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Mutual Fund Attributes and Investor Behavior

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Abstract

I study the dynamics of investor cash flows in socially responsible mutual funds. Consistent with anecdotal evidence of loyalty, the monthly volatility of investor cash flows is lower in socially responsible funds than in conventional funds. I find strong evidence that cash flows into socially responsible funds are more sensitive to lagged positive returns than cash flows into conventional funds, and weaker evidence that cash outflows from socially responsible funds are less sensitive to lagged negative returns. These results indicate that investors derive utility from the socially responsible attribute, especially when returns are positive.

I. Introduction

Mutual fund companies continually introduce new types of funds in an effort to attract investor capital and maximize assets under management. The decision to introduce a new type of fund is affected by a number of variables, including investor demand for the fund's attributes. As argued by Khorana and Servaes (1999), new fund types in high demand generate capital inflows and incremental revenue for the fund company. Subsequent investor behavior, however, may affect the operating costs and viability of the new funds. If a new fund type draws myopic investors, for example, then shareholder subscription and redemption activity may be more volatile and difficult to manage. In this paper, I study a specific fund type—socially responsible (SR) equity mutual funds—in order to explore investor decision making in new funds.

According to the Social Investment Forum (SIF) (2001), assets invested in all socially screened portfolios exceeded \$2 trillion in 2001 with \$136 billion invested in mutual funds, reflecting increased awareness of social responsibility and corporate ethics in the investment community. SR investing integrates personal values and societal concerns with the investment decision via shareholder

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activism, community investment, and, most visibly, investing with social screens. Social screens often exclude securities of companies in particular industries, as well as subjecting companies to qualitative criteria involving social or environmental causes. To illustrate, consider the Domini Social Index, which was created in 1990 by Kinder, Lydenberg, Domini & Company, and which incorporates both exclusionary and qualitative screens. As described by Statman (2000), securities of companies that derive 2% or more of sales from military weapons systems, derive any revenues from the manufacture of alcohol or tobacco products, or derive any revenues from the provision of gambling products or services are not eligible for inclusion in the index. Qualitative screens include a company's record on diversity, employee relations, and the environment. CSX Corporation, for example, was dropped from the index in 1998 for a poor environmental and safety record, whereas Compuware Corporation was added in 1999 for success with a diversity program and employee relations.

Research regarding SR investing has to date focused exclusively on whether there is a difference between the performance of socially screened portfolios and that of conventional funds. In the spirit of Markowitz (1952), social screens may constrain portfolio optimization. A natural question to address is whether these constraints are binding on performance, that is, whether the risk-adjusted returns of socially screened investment vehicles are inferior to those of conventional investments. Alternatively, social screens might serve as filters for management quality and hence generate superior risk-adjusted returns. Derwall, Guenster, Bauer, and Koedijk (2005), for example, find that companies rated highly for environmental performance outperform those rated poorly. Other studies of SR investing, including Hamilton, Jo, and Statman (1993), Statman (2000), and Bauer, Koedijk, and Otten (2005), compare the risk-adjusted returns of SR mutual funds to the risk-adjusted returns of matched conventional funds and find that SR mutual funds perform no differently than conventional funds. Bauer et al. point out that in the early part of their sample, from 1990 to 1993, SR mutual funds underperformed their conventional counterparts, perhaps indicating a learning phase. Geczy, Stambaugh, and Levin (2003) use a different approach to measuring performance: the Bayesian framework of Pástor and Stambaugh (2002). Under the assumption that investors possess a diffuse prior belief about managerial ability and use the Capital Asset Pricing Model (CAPM) to select funds, Geczy et al. also find the performance of SR and conventional funds to be comparable. The general conclusion one can draw from existing studies is that SR mutual fund performance is not significantly different from the performance of funds that do not screen on social criteria.

Another important question—and one that has not yet been addressed by the literature—is whether the behavior of investors in SR mutual funds differs from the behavior of investors in conventional funds. Studying the behavior of SR investors is important from an industry perspective: cash flows into and out of mutual funds from shareholder subscriptions and redemptions can pose a substantial burden on fund managers, as well as passive mutual fund shareholders. For this reason, identifying sources of stable investment should be of practical interest to mutual fund companies. Studying SR investors is also important from an academic perspective: the SR attribute provides a natural behavioral experiment. Geczy et al. (2003) report anecdotal evidence that SR investors withdrew capital at a slower rate than investors in conventional funds during the 1999 to 2001 period, suggesting that SR investors are more loyal. In this paper, I study the behavior of SR investors more comprehensively, controlling for other factors that might explain differences across SR and conventional funds.

On the one hand, investors in SR funds may have decided to invest as part of a standard risk-reward optimization. If so, then traditional asset pricing models should adequately describe the decision to initially invest in the fund, and subsequent decisions to change allocation to the fund. On the other hand, investors in SR funds may derive utility from owning the securities of companies that are consistent with a set of personal values or societal concerns. In other words, they may have a multi-attribute utility function—one that incorporates an additional aspect of their investment choice. These investors may view investing in an SR fund as consuming the SR attribute. In order to smooth consumption of the attribute, subscription and redemption activity may be more regular in SR funds than in conventional funds. I use the net of aggregate investor subscriptions and redemptions, or fund flow, to measure shareholder activity. Consistent with the intuition that the SR attribute smoothes allocation decisions, I find that over the 1991 to 2002 period, the monthly volatility of fund flow in SR funds is significantly lower than conventional fund flow volatility.

Studying the relation between fund flow and fund performance provides additional insight. I present several competing hypotheses regarding the manner in which the SR attribute affects investor decision making, each of which makes an empirical prediction for the flow-performance relation. I find that the sensitivity of fund flow to lagged positive returns is higher in SR funds than in conventional funds. This result is consistent with both a model of rational learning, in which SR investors have more diffuse prior beliefs about the SR strategy, as well as a conditional utility function in which SR investors derive utility from consuming the SR attribute if the investment is warranted on its financial merits alone. To distinguish between the two, I measure the flow-performance and fund flow volatility separately for subsets of the sample based on fund age. If SR investor behavior is governed by a conditional utility function, then differences between SR funds and conventional funds should persist. If SR investor behavior is instead governed by rational learning, then differences between SR funds and conventional funds should disappear over time as the precision of prior beliefs converges. I find that the differences between SR and conventional funds are significant for young and mature funds alike; hence, the conditional utility function appears to capture behavior better than a model of rational learning.

