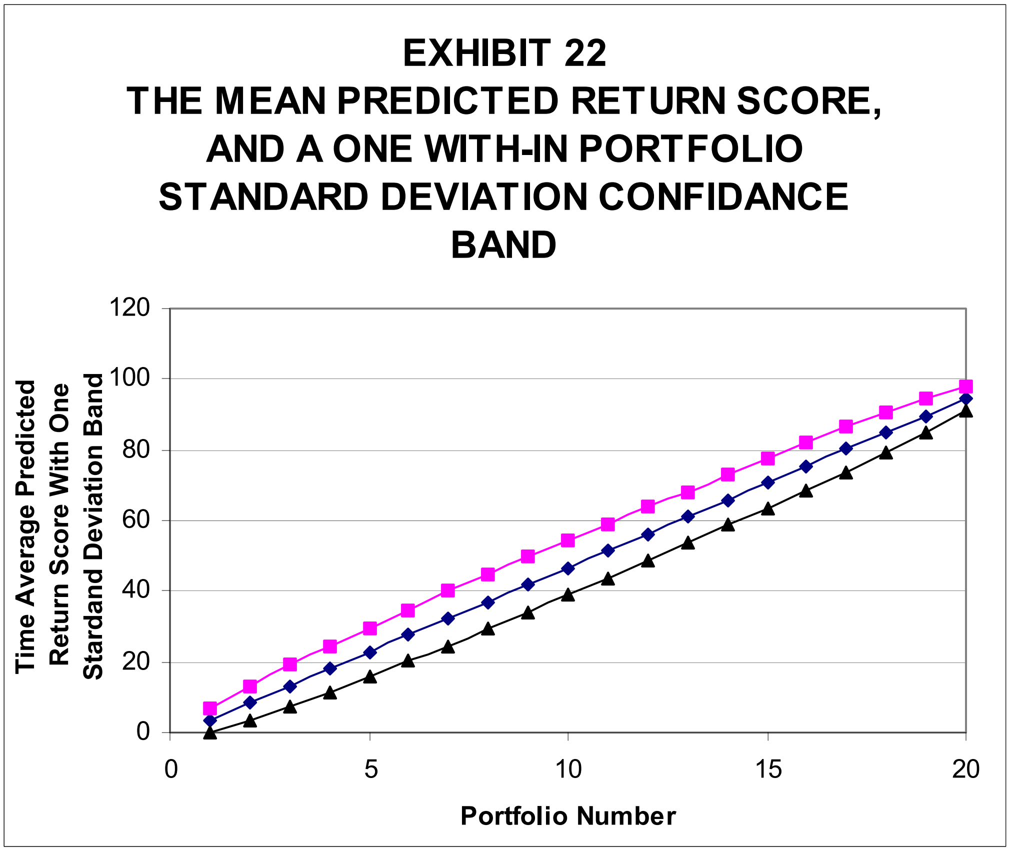
EXHIBIT 21
THE AVERAGE WITHIN-PORTFOLIO STANDARD DEVIATION OF EACH CONTROL VARIABLE: A PLOT GIVING THE AVERAGE ONE STANDARD DEVIATION BAND ABOUT THE MEAN FOR EACH PORTFOLIO











<u>Comments</u>:

1. The predicted return score is the output of the forecast model. A quarterly return score for a security is generated a from quarter's coefficients multiplied by the start-of-quarter variable values for each security. The portfolio return score is the security-weighted average of the return scores for the securities in the portfolio. The mean score plotted for each portfolio is the time average tabulated in Exhibit 5.

2. The within-portfolio standard deviation is computed relative to each portfolio's mean return score. The plot here gives the time average of a one standard deviation confidence band for each ranked portfolio. Thus, the upper and lower lines in the plot give time-average one standard deviation confidence bands relative to the time average mean return.

