Managing Risk Exposures of

Socially Screened Portfolios

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September 9, 1999

Abstract
Equity portfolios whose selection of securities is subject to social responsibility screening represent different sets of economic opportunities from, and hence generally produce different returns from, those of more broadly based market indices. In this paper, we use two separate multi-factor models to demonstrate that these differences in return probably do not arise from the socially responsible behavior of the included companies, but rather from economic and sector exposures that are the implicit result of social screening of portfolio securities. It also demonstrates that the usage of such multi-factor models can reduce the differences in mean monthly return between screened and unscreened index portfolios to a minimal level, while also meaningfully reducing the differences in month to month performance.

The authors wish to extend thanks to Adam Apt, Erik Witkowski and Eric Thaller of Northfield for their editorial and computational assistance.

Introduction

Equity portfolios whose selection of securities is subject to social responsibility screening represent different sets of economic opportunities from, and hence generally produce different returns from, those of more broadly based market indices.

This simple fact has produced a great deal of debate, with critics of social investing claiming either that a) markets are efficient, so any social screen is bound to impose a diversification cost; or b) markets are inefficient, and social screening will interfere with active management strategies. Claims that screened portfolios are bound to underperform have lost some of their force in recent years, however, due to the strong performance of the Domini Social Index, a widely-used benchmark for screened accounts. From its inception in May 1990 through March 1999, the Domini Index had a total return of 470%, as compared with 389% for the S&P 500 (see Kinder, Lydenberg, Domini, & Co., 1999). A brief description of the Domini Index appears in **Domini Social Index** (Appendix III).

This has given rise to a new debate over the source of these outstanding returns. Using the BARRA performance attribution system, Luck (1993, 1998) finds that roughly half of the DSI's outperformance since inception was due to stock selection, which was, in turn, a function of the social screens. This raises the possibility that there is some kind of "social factor", which affects returns.

Numerous other studies, however, have failed to find such a factor. Dhrymes (1998) tests 17 of the factors in a widely-used database of corporate social responsibility and finds that "in the aggregate there are not perceptible and consistent differences in the (expected or mean) rates of return between firms which are deemed to be socially responsible vis-a-vis the entire universe investigated." Hamilton, Jo, and Statman (1993) find that the performance of screened and unscreened mutual funds are indistinguishable.

In this paper, we use two separate multi-factor models to show that the return differences between the Domini Social Index and S&P 500 probably do not arise from the socially responsible behavior of the included companies, but rather from economic and sector exposures that are the implicit result of social screening of portfolio securities. We also find that the usage of such multi-factor models can reduce the differences in mean monthly return between screened and unscreened index portfolios to a minimal level, while also meaningfully reducing the differences in month to month performance.

Analytical Procedure

We began with the membership list of the Domini 400 Social Index over time as provided by Kinder, Lydenberg and Domini. The membership lists were converted to the appropriate file formats, and ticker symbols that had been changed over time were revised back to their "as of" tickers so as to match with the data sets of the Northfield models and software. For the members of the DSI, we were able to match 99.3% of observations (each observation consisting of the existence of one stock for one month) to the appropriate Northfield data. For the Standard & Poors 500 index used for comparison, the match was better than 99.5%.

All of our analytical procedures were run for the period from May of 1990 through January 1999. To test the robustness of our results, two time sub-samples were tested. The first was from May of 1990 through August of 1995. The second was from September of 1995 through January of 1999. We used a three-step process:

Step 1 – Factor Model Attribution Analysis of Domini Social Index
Our first step was to run a performance attribution of the DSI 400 against the S&P 500 for the period May of 1990 through January 1999, using the endogenous factor model described in **Fundamental Risk Model** (Appendix I). This model is an extended version of the Capital Asset

Pricing Model. We also ran a performance attribution of a portfolio (CORE) which consisted only of the 250 Domini stocks that are also members of the S&P 500.

Step 2 – Reweighting Using APT Model

We then used our Arbitrage Pricing Theory style model to construct a series of reweighted DSI portfolios. The reweighted portfolios were designed to mimic the behavior of the S&P 500 by matching the factor loadings of the revised DSI to factor loadings of the S&P 500 and to minimize stock specific (non factor) risk as much as possible. The APT model uses seven macroeconomic variables as its factors. The APT model is described in **APT Equity Risk Model** (Appendix II). The optimization software used is an asymptotic quadratic programming algorithm of Northfield's own design. The initial "optimized" DSI portfolio was constructed on April 30, 1990 and was rebalanced at the end of each calendar quarter, with a final rebalancing at August 31, 1995. Rebalancing procedures involved no constraint on position sizes or number of securities. Transaction costs were assumed at $.20 per share. The identical optimization procedure was then applied to the CORE portfolio.