I also find weaker evidence that the sensitivity of fund flow to lagged negative returns is lower in SR funds than in conventional funds, indicating that the utility derived from consuming the SR attribute may mitigate the tendency to shift capital away from poorly performing SR funds. Lastly, I conduct several additional tests to ensure the robustness of the paper's main results. Statistical significance is maintained when standard errors are measured using a least absolute deviations (LAD) approach, which minimizes the impact of outliers. Differences between SR and conventional funds are qualitatively consistent when measured separately across two subperiods.

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The rest of this paper is organized as follows. Section II presents competing hypotheses for the behavior of SR investors. Motivating assumptions are drawn from existing literature. In Section III, I describe the data. Section IV presents the empirical methods and results. Special attention is paid to the construction of a control group. I summarize the findings in Section V.

II. Hypothesis Development

This section develops competing hypotheses for the behavior of investors in SR funds. Subsections A and B review the mutual fund flow-performance relation and fund flow volatility in a general setting to provide a context for the alternative hypotheses. Subsection C lists the hypotheses, motivates them with assumptions supported by existing research, and discusses empirical predictions.

A. The Flow-Performance Relation

As argued by Jensen (1968), a corollary of the efficient market hypothesis is that average risk-adjusted mutual fund returns should reflect only the expenses incurred in the course of managing the fund. Time-series variation in mutual fund performance should be random; hence, investors should not be concerned with past performance but rather with fund expenses as these are to some extent endogenous. Prior studies of the flow-performance relation, however, report strong evidence that a mutual fund's past performance influences subsequent subscription and redemption activity. See, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), Busse (2001), and Del Guercio and Tkac (2002). The relation is often found to be asymmetric, such that poor performers are not punished to the same extent that strong performers are rewarded.

In the context of the efficient market hypothesis, the observed flow-performance relation is a financial anomaly. One explanation for the flow-performance anomaly is that investor actions may be driven at least in part by psychological biases. These biases can be modeled as errors in the Bayesian updating performed by investors when making an investment decision. One example is the tendency for people to simplify difficult problems by ignoring prior beliefs and acting exclusively on recent observations. Kahneman and Tversky (1982) label this the representative heuristic. The representative heuristic predicts that mutual fund investors disregard prior beliefs regarding managerial ability and instead simply subscribe to recent top performers and redeem from recent poor performers.

Brav and Heaton (2002) provide an alternative explanation for the flow-performance anomaly. If a relevant feature of the economy is unobservable, e.g., managerial ability, then the anomaly can be explained by rational learning. Empirical research in the equities market has reported a long list of anomalies that some fund managers may be able to exploit on a consistent basis to generate superior returns.[1] Ippolito (1992), Lynch and Musto (2003), and Berk and Green (2004), among others, interpret the flow-performance relation as a reflection of investors

[1]For examples of stock market anomalies, see Basu (1977), Banz (1981), Keim (1983), Reinganum (1983), Blume and Stambaugh (1983), De Bondt and Thaler (1985), (1987), Jegadeesh and Titman (1993), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994).

updating their beliefs about managerial ability and expected mutual fund returns. I focus on this rational learning explanation for the flow-performance relation because it does not depend on any assumptions about specific psychological biases for which consensus has not been reached in the literature.

B. Fund Flow Volatility

Investors subscribe to and redeem from mutual funds for at least three reasons. First, as described above, changes in expectations of mutual fund performance may motivate investors to reallocate capital among their investments. Second, since mutual funds can be traded daily, investors may move capital into and out of them to address their liquidity needs. Third, Massa (2003) argues that investors may subscribe to or redeem from specific mutual funds in order to change their consumption of or exposure to attributes other than expected return and risk.

There are two benefits to using fund flow volatility as a measure of investor behavior. First, the volatility of monthly fund flows captures the net effect of investors' decisions without forcing any structure on the decision making process. This avoids problems associated with misspecification, though it does not provide much insight into how investors perceive their mutual fund investment. Second, from a practical perspective, the primary concern of mutual fund companies is likely to be the overall variability of investor cash flows, since this captures the burden that active investors place on fund companies and passive shareholders through trading.[2] Not surprisingly, many mutual fund companies have imposed redemption fees to discourage investors from strategically exploiting the liquidity provided to them.[3]

C. Alternative Hypotheses for SR Investor Behavior

I list below three testable hypotheses regarding the flow-performance relation and fund flow volatility of SR funds relative to conventional funds.

Hypothesis 1. The flow-performance relation and fund flow volatility of SR funds is equal to that of conventional funds.

The first hypothesis is motivated by the assumption that investor preferences can be represented by a utility function defined over the moments of a portfolio's return distribution. This assumption is the basis of the standard finance paradigm underlying, for example, the CAPM of Sharpe (1964), Lintner (1965), and Mossin (1966) in which utility is a function solely of expected return and variance. When investors learn about expected return in a multi-period setting, then the standard finance paradigm can generate a mutual fund flow-performance relation and fund flow volatility. Berk and Green (2004) present a model in which rational Bayesian investors use past mutual fund performance to update beliefs about managerial ability as manifested in expected returns. They derive a positive relation between

[2]Edelen (1999) finds that liquidity-motivated trading reduces abnormal returns by over 1% per year in his sample of mutual funds.

[3]See Goetzmann, Ivkovich, and Rouwenhorst (2001) and Boudoukh, Richardson, Subrahmanyam, and Whitelaw (2002) for a description of how active investors can expropriate value from international mutual funds.

past performance and subsequent fund flow, resulting from a rational reallocation of capital to better managers. Fund flow volatility increases in the sensitivity of investors to past performance.

The first hypothesis implies that investors assess SR funds the same way that they assess other funds as simply another candidate investment for the portfolio optimization problem. If so, then after controlling for other relevant variables such as fund age and fund size, the flow-performance sensitivity and fund flow volatility of SR funds will equal that of conventional funds.

Hypothesis 2. The flow-performance relation of SR funds is stronger than that of conventional funds.