EXHIBIT 23
THE COMPARATIVE RETURN POSSIBILITY CROSS-SECTIONS WITH THE EARNINGS-PRICE RATIO AND THE BOOK-TO-MARKET RATIO ADDED TO THE SET OF CONTOL VARIABLES

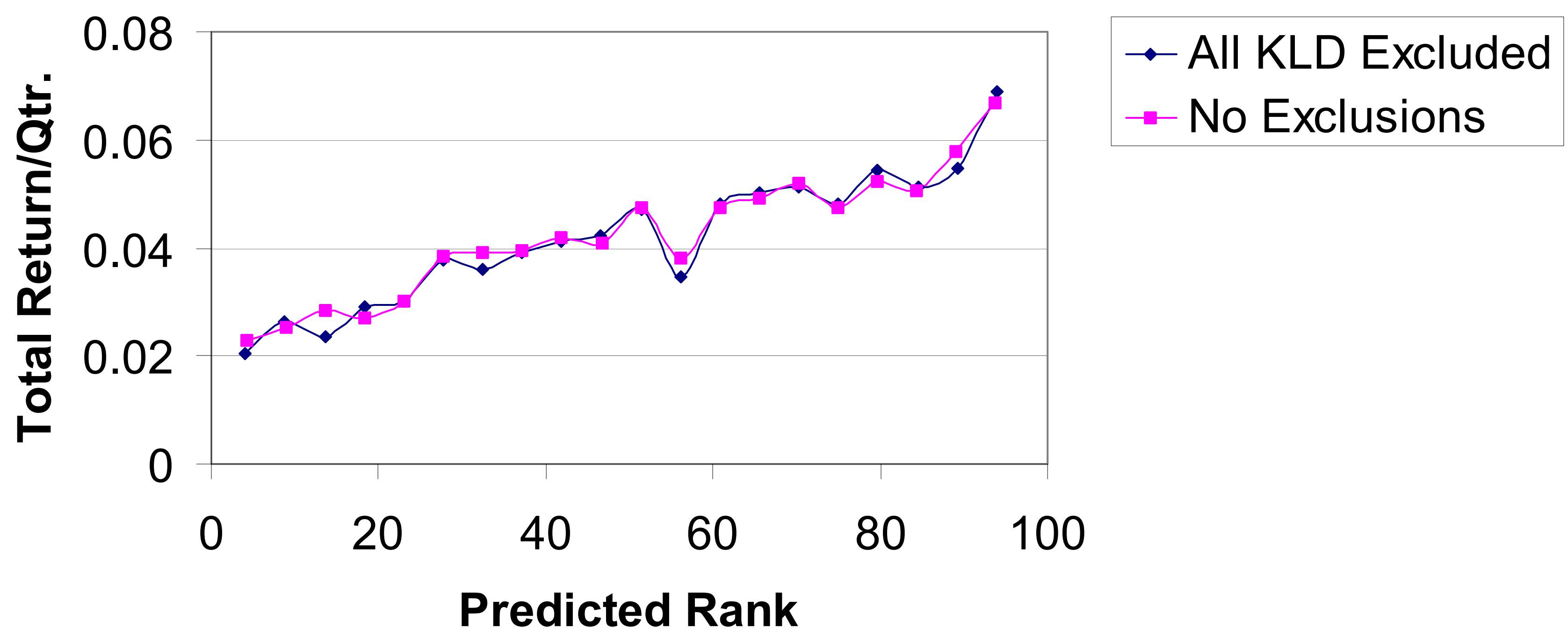


EXHIBIT 24
POPULATION MEAN VALUES FOR EACH CONTROL VARIABLE FOR THE OVERALL SECURITY SAMPLE AND EACH OF THE SCREENED SUB-SAMPLES

	Beta	Sales Growth	Size (Billions $)	Dividend Yield
No Exclusions: Overall Sample	1.09	20.91%	1.65	1.82%
Defense 1	1.09	21.40%	1.44	1.77%
Defense 2	1.09	21.55%	1.26	1.74%
Defense 1&2	1.09	22.09%	1.03	1.69%
Alchohol, Tobacco, and Gambling 1	1.09	20.92%	1.63	1.82%
Alchohol, Tobacco, and Gambling 2	1.09	20.97%	1.60	1.81%
Alchohol, Tobacco, and Gambling 1&2	1.09	20.98%	1.59	1.81%
Environment 1	1.09	21.12%	1.42	1.80%
Environment 2	1.09	21.18%	1.52	1.79%
Environment 1&2	1.09	21.40%	1.28	1.77%
Nuclear 1&2	1.09	21.05%	1.57	1.79%
All KLD Exclusions	1.09	22.42%	0.87	1.65%

Comment:

For Each KLD Exclusion, the excluded securities have above-average size. Thus, the screened sub-sample drops in average-size. In combination, the size decrease is substantial.