Step 3 – Factor Model Attribution of Reweighted Portfolios

We then took the time series of optimized DSI portfolios and ran a performance attribution study identical to that performed on the original DSI. Finally, we took the optimized core portfolios (CORO) and ran another performance attribution study.

Results May 1990 through January 1999

For the entire sample from May of 1990 through January 1999, the mean monthly return for the DSI was 1.77 (standard deviation 4.13), while the mean monthly return for the S&P 500 was 1.59

(3.84).[1],[2] Of this .18% (.80) per month advantage to the DSI, .06% (.24) per month was attributable under the CAPM to the DSI's having a higher average beta of 1.10 (1.04 for the S&P), while .12% (.76) per month is considered extraordinary return as defined by Jensen's alpha. Of the .12% per month of alpha, .02 (.38) arose from "bets" on fundamental portfolio characteristics such as average company size, P/E ratio, levels of financial leverage, etc. A .1% (.40) monthly contribution to alpha was attributable to differences in industry composition. Stock-specific returns were zero to two decimal places of rounding. The very small and insignificant stock specific return suggests that the DSI portfolio was acting in accordance with its factor and industry exposure. The active systematic and industry contributions were significant at the 95% level. The statistically significant industry effect is consistent with prior studies by Luck and Pilotte. The earlier Kurtz and diBartolomeo study did not find a statistically significant industry effect, but that study was done with a somewhat different analytical model for attribution. The differences between the model used in this study and the earlier version of the model are presented in Appendix I.

The DSI exhibited a slightly higher overall volatility (standard deviation) of return 4.13% per month, as compared to 3.84% per month for the S&P. This is consistent with the slightly higher beta of the DSI. The volatility (SD) of relative return was .80% per month. The difference in overall mean returns was statistically significant.

The results for the CORE portfolio were very similar to those for the DSI, with a beta 1.11, active systematic contribution of .07% (.23) per month. Also present were a factor policy contribution of negative .03% (.34) per month, an industry weighting contribution of .16% (.57), and a stock

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[1] The returns reported from our analytical software will vary very slightly from the reported returns on the published indices (DSI and S&P). The differences arise from two sources. First is the small number of missing observations noted above. The second is that our indices' constituent histories are really a time series of month-end "snap-shots". To the extent that there was a membership change in an index that did not fall on a month-end, a small but random discrepancy was introduced. For purposes of comparability, all portfolios and indices are handled in this fashion.

[2] While the optimization procedure did take transaction costs into account for the purpose of doing the reweighting, the return results for all indices and portfolios are gross of transaction costs for reasons of comparability (both with each other and with published indices).

specific contribution of negative .01% (.81) per month. The mean monthly return to the CORE portfolio was 1.76% (4.17). The difference in monthly returns had a mean of .19% (.86) per month. As before, the active systematic and industry contributions are significant, each at the 95% level. The stock-specific portion was again small and quite insignificant. The difference in overall mean returns was statistically significant.

For the entire period, the optimized DSI (DSIO) portfolio had a monthly mean return of 1.49%, close to that of the S&P 500. The mean monthly difference in return was reduced to negative .06% (.64). The average beta of the DSIO portfolio was reduced 1.03, just below that of the S&P 500. While the industry contribution of .09% monthly remained significant at the 95% level, neither the overall difference in returns, nor any of the other components were significant.

The overall return of the DSIO actually had a slightly lower volatility than the S&P (3.78% versus 3.86%). This difference is not significant. The volatility of relative return was reduced from .83% per month with the DSI to .60% per month with DSIO. More importantly, the mean monthly difference was reduced by about two-thirds from .18% per month to only .06%. The difference in means also lost statistical significance. The DSIO portfolio had a range of 150 to 190 positions at various points during the period under study. The system tended not to hold all stocks, due to the assumption of transaction costs.

For the optimized intersection portfolio (CORO) a picture almost identical to the optimized DSIO portfolio emerges. The mean monthly difference in return from the S&P 500 was reduced from .19% (.86) per month to negative .04% (.66). Only the industry contribution to relative returns retained statistical significance. The overall volatility of CORO was slightly below that of the S&P, at 3.79% versus 3.86%. The CORO portfolio ranged from 150 to 180 positions during the period of the study.