The second hypothesis can also be motivated by the standard finance paradigm with the additional assumption that prior beliefs regarding the expected return of SR funds are more diffuse than prior beliefs about conventional funds. Chevalier and Ellison (1997) find that the flow-performance sensitivity of young funds is stronger than that of mature funds, suggesting that beliefs about funds with limited track records are more diffuse. The SR strategy is relatively new and constitutes only a small fraction of the U.S. mutual fund industry as I show in the next section; hence, it seems reasonable to assume investors are uncertain about the performance of the SR strategy. Indeed, the existing SR literature focuses exclusively on measuring the difference in performance between SR and conventional strategies because it is an open question. Rational investors assessing an SR fund, therefore, may have more diffuse prior beliefs about the effectiveness of the SR investment strategy compared to priors for conventional funds, and may give more weight to recent observations of SR fund performance than to recent observations of the performance of other funds. The assumptions of rational learning and diffuse prior beliefs, then, predict that capital inflows and outflows are more sensitive to performance in SR funds than in other funds.

Alternatively, the second hypothesis can be motivated by the assumption that preferences of SR investors can be represented by a multi-attribute utility function defined over the moments of a portfolio's return distribution *and* a variable representing whether the investment decision is SR. The assumption is consistent with the joint goals of social responsibility and financial performance that fund companies generally stress when advertising SR funds. To illustrate, consider this excerpt from the Domini Social Investments Web site (www.domini.com):

> Our shareholders invest with us for a variety of reasons, ranging from meeting important financial goals such as retirement or savings for college to building personal wealth, but one thing they all share in common is an understanding of the importance of their investment decisions. At Domini Social Investments, we are dedicated to making your investment decisions count—for your personal financial benefit, as well as for your broader hopes for a healthier environment and a more just and humane economy.

The assumption is also consistent with Statman (1999) who argues that, in contrast to the standard paradigm, behavioral finance views the investment decision as a type of product choice, so that "value-expressive" characteristics of an asset affect its desirability. Admittedly, there is no evidence in the existing finance literature to suggest that investors pay attention to attributes unrelated to performance. A survey of mutual fund investors in Capon, Fitzsimons, and Prince (1996), for example, asks investors to reveal which criteria they use to select funds. On a scale of 1 (not at all important) to 5 (extremely important), Investment Performance Track Record received a mean of 4.62, whereas Community Service/Charity Record received a 1.09. My sample, though, represents a group of investors with a revealed preference for SR funds, and one purpose of this paper is to determine whether the SR attribute by itself is important for this group.

I assume that SR investors can derive additional utility from consuming the SR attribute, but only if the SR investment would have been selected on its financial merits alone. I refer to this as a conditional utility function. The notion that the investment decision is conditional on satisfactory levels of risk and expected return is consistent with laws governing the actions of fiduciaries in most states. The Uniform Law Commissioners promulgated the Uniform Prudent Investor Act (UPIA) in 1994, and it has since been adopted in 44 states.[4] Section 2(b) states "a trustee's investment and management decisions respecting individual assets must be evaluated not in isolation but in the context of the trust portfolio as a whole and as a part of an overall investment strategy having risk and return objectives reasonably suited to the trust." Thus, unless the terms of the trust specify a preference for the SR attribute, a fiduciary cannot invest in an SR fund if it would adversely affect financial performance.

If SR investor utility functions are conditional, then the flow-performance relation in SR funds may be stronger than that of conventional funds. Positive returns may attract larger inflows for SR funds than conventional funds, since SR investors rationally revise upward their expectations of fund performance as would investors in conventional funds, and additionally SR investors may increase their investment in the SR fund to consume the SR attribute.

In order to differentiate between the two motivating assumptions for the second hypothesis, note that they generate different predictions for fund flow volatility. If the assumption of rational learning with diffuse prior beliefs is driving a stronger flow-performance relation, then fund flow volatility would be higher in SR funds than in conventional funds. The reason is that under this assumption, the only difference between the two groups of funds is the flow-performance sensitivity. If the assumption of a conditional, multi-attribute utility function is driving a stronger flow-performance relation, then fund flow volatility in SR funds may be equal to or lower than the fund flow volatility of conventional funds. If investors derive utility from consuming the SR attribute, then one might expect lower liquidity trading if substitutes are available, thereby offsetting the higher volatility resulting from the flow-performance sensitivity.

One can also distinguish between the two explanations for the second hypothesis by measuring the difference between SR funds and conventional funds as funds age. If SR investor behavior is governed by preferences that are represented by a multi-attribute utility function, then differences between SR funds and conventional funds should persist. If SR investor behavior is instead governed by

[4]Source: www.ncculs.org.

rational learning with diffuse priors, then differences between SR funds and conventional funds should disappear over time as the precision of prior beliefs converge. Following Chevalier and Ellison (1997), I examine the flow-performance relation and fund flow volatility for subsets of my sample split by the age of the fund. Young funds are defined as those aged five years or less, whereas mature funds are those aged six years or more.

Hypothesis 3. The flow-performance relation of SR funds is weaker than that of conventional funds, and the fund flow volatility of SR funds is lower than that of conventional funds.

The third hypothesis can also be motivated two ways. The first motivation is the assumption that preferences of SR investors can be represented by a multi-attribute utility function defined over the moments of a portfolio's return distribution and a variable representing whether the investment decision is SR as before, except now the utility function is additive in the attributes. As defined by Keeney and Raiffa (1993), an additive utility function is permitted when attributes are utility independent, i.e., preferences for one attribute are unaffected by the level of the other attribute. Additive utility functions are common in the product choice literature given their tractability. Massa (2003) and Hortaçsu and Syverson (2004), for example, both assume an additive utility function in their analyses of product choice in the mutual fund industry. The assumption of an additive utility function implies that the utility derived from the SR attribute is separable from and substitutable for the utility derived from an investment's risk and return. An important caveat to the assumption of an additive utility function is that it is inconsistent with the UPIA because it allows for a trade-off between performance and the SR attribute. The assumption of an additive utility function, therefore, only is relevant when investment decisions are made by investors on their own behalf, or in the case of trusts with a specific SR mandate.

