# Explaining and Controlling the Returns on Socially Screened US Equity Portfolios


**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 almost nothing, also while meaningfully reducing the differences in month to month performance.



The analytical results discussed herein are the subject of a forthcoming paper by Professor Donald Collat of the Harvard Business School, Dan diBartolomeo of Northfield, and Lloyd Kurtz of Harris, Bretall, Sullivan and Smith. This document should be considered a draft only and all responsibility for errors lies with the presenter. Not for quotation or attribution without permission of the all of these authors. The presenter wishes to extend thanks to Adam Apt and Erik Witkowski 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. 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 almost nothing, also while 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 which 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%.

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 August 1995. The attribution process is based on an endogenous factor model that is described in **Fundamental Risk Model** (Appendix I), which is an extended version of the Capital Asset Pricing Model.

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 membership 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.

The mean monthly return for the DSI was 1.23 (sd = 3.71), while the mean monthly return for the S&P 500 was 1.11 (3.41). Of this .12% (.83) per month advantage to the DSI, .05% (.24) per month was attributable under CAPM to the DSI's having a higher average beta of 1.06, while .07% (.89) per month is considered extraordinary return as defined by Jensen's alpha. Of the .07% per month of alpha, -.09 (.39) arose from "bets" on fundamental portfolio characteristics such as average company size, P/E ratio, levels of financial leverage, etc. A .17% (.59) monthly contribution to alpha was attributable to differences in industry composition. Stock-specific returns were credited with -.01% (.94) contribution. The very small and insignificant stock specific return suggests that the DSI portfolio was acting in accordance with its factor and industry exposure. Both the industry and factor policy contribution to alpha were statistically significant at the 90% level and the industry contribution was significant at the 95% level.

The DSI exhibited a slightly higher overall volatility (standard deviation) of return 3.71% per month, as compared to 3.41% per month for the S&P. This is consistent with the beta of 1.06. The volatility (SD) of relative return was .83% per month.

The next step was to run the performance attribution of a portfolio (CORE) which is the intersection of the DSI and S&P membership lists at each point in time. The results were very similar to those for the DSI, with a beta 1.06, active systematic contribution of .05% (.23) per month , a factor policy contribution of -.08% (.30) per month, an industry weighting contribution of .16% (.61), and a stock specific contribution of .03% (.78) per month. The mean monthly return to the core portfolio was 1.21% (3.69). The difference in monthly returns had a mean of .1% (.81) per month. As before, the factor and industry contributions are significant, each at the 95% level. The stock-specific portion was again small and quite insignificant.

We next undertook to use 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.

We then took the time series of optimized DSI portfolios and ran a performance attribution study identical to that performed on the original DSI. For the entire period, the optimized DSI (DSIO) portfolio had a monthly mean return of 1.11%, almost identical to the S&P 500. The mean monthly difference in return was reduced to -.01% (.60). The average beta of the DSIO portfolio was reduced to be equal to that of the S&P 500. While the same pattern of factor, industry and stock specific contributions to alpha persisted, the factor policy contribution was no longer statistically significant at .07% (.40) per month. The industry contribution remained significant at the 95% level.

The overall return of the DSIO actually had a slightly lower volatility than the S&P (3.35% versus 3.41%). 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. 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.

Finally, we took the optimized core portfolios (CORO) and ran the performance attribution. Again a picture almost identical to the optimized DSIO portfolio emerges. The mean monthly difference in return from the S&P 500 was reduced from .1% (.81) per month to .02% (.59). Only the industry contribution to relative returns retained statistical significance. The overall volatility of CORO was slightly below the S&P, at 3.36% versus 3.41%. The CORO portfolio ranged from 150 to 180 positions during the period of the study.

It should be noted that 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 before transaction costs for reasons of comparability (both with each other and with published indices).

**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 being longer, its is likely that periods when the DSI would have underperformed 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 beta's. As discussed in diBartolomeo and Kurtz (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 the growth orientation. During the sample period the unscreened S&P/Barra Growth Index produced a mean monthly return of 1.09% (3.71) while the unscreened S&P/Barra Value Index produced a mean monthly return of 1.07% (3.29).

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 meaningfully reduce 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 .83 per month before optimization to .60 per month after optimization, a decrease of about 28%. We can further reduce the tracking error by owning more stocks and making more frequent rebalancings. Unfortunately, this would incur transaction costs which 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. 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.

The APT is really an extension of the Law of One Price. That is, 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 which had different risks from the S&P 500 and had 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 returns were the same. As we have only sixty four data points, we need to be a little modest about the significance of this, but it is a result worthy of some attention.

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 exclusion of certain industries subject to industry-specific risks may not be able to be hedged away even with sophisticated risk management techniques. For example, consider the tobacco industry, where regulatory and product liability issues dominate any influence from the macroeconomy.

Although the beta difference between the DSI and CORE versus the S&P was statistically significant ($t > 40$), it accounted for a relatively small contribution to relative return volatility. The "active systematic" portion of the difference in returns was .05 (.24), which was not significant. The lack of significance arises from the volatility of the market and the shortness of the sample period. This suggests that trying to reduce the beta of the DSI or CORE to that of the S&P 500 by merely holding cash is not a viable option if one is attempting to control relative as well as absolute return volatility. It does help with relative risk to a small extent. The monthly active systematic returns associated with the beta differences between the DSI and S&P 500 had standard deviation of .24 (or a variance of $.24^2$). The difference in total returns had a standard deviation of .83 per month (or variance of $.83^2$). If we match the betas by using cash we reduce the standard deviation of relative total returns (tracking error) to $(.83^2 - .24^2)^{.5} = .79$. If one is trying to reduce only absolute volatility, using some cash to bring the beta value to match the S&P 500 would work satisfactorily.

**References**

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

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

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

**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
$\beta_{it}$ = 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)
$\alpha_{kt}$ = 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 ($\beta_{it}$) for each stock. To get the $\beta_{it}$ 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
$\varepsilon_{it}$ = 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.

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

$\beta_{kt}$ = sensitivity of beta values with respect to differences from stock to stock in exposure to fundamental characteristic k at time t
$\zeta_{it}$ = error term for the beta of stock i at time t

We assume then that the $\beta_{kt}$ 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 $\beta_{kt}$ values, we estimate the contemporaneous value for $\beta_{it}$.

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

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 $\beta_{it}$ values into the equation (1) above and run a cross-sectional regression to estimate the $\alpha_{kt}$ 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 diBartolomeo and Kurtz (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 bio-technology.

## 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:

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

$P_{kt}$ = unexpected change in macroeconomic variable k during period t
$\beta_{ik}$ = 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 $\beta ik$ 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