Results for the Sub-Periods

Results for the two sub-periods, May 1990 through August 1995 and September 1995 through January 1999, were generally very consistent with the results for the overall period. Table 1 presents each of the result values for the entire period, and each of the sub-periods for the DSI and DSIO portfolios. An identical pattern is observed for the CORE and CORO portfolios.

The one major difference between the two sub-periods has to do with active systematic risk or beta. During the first half of the study, all of the test portfolios had higher beta than the S&P 500 resulting in a positive return contribution from active systematic risk (in a rising market). In the second subperiod, both the DSIO and CORO portfolios had beta 1.09 as compared to the S&P 500 at 1.14 as measured by the model. As the market continued to rise during the second sub-period, the lower beta resulted in a negative return contribution from active systematic risk.

Conclusions

The initial performance attributions of the DSI and CORE portfolios suggest that the relative outperformance of the DSI over the period of the study was consistent with the factor and industry "bets" implicit in the social screening process. There was no evidence of a "social" factor. Had the available sample period been longer, it is likely that periods when the DSI underperformed the S&P 500 would have been evident.

The DSI portfolio is more growth oriented than the S&P 500. This arises implicitly from the screening process and can be observed from the fundamental characteristics of the portfolios and the distribution of industry participation. The DSI and CORE portfolios both exhibited higher average betas. As discussed in Kurtz and diBartolomeo (1996), the DSI has also had different macroeconomic exposures than the S&P 500.

The slightly higher return and volatility of the DSI as compared to the S&P 500 is consistent with return effects of growth orientation. During the sample period the unscreened Russell 1000 Growth Index produced a mean monthly return of 1.69% (4.22) while the unscreened Rusell 1000 Value Index produced a mean monthly return of 1.46% (3.63).

There was no meaningful difference in the returns relative to S&P 500 of the behavior of the DSI and CORE portfolios. Inclusion of non-S&P stocks in the DSI seemed to have no significant impact on the results. This probably arose from the fact that the S&P 500 members are generally larger capitalization companies and hence dominate the value weighted DSI anyway.

Using the minimum relative variance optimization with respect to an APT model, we were able to reduce meaningfully the volatility of relative performance between the DSIO and CORO portfolios, each versus the S&P 500. In the case of the DSI versus S&P 500, it dropped from .80 per month before optimization to .64 per month after optimization, a decrease of about 20%. We can further reduce the tracking error by owning more stocks and making more frequent rebalancings. Unfortunately, this would incur transaction costs that would reduce overall returns. For most people, the result would not be worth the cost.

The differences in mean monthly performance between the optimized portfolios and the S&P 500 were reduced to almost nothing during the first sample period. For both the second part of the sample and the overall sample, the difference in mean monthly performance were reduced to minimal levels that were not close to any statistical significance. This is empirical support for the APT as an equilibrium theory. More important to social investors, it suggests that the DSIO and CORO are, in fact, unbiased proxies for the S&P 500.

In this particular time period, the optimized DSIO and CORO portfolio underperformed their basic DSI and CORE portfolios. This should not be taken as a failure of the optimization process. The purpose of our exercise was to reduce the relative return of the portfolios to the S&P 500 to insignificant levels. This was accomplished. The fact that conditions were more favorable to the DSI industry make-up rather than that of the S&P 500 during the sample period is coincidental. In another sample period, where the DSI underperformed the S&P 500, the optimized portfolios would have likely outperformed their basic counterparts.

The Arbitrage Pricing Theory is really an extension of the Law of One Price. The price we pay, for investment returns in excess of the risk free rate, is the taking of risk. In an efficient market, if two investors take similar risks, they should get similar returns. In any empirical study of the APT, we are really doing a joint test of two things. First, the theory and second, that the set of factors we have selected to define risk are the "right" factors.

In the case of this study, we took the DSI portfolio that had different risks from the S&P 500 and had statistically significantly different returns. We then modified the DSI portfolio through optimization so that it would have the same risks as the S&P 500. If the APT holds and we have right set of factors, the returns should be the same. The two sets of returns we obtained were then not distinguishable to a statistically significant degree. The returns were effectively identical during the first sub-period. There was a slight difference in the second sub-period but it was far from significant.

Even with the APT optimization removing differences in macroeconomic exposures between DSIO, CORO and the S&P 500, the industry contribution to relative return remained statistically significant. This suggests that we are not able to hedge away certain industry-specific risks, even with sophisticated risk management techniques. For example, consider the tobacco industry, where regulatory and product liability issues dominate any influence from the macroeconomy.
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References

Chen, Nai-fu, Richard Roll and Steven Ross, "Economic Forces and the Stock Market", *Journal of Business*, 1986

Dhrymes, Phoebus J, "Socially Responsible Investment: Is It Profitable?" *The Investment Research Guide to Socially Responsible Investing,* Plano, Texas: Investment Research Forums, 1998.