To derive an empirical prediction for the flow-performance relation, consider a standard utility function of the form $U = \mu - \theta\sigma^2$, where μ and σ^2 are the expected return and variance of an investor's portfolio of mutual funds. Now consider an additive utility function of the form $U = w(\mu - \theta\sigma^2) + (1 - w)S$, where $0 \leq w \leq 1$ and S is an indicator function which equals 1 if the portfolio satisfies an investor's demand for the SR attribute and 0 otherwise. Suppose that the investor updates beliefs about the portfolio's expected return by observing its realized return. Changes in μ affect utility at the rate of $dU/d\mu = w$, and the resulting change in utility may cause a reallocation of assets. For an SR investor, $w < 1$, and utility is less affected by a change in μ than for a conventional investor for whom $w = 1$. If this is the case, an SR investor will have less incentive to switch funds for a given change in μ than a conventional investor, and the flow-performance relation will be weaker in SR funds than in conventional funds.

A weaker flow-performance relation would result in lower fund flow volatility. In addition, if SR investors have multi-attribute utility functions, then one can view investing in SR funds as consumption of the SR attribute. The asset pricing models of habit formation predict consumption smoothing. Abel (1990), for example, derives a model in which utility of consumption is affected by levels of past consumption. The additive utility assumption, therefore, predicts that the volatility of fund flow is lower in SR funds than in conventional funds, resulting from consumption smoothing by SR investors.

A second assumption that leads to the same predictions of lower fund flow volatility and a weaker flow-performance relation is that at least some SR capital is directed by a clientele with a long-term horizon. The trusts of some charitable foundations or University endowments, for example, may require a certain quantity of investment in SR vehicles.[5] If this captive capital constitutes a larger fraction of SR funds than of conventional funds, then one would expect lower fund flow volatility and weaker flow-performance relations in SR funds. Alternatively, institutional investors may view the SR attribute pertinent to long-term financial competitiveness. The Enhanced Analytics Initiative,[6] for example, is a consortium of European institutional investors supporting sell-side research on "extra-financial" issues, including social and environmental responsibility, defined as "fundamentals that have the potential to impact companies' financial performance or reputation in a material way, yet are generally not part of traditional fundamental analysis." If investors in SR funds view extra-financial issues with a long-term horizon, then short-term variation in SR fund performance may impact fund flow less than variation in conventional fund performance.

Unfortunately, the Center for Research in Security Prices (CRSP) mutual fund database, described next, does not permit direct measurement of the level of institutional versus retail investment. Massa (2003), however, argues that fund companies establish fee structures for each fund to appeal to the horizon of the representative investor with larger loads and lower 12b-1 fees consistent with a longer-term horizon. Nanda, Wang, and Zheng (2005) find that when mutual funds offer multiple share classes of a single fund, the investors who select the share class with lower loads have shorter investment horizons and display greater performance sensitivity. I compare the loads and 12b-1 fees of SR and conventional funds and find no substantial difference, suggesting that fund companies do not anticipate any difference in investor horizon. For this reason, I do not pursue the assumption that SR investors have a longer-term horizon.

III. Data and Summary Statistics

This section describes the data used in the study. Summary statistics of the SR and conventional funds are presented and used to motivate some of the features of the empirical methodology.

The primary data source is the CRSP Survivor Bias-Free U.S. Mutual Fund Database, covering the period 1961 through 2002. A list of mutual funds classified as "socially screened" was obtained from the SIF.[7] The SIF queries investment managers, institutional investors, and mutual fund companies regarding their social screening and shareholder advocacy activities, and uses the results to verify existing data on SR investing from Morningstar, Wiesenberger, and other media sources. The SIF classifies mutual funds as socially screened if the manager uses one or more social screens as part of a formal investment policy, or

[5] I thank the editor, Stephen Brown, for this suggestion.

[6] Source: www.enhanced-analytics.com.

[7] I thank Todd Larsen at the SIF.

sponsors shareholder resolutions on social responsibility issues. To the extent that the SIF's classification scheme establishes a low hurdle for inclusion, my results should be biased toward the null hypothesis that attributes of the conventional and SR funds, and their respective shareholders, are equal.

I use the SIF list to separate the CRSP funds into two groups: conventional funds and SR funds. A total of 263 unique matches is found between the SIF list and the CRSP funds. From these, I eliminate 58 for having an insufficient exposure to equities, leaving 205 for analysis. I focus on equity funds since their volatility and cross-sectional variation offer the richest opportunity for studying the dynamics of fund flow. I classify a fund as an equity fund by tracking its year-end allocation to equities, as listed in the CRSP database, over the fund's life. If a fund's year-end allocation reaches 75% or higher at some point during the fund's life, it is included in the study. This decision rule avoids inadvertently dropping equity funds that feature temporarily reduced exposure to equities.[8]

In the empirical analysis, I create a matched sample of SR and conventional funds based in part on the funds' risk exposures. To estimate these, I require monthly returns of the market index, the Fama and French (1993) size and book-to-market factors, a momentum factor, and a risk-free security.[9] The equity series are constructed from the CRSP equity database, and I represent the risk-free rate by the 90-day U.S. Treasury Bill Discount from Datastream (code TBILL90).

Table 1 lists the number of funds, the average and median year-end total net assets per fund, and the average and median age of the funds year by year for equity funds in the CRSP database.[10] Statistics for the years 1980 to 2002 are reported. The explosive growth of the mutual fund industry is apparent with the number of conventional funds increasing from 348 in 1980 to 8,009 in 2002.[11] The median age of the conventional mutual funds decreases with the new introductions from 15 years in 1980 to six years in 2002. The SR sample is much smaller, reaching a maximum of 188 funds in 2001. Figure 1 depicts the growth in the mutual fund industry. Even though the SR category is just a few percent of the size of the overall mutual fund industry, its growth, both in terms of the number of funds and total assets under management, generally tracks the overall industry.

Figure 2 shows the value-weighted average return of the conventional and SR funds year by year. These two series are similar, though there are large differences in returns in the late 1990s. Table 2 compares the equal-weighted average

[8]To ensure that the procedure is reasonable, I compare year by year the total net assets of equity funds in the CRSP database, following my classification scheme, to the total net assets of equity funds as reported by the Investment Company Institute (2003). In unreported tests, the two series track each other closely, indicating that the procedure conforms to a standard classification of funds.

[9]The Fama-French and momentum factors were obtained from Ken French's Web site at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[10]The CRSP database appears to have a year 2000 problem affecting some of its records of the year in which a fund is founded. Over 800 funds are reported as being founded in years 1900, 1901, 1902, or 1903. However, the oldest mutual fund is typically recognized as the MFS Massachusetts Investors Trust, founded in 1924. So, for those funds with a foundation year of 1900–1903, 100 years were added to their foundation year.

[11]The number of funds is larger than reported elsewhere since the CRSP has separate records for each share class of a mutual fund. In 2002, for example, ICI reports 4,756 equity funds versus the 8,009 reported in Table 2.

TABLE 1

Summary Statistics

Listed are the number, median and average size (in USD millions), and median and average age, by year, of equity mutual funds in the CRSP database for years 1980 through 2002. A fund is included in a given year if it has positive year-end total net assets. A fund is considered an equity fund if the fraction of assets invested in equities reaches at least 75% while the fund is in the database. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds.

	Conventional					SR				
	No. of Funds	Med. Size	Avg. Size	Med. Age	Avg. Age	No. of Funds	Med. Size	Avg. Size	Med. Age	Avg. Age
1980	348	48.9	135.0	15	20.5	7	105.8	263.3	11	19.0
1981	368	45.2	120.4	16	20.4	8	64.1	248.9	11	17.8
1982	398	56.2	145.0	16	20.0	9	108.1	286.3	12	16.8
1983	440	74.1	186.7	16	19.1	9	47.3	362.8	13	17.8
1984	507	64.5	172.4	16	17.6	9	60.0	401.7	14	18.8
1985	600	71.5	207.1	14	16.0	12	36.0	425.7	14	15.3
1986	723	68.6	228.7	6	14.3	14	57.4	489.8	11	14.1
1987	857	60.3	213.3	5	13.1	17	65.8	472.3	6	12.7
1988	955	49.1	206.0	5	12.7	18	54.9	499.5	6	12.9
1989	1,017	58.4	245.8	6	12.7	18	136.9	668.4	7	13.9
1990	1,155	47.4	213.7	6	12.1	23	30.7	539.8	7	12.0
1991	1,318	58.6	278.1	6	11.5	23	51.2	723.1	8	13.0
1992	1,604	53.1	290.3	6	10.1	26	65.4	769.6	7	12.5
1993	2,165	56.4	323.0	4	8.3	30	92.8	826.7	7	11.8
1994	2,865	38.9	279.7	3	7.2	51	26.6	494.0	3	7.9
1995	3,517	35.3	326.4	3	6.7	62	31.4	567.6	2	7.6
1996	4,249	36.4	365.7	3	6.4	77	29.6	614.4	3	7.1
1997	5,343	36.7	393.3	3	6.0	111	18.6	643.2	3	6.0
1998	6,438	30.1	407.9	4	5.9	128	32.4	738.4	3	6.1
1999	7,249	34.5	487.6	4	6.1	160	22.4	617.1	3	6.0
2000	7,971	34.7	435.2	4	6.3	184	23.1	493.6	4	6.1
2001	8,247	31.3	366.2	5	6.8	188	25.5	472.7	5	6.9
2002	8,009	26.7	299.2	6	7.6	185	20.1	418.4	6	7.8

return of the SR funds to the average return of the conventional funds year by year from 1990 to 2002. This period was selected due to the small number of SR mutual funds prior to 1990. The table shows the difference in average returns, as well as a significance level determined using a t-test for means. The difference is statistically significant at the 5% level in 1992, 1993, and all years 1997–2000, with a magnitude ranging from -7.2% in 1993 to 7.3% in 1997.[12] This result indicates the need to control for differences in portfolio composition when comparing the SR and conventional funds.

IV. Empirical Methodology and Results

This section describes the empirical methodology and presents the results. Subsection A reviews the procedure used to infer fund flow. Subsection B explains the construction of a control group. Subsection C reports the estimates of fund flow volatility. Subsection D shows the flow-performance regression analysis. Subsection E discusses robustness tests.

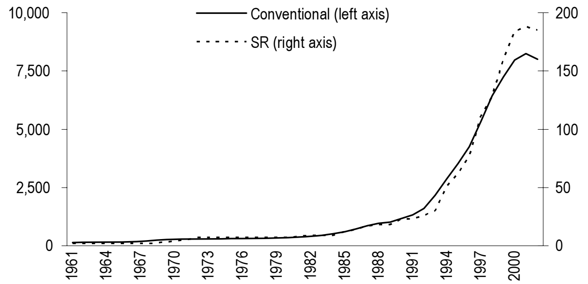
[12]This result is consistent with the findings of Bauer et al. (2005) and their "learning" hypothesis. In the four years prior to 1994, SR funds underperformed in half of the years, while in the subsequent time period only one in four of the years in which there were significant differences favored conventional funds.

FIGURE 1

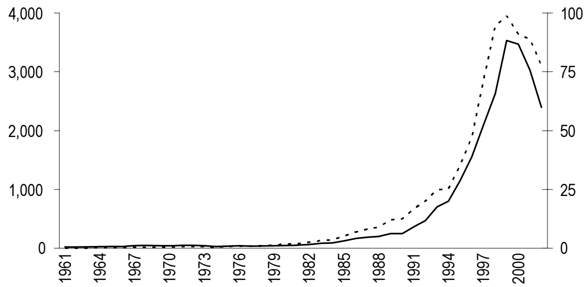
Growth in the Mutual Fund Industry

Graph A shows the total number of equity funds in the CRSP database with positive year-end total net assets, by year. Graph B shows the total net assets of equity funds in the CRSP database with positive year-end total net assets, by year. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds.