Diltz, J. David. "Does Social Screening Affect Portfolio Performance?" *Journal of Investing,* Spring 1995.

Hamilton, S., H. Jo, and M. Statman, "Doing Well While Doing Good? The Investment Performance of Socially Responsible Mutual Funds." *Financial Analysts Journal,* November/December 1993.

Kinder, Lydenberg, Domini, & Co., *The Domini 400 Social Index: Statistical Review,* March 1999.

Kurtz, Lloyd and Dan diBartolomeo, "Socially Screened Portfolios: An Attribution Analysis of Relative Performance", *Journal of Investing*, Fall 1996.

Luck, Chris and Nancy Pilotte, "Domini Social Index Performance", *Journal of Investing*, Fall 1993.

Luck, Chris, "Domini Social Index Performance", *The Investment Research Guide to Socially Responsible Investing,* Plano, Texas: Investment Research Forums, 1998.

Rosenberg, Barr, "Extra Market Components of Covariance in Security Markets", *Journal of Financial and Quantitative Analysis*, 1974.

Table 1 DSI/DSIO Monthly Return Statistics Relative to S&P 500
(Asterisk indicates statistical significance at the 95% level)

DSI/DSIO	*Full Period*		*First Sub-Period*		*Second Sub-Period*	
Total	1.77	1.49	1.23	1.11	2.46	2.09
Active	.18*	-.06	.12*	.00	.22*	-.15
Systematic	.06*	-.02	.05*	.01	.07*	-.07*
Alpha	.12*	-.03	.07	.00	.15	-.08
Factor	.02	-.06	-.09	-.06	.00	-.07
Industry	.10*	.09*	.17*	.11*	.13*	.07*
Stock	.00	-.06	-.01	-.06	.02	-.06

Appendix I

Description of Fundamental Model

The Fundamental Factor Model is a multiple factor model used to explain the covariance among US stock returns. In this model, it is assumed that beta can explain some but not all of the structure of the covariances. For a detailed derivation, see Rosenberg (1974). There are sixty seven factors (items of commonality). The sixty-seven factors consist of beta, eleven fundamental company characteristics, and fifty-five industry groups. The model can be written as:

$$R_{it} = R_{ft} + \beta_{it} (R_{mt} - R_{ft}) + \Sigma_{k = 1 \text{ to } 66} (E_{ikt} * \alpha_{kt}) + e_{it} \qquad (1)$$

R_{it} = return on stock i during period t
β_{it} = estimated beta of stock at time t
R_{mt} = return on the market (our reference universe) during period t
R_{ft} = risk free rate of return during period t (three month Treasury bill)
E_{ikt} = exposure of stock i to factor k at time t (exposures are standardized values of continuous variables such as P/E, dummy variables for industry membership)
α_{kt}= Jensen's alpha associated with factor k during period t
e_{it} = error term associated with stock i during period t

Essentially, it is nothing more than a standard CAPM with an effort made to sub-divide the alpha term into 66 components. To the extent we can associate portions of alpha to common factors we increase the ability of the model to explain covariance, unlike the simple CAPM, which assumes that beta alone explains all covariance among securities.

The model is estimated each month in two steps. In the first step, we get prelimary estimates for the beta values (β_{it}) for each stock. To get the β_{it} values, we first run a traditional CAPM time series (60 months) regression of stock i's return against the market to get B_i.

$$R_{it} = R_{ft} + B_i * (R_{mt} - R_{ft}) + \varepsilon_{it} \qquad (2)$$

B_i = preliminary estimate of beta on stock i
ε_{it} = error term for stock i during period t under traditional CAPM assumptions

To improve the quality of fit of the model ($e_{it} < \varepsilon_{it}$), we can allow the beta values for each stock to vary over time. For example, it can be observed that highly levered companies have higher beta values. We could then imagine that a company that has just taken on a great deal of debt to finance an acquisition would have its beta increase. To capture the changes in beta values over time for a given company, we start by using a cross-sectional regression to estimate the relationships between beta values and company characteristics across the universe.

$$B_i = \Sigma_{k = 1 \text{ to } 66} E_{ikt} * \beta_{kt} + \zeta_{it} \qquad (3)$$

β_{kt} = sensitivity of beta values with respect to differences from stock to stock in exposure to fundamental characteristic k at time t

ζ_{it} = error term for the beta of stock i at time t

We assume then that the β_{kt} values that are derived from an analysis across the universe of companies can then be applied to a single company as its characteristics change through time. One we have the β_{kt} values, we estimate the contemporaneous value for β_{it}.

$$\beta_{it} = \Sigma_{k = 1 \text{ to } 66} E_{ikt} * \beta_{kt} \qquad (4)$$

Incidentally, this rather complicated procedure for getting a beta has one additional benefit. We can get a reasonable estimate of beta for a stock with no return history, such as an initial public offering. Even though it has no return history, fundamental characteristics such as P/E, yield, and industry are immediately observable and equation (4) can still be used.