Graph A. Number of Equity Funds



Graph B. Total Net Assets of Equity Funds (in USD billions)



A. Fund Flow

Fund flow can be computed directly from a record of shareholder activity as in Warther (1995) and Edelen (1999), but is usually inferred from changes in a fund's total net assets and returns due to difficulty in obtaining reliable subscription and redemption data. I infer fund flow several ways. Let $R_{i,t}$ denote the holding period return for a mutual fund investor in fund i between times t and $t-1$, i.e.,

$$R_{i,t} = (NAV_{i,t} - NAV_{i,t-1} + D_{i,t})/NAV_{i,t-1}, \tag{1}$$

where $NAV_{i,t}$ is the fund's net asset value per share and $D_{i,t}$ are the distributions received per share by the mutual fund investor during the period.[13] Let $TNA_{i,t}$ denote the total net assets of a mutual fund at time t. Fund flow can be estimated as:

$$DF_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}), \tag{2}$$

[13]The Investment Company Act of 1940 permits mutual funds to distribute realized capital gains and income from assets held by the fund to mutual fund investors each year in order to pass the responsibility of paying taxes on distributions to fund shareholders.

FIGURE 2

Performance of Mutual Fund Industry

Depicted is the value-weighted average return of equity funds in the CRSP database by year. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds.

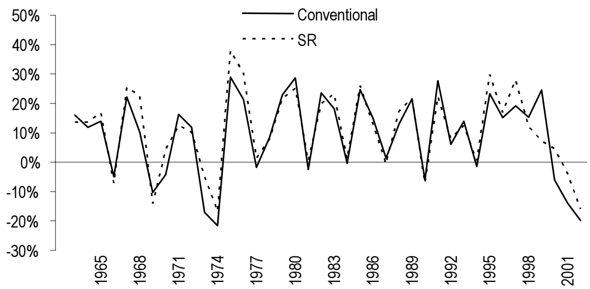


TABLE 2

Equally-Weighted Percentage Returns

Listed is the equally-weighted percentage return of two groups of equity mutual funds in the CRSP database for years 1990 through 2002. A fund is included in a given year if it has positive year-end total net assets. A fund is considered an equity fund if the fraction of assets invested in equities reaches at least 75% while the fund is in the database. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds. The *p*-value corresponds to a *t*-test for means.

Year	SR	Conventional	Difference	*p*-Value
1990	−6.4	−6.5	0.2	0.9308
1991	27.3	28.4	−1.1	0.6026
1992	9.0	5.7	3.4	0.0411
1993	9.0	16.2	−7.2	0.0000
1994	−0.9	−2.0	1.1	0.3533
1995	22.7	22.0	0.7	0.6069
1996	14.0	14.8	−0.8	0.3535
1997	22.6	15.4	7.3	0.0000
1998	15.3	9.5	5.8	0.0007
1999	23.2	30.0	−6.8	0.0127
2000	−1.1	−3.7	2.7	0.0309
2001	−10.2	−11.8	1.6	0.1233
2002	−19.8	−19.7	−0.1	0.8703

where $DF_{i,t}$ denotes dollar flow. Dollar flows in (2) are often rescaled to percentage flows by dividing $DF_{i,t}$ by $TNA_{i,t-1}$ as in Del Guercio and Tkac (2002), Sirri and Tufano (1998), and Barber, Odean, and Zheng (2005). These calculations assume all flow occurs at the end of the period. Sirri and Tufano (1998) and Zheng (1999) also compute flows assuming they occur at the beginning of the period:

$$(3) \qquad DF_{i,t} \quad = \quad TNA_{i,t}/(1+R_{i,t}) - TNA_{i,t-1},$$

and their results are qualitatively unchanged. In my analysis, I focus on percentage flows, i.e., $F_{i,t} = DF_{i,t}/TNA_{i,t-1}$. I compute fund flows two ways, consistent with (2) and (3), for robustness. In all cases, the results are qualitatively similar across these two measures.

Fund companies often merge the assets of two or more funds, sometimes as a means of eliminating poorly performing funds. Fund mergers are observationally equivalent to subscriptions for the recipient fund, and may distort estimates of fund flow, fund flow volatility, and the flow-performance relation. To eliminate the impact of mergers, I use the CRSP merger file to reduce dollar flows in the recipient fund by the assets of the merged fund. The assets of the merged fund are taken from the last observation of the fund in the CRSP total net assets file.

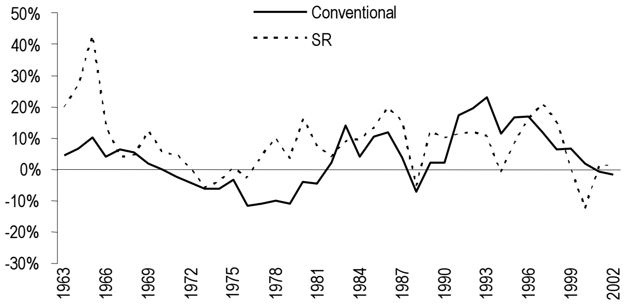
The CRSP database provides annual records of fund total net assets between 1961 and 1969, quarterly records between 1970 and 1991, and monthly records thereafter. The database provides monthly fund returns throughout. I use annual observations of fund flow and performance when studying the flow-performance relation, and monthly observations of fund flow when computing flow volatility. Visual inspection of the data indicates a number of extreme observations of total net assets, some of which are subsequently reversed, indicating possible misplacement of the decimal point. For this reason, I remove observations of fund flow below −90% and above 1,000%. There are 658 such cases out of 105,355 annual observations of fund flow, and 463 cases out of 1,207,401 observations of monthly flow.

Figure 3 shows the aggregate fund flow for conventional funds and SR funds. This figure depicts the growth of the entire industry: dollar fund flow is aggregated across funds, and this is divided by the beginning-of-year total net assets aggregated across funds. There is a common component to the time-series variation in SR and conventional fund flow. For this reason, the matching procedure described next ensures that the conventional funds I select for a control group are aligned in time with the SR funds.

FIGURE 3

Aggregate Fund Flow of Mutual Fund Industry

Depicted is the aggregate fund flow as a percentage of beginning-of-year assets of equity funds in the CRSP database by year. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds.



B. Control Group

In order to measure the impact of the SR attribute on the behavior of SR investors relative to the behavior of investors in conventional funds, I need to control for other variables that might affect estimates of fund flow volatility and performance sensitivity.

1. Risk Exposures

Existing SR studies, including Luther, Matatko, and Corner (1992), Guerard (1997), and Bauer et al. (2005), find differences in the risk exposures of SR and conventional funds.[14] These studies focus on performance, and naturally control for differences in risk. In my study, controlling for differences in risk is also important to ensure that any difference in investor behavior is due to the SR attribute rather than differences in portfolio composition.

There is some debate regarding which risk exposures affect fund flow. Gruber (1996) shows that fund flow is positively related to lagged abnormal returns as measured by both single- and multi-factor asset pricing models. Del Guercio and Tkac (2002), however, show that Morningstar ratings subsume abnormal returns in the flow-performance relation for mutual funds. For robustness, I measure risk exposures using two models of returns. First, I measure exposure to market risk by the CAPM:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,M}(R_{M,t} - R_{f,t}) + \varepsilon_t, \tag{4}$$

where R_p is the return of fund p, R_f is the riskless rate of return, and R_M is the return of a market proxy. Second, I measure exposure to market risk, as well as the size, value, and momentum factors using the following four-factor model from Carhart (1997):

$$\begin{aligned} R_{p,t} - R_{f,t} = {} & \alpha_p + \beta_{p,M}(R_{M,t} - R_{f,t}) + \beta_{p,SMB}R_{SMB,t} \\ & + \beta_{p,HML}R_{HML,t} + \beta_{p,UMD}R_{UMD,t} + \varepsilon_t, \end{aligned} \tag{5}$$

where R_{SMB} is the return of the size factor, R_{HML} is the return of the value factor, and R_{UMD} is the return of the momentum factor.

Table 3 summarizes the regression statistics estimated from the two risk models by reporting the 25th, 50th, and 75th percentile values of the cross-sectional distributions of the SR and conventional fund β coefficients. I require a minimum of 24 months of returns when estimating the models of risk, reducing the sample size of SR funds from 205 to 187. Panel A shows the results for the CAPM. The median adjusted R^2 is 66.52% for the conventional funds and 79.82% for the SR funds, indicating that there are a substantial number of conventional funds with strategies that are not fully captured by the CAPM. Note that the distributions of CAPM β_M are quite similar, though with medians of 0.8378 for the conventional funds and 0.8480 for the SR funds. Panel B shows the results for the four-factor model. The median adjusted R^2 increases to 81.58% and 87.12% for the conventional and SR funds, respectively. The SR funds feature a significantly smaller exposure to the size factor than the exposure of conventional funds. Since the size factor equals the return of small stocks minus the return of large stocks,

[14]Luther et al. (1992) document a bias toward small capitalization stocks in their study of U.K. SR funds over the 1984 to 1990 period. Similarly, Guerard (1997) finds that those stocks screened from the Vantage Global Advisors universe of 1,300 stocks are considerably larger and more value-oriented than stocks that pass the screens from 1990 to 1994. In contrast, Bauer et al. (2005) find that SR funds, both U.S. and international, tend to place greater weight on large stocks than conventional funds, resulting in a smaller exposure to the Fama and French (1993) small minus big factor than conventional funds.

this means that the SR funds in the sample are weighted toward larger capitalization stocks relative to conventional funds, consistent with the results of Bauer et al. (2005). The SR funds also have a significantly smaller exposure to momentum stocks. Note that the interquartile ranges of the β coefficients of SR funds are narrower than those of the conventional funds. The size, value, and momentum factor coefficients have ranges of 0.4649, 0.4375, and 0.1991, respectively, for the conventional funds versus 0.3655, 0.3015, and 0.1361 for the SR funds.[15] Differences in portfolio composition in conjunction with investor demand for particular styles could explain any difference in the flow-performance relation of SR and conventional funds. I control for differences in portfolio composition by matching SR funds to conventional funds using the risk exposures as matching criteria.

TABLE 3

Fund Characteristics

Listed are values of the 25th, 50th, and 75th percentiles of the cross-sectional distribution of OLS adjusted R^2 and parameter estimates for two regressions describing the portfolio composition of two samples of equity mutual funds taken from the CRSP database. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds. Panel A shows the results for the Capital Asset Pricing Model: $R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,M}(R_{M,t} - R_{f,t}) + \varepsilon_t$. Panel B shows the results for the four-factor model, which equals the CAPM augmented with size (*SMB*), value (*HML*), and momentum (*UMD*) factors. The regressions are estimated once for each fund with at least 24 consecutive months of return data.

Panel A. CAPM

	R^2	α	β_M
Conventional Funds (N = 9,189)			
25th	0.5159	−0.0045	0.6669
50th	0.6652	−0.0017	0.8378
75th	0.8122	0.0011	1.0517
SR Funds (N = 187)			
25th	0.6716	−0.0032	0.7146
50th	0.7982	−0.0016	0.8480
75th	0.9016	0.0000	1.0034
Difference in Means			
Conv.	0.6398	−0.0016	0.8974
SR	0.7598	−0.0015	0.8737
Difference	−0.1200	−0.0001	0.0237
p-value	0.0000	0.6972	0.2987

Panel B. Four-Factor Model

	R^2	α	β_M	β_{SMB}	β_{HML}	β_{UMD}
Conventional Funds (N = 9,189)						
25th	0.6574	−0.0053	0.7326	−0.0484	−0.1884	−0.0494
50th	0.8158	−0.0025	0.8763	0.1413	0.0241	0.0436
75th	0.8887	0.0000	0.9990	0.4165	0.2491	0.1497
SR Funds (N = 187)						
25th	0.7767	−0.0041	0.7538	−0.1287	−0.1032	−0.0565
50th	0.8712	−0.0017	0.8778	0.0196	0.0329	0.0176
75th	0.9308	0.0001	0.9571	0.2368	0.1983	0.0796
Difference in Means						
Conv.	0.7489	−0.0025	0.8814	0.2000	0.0071	0.0312
SR	0.8368	−0.0018	0.8679	0.0972	0.0193	0.0090
Difference	−0.0879	−0.0007	0.0135	0.1028	−0.0122	0.0222
p-value	0.0000	0.0383	0.3565	0.0000	0.6029	0.0795

[15]The tighter range of factor coefficients for SR funds is consistent with the argument in Geczy et al. (2003) that SR funds offer less opportunity than conventional funds for exposure to risk factors. This hampers the performance of portfolios of SR funds relative to the performance of portfolios of conventional funds in their analysis as a result.