Once the beta values are estimated, we can substitute the β_{it} values into the equation (1) above and run a cross-sectional regression to estimate the α_{kt} values. The observations in all cross-sectional regressions are weighted by square root of market capitalization. This weighting compensates for the skewness in the distribution of market capitalization. If the observations are equally weighted, the analysis is biased toward small capitalization names which are far more numerous. If the observations are capitalization weighted, the effective number of observations gets far too small for the large number of independent variables.

In this analysis, the return on the market (R_m) is the return on a reference universe of all US stocks with more than $250 million market capitalization. This return computation is weighted by square root of market capitalization.

For the purpose of historic performance attribution, the usage of the model is simple. Since the factor exposures of each stock in portfolio sum to the factor exposures of the portfolio, equation (1) also holds for portfolios. Once all items in equation (1) have been estimated at the stock level we can calculate the beta and factor exposures for a given portfolio and immediately observe which "bets" paid off and which did not during a particular period.

There are several differences between the earlier fundamental model used previously in Kurtz and diBartolomeo (1996) and the current one. The first change is that the Earnings/Working Capital ratio, which was a factor in the earlier model has been dropped. A fifty-two week Relative Price Strength (traditional technician's calculation) indicator has been added to the current model.

The second change in the model is that the Capitalization factor used in the first model has been replaced with a Log of Capitalization factor in the newer model. As the distribution of raw capitalization is highly skewed, transforming to log of Capitalization gives a nearly normal distribution, resulting in a better regression against returns that are nearly normally distributed.

Lastly, the industry scheme of the model has been changed substantially. The earlier industry scheme was based on SIC codes. In the current model, both the industry taxonomy and the classification of firms into industries was done manually with the assistance of the analyst staffs at two investment management firms. This resulted in industry mapping which was much more reflective of current business conditions than the earlier model, such as inclusion of new industry groups for software and biotechnology.

Appendix II

Description of the APT model

Our APT model is a multiple factor model of the covariance of US stock returns. In this model, the factors of commonality are the sensitivity of the stock returns to unexpected shifts in economic conditions as measured by seven specified macroeconomic variables. The model is a variant of the original of APT model, applied to the US equity market. For further discussion see Chen, Roll and Ross (1986). Such a model has the form:

$$R_{it} = R_{ft} + \Sigma_{k = 1 \text{ to } 7} P_{kt} * \beta_{ik} + e_{it} \quad (5)$$

P_{kt} = unexpected change in macroeconomic variable k during period t
β_{ik} = sensitivity of returns on stock i to changes in variable k

For each stock we run a separate time series regression over 60 months to estimate the βik values. The entire process is updated every three months on a rolling basis.

The economic variables used in the model are:

1. Industrial Production
2. Inflation
3. Housing Starts
4. Oil Prices
5. Foreign Exchange Value of the US$
6. Yield Spread between 1 Year Treasury Notes and 20 Year Treasury Bonds
7. Yield Spread between BAA bond index and AAA bond index

Appendix III

Domini Social Index Composition

Source: Kinder, Lydenberg, Domini & Co., Inc.

The Domini Social Index is a market capitalization-weighted common stock index modeled on the Standard & Poor's 500 (S&P 500).

In 1990, KLD created the DSI by starting with the companies in the S&P 500.

KLD first applied a set of exclusionary screens, eliminating companies involved in alcohol, tobacco, gambling, military contracting, nuclear power, or with operations in South Africa.

Next, KLD applied qualitative screens in the areas of community, diversity, employee relations, environment, and product safety. Approximately 250 companies remained after this screening process.

KLD then looked at large capitalization companies not in the S&P 500 that passed the exclusionary screens and, in most cases, exhibited an outstanding record in one of the qualitative screening areas. From these, KLD selected approximately 100 companies to provide broad industry representation.

Finally, KLD added 50 firms with exceptional social characteristics.

For further information on the Domini Social Index see: http://www.kld.com/wdomi.html