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2. Life Cycle

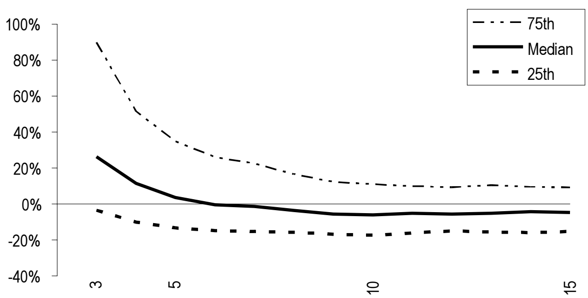
Another determinant of fund flow and the flow-performance relation that may cloud inference regarding SR and conventional funds is the general life cycle of mutual funds. As argued in Section II, a Bayesian investor may have a more diffuse prior belief regarding the expected performance of a young fund relative to the corresponding prior for an established fund, resulting in higher flow-performance sensitivity. Figure 4 shows for both the conventional funds (Figure 4, Graph A) and SR funds (Figure 4, Graph B) the 25th, 50th, and 75th percentile values of the cross-sectional distribution of fund flow F for fund years defined by the age of the fund. In both graphs, the distribution is characterized by lower values as funds age. The median for conventional funds is approximately 25% at age three, for example, and close to zero at age six. Clearly, I need to control for age since SR and conventional funds may differ in performance sensitivity not because of the SR attribute, but simply because the SR funds may in aggregate be younger or older than the other funds.

FIGURE 4

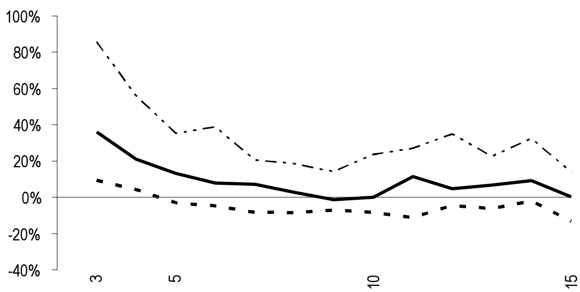
Fund Flow as a Function of Fund Age

Depicted are values of the 25th, 50th, and 75th percentiles of the cross-sectional distribution of fund flow for funds categorized by fund age in years. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Conventional" refers to all other equity funds.

Graph A. Conventional Funds



Graph B. SR Funds



Related to age and its impact on the flow-performance relation is the size of a mutual fund. Sirri and Tufano (1998), among others, show that smaller funds tend to attract larger percentage inflows, suggesting that as funds increase in size, the relation between flow and performance may weaken. To control for life cycle effects, then, I match SR and conventional funds by age and fund size as described next.

3. Matching Procedure

One approach to control for variables that may explain the dynamics of fund flow is to include additional explanatory variables in the regression analysis. However, the assumption of linearity may be inappropriate as evidenced by the relation between fund flow and fund age in Figure 4. An alternative approach is to construct a matched sample of SR and conventional funds. I use two matching procedures, corresponding to the two models of risk described above.

I apply some exclusionary criteria to observations of fund flow at the outset. For each SR fund, only those conventional funds with first and last years in the database that are within three years of the first and last years of the SR fund under consideration are eligible as candidates. This restriction ensures that the funds will experience similar macroeconomic time-series effects. To control for age, the conventional fund must be no more than three years younger or older than the SR fund. In addition, only no-load conventional funds are eligible candidates for no-load SR funds, and only conventional funds with a load are eligible for SR funds with a load. This restriction controls for any relation between loads and the dynamics of fund flow.

For a given SR fund, all eligible conventional funds are scored based on the distance between the conventional fund's size and β coefficients and the SR fund's size and β coefficients. I measure the distance relating how close the SR fund (i) is to each of the conventional funds (j) using the following algorithm:

$$(6) \qquad Distance_{i,j} = \sum_{k=1}^{N}((\beta_{i,k} - \beta_{j,k})/\sigma_k)^2 + ((TNA_i - TNA_j)/\sigma_{TNA})^2,$$

where N is the number of risk factors in the two models, β_k are the risk coefficients, σ_k is the cross-sectional standard deviation of the risk coefficients, TNA is the maximum size reached by the fund, and σ_{TNA} is the cross-sectional standard deviation of TNA. Scaling by standard deviation normalizes the weights placed on each matching criterion. For each annual observation of SR fund flow, fund flows from the three conventional funds with the shortest distance to the SR fund are added to the control group.

C. Volatility of Monthly Fund Flows

Table 4 lists summary statistics of the cross-sectional distributions of fund flow for the SR funds and the control group. Volatility is simply the time-series standard deviation of monthly flow using all consecutive observations for each fund for the period 1991–2002. Recall that the CRSP records monthly observations of TNA starting in 1991. "All" shows results when flow volatility is computed over a fund's entire life, "Young" shows results when flow volatility is computed for fund age five years or less, and "Mature" shows results when flow volatility is computed for fund age six years or greater. A volatility estimate must contain at least 12 observations to be included in the analysis.

TABLE 4

Monthly Fund Flow Volatility Comparisons

Listed are values of the 25th, 50th, and 75th percentiles of the cross-sectional distribution of monthly volatility of percentage fund flows for two samples of equity mutual funds taken from the CRSP database. "All" shows results when flow volatility is computed over a fund's entire life, "Young" shows results when flow volatility is computed for fund age five years or less, and "Mature" shows results when flow volatility is computed for fund age six years or greater. Also shown are the averages and two-sided *p*-value of *t*-tests for a significant difference. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "Matched" refers to a subset of all other equity funds, and consists of three conventional funds for each SR fund matched on size, age, start date, and the β coefficients from the four-factor model. To be included in the analysis, a volatility estimate must contain at least 12 consecutive months of flow data.

	All Funds		Young Funds		Mature Funds	
	Matched	SR	Matched	SR	Matched	SR
25th	0.0555	0.0462	0.0634	0.0502	0.0226	0.0182
50th	0.0955	0.0772	0.1052	0.0854	0.0355	0.0268
75th	0.1492	0.1261	0.1649	0.1440	0.0754	0.0519
No. of obs.	456	152	429	143	210	70
Avg.	0.1455	0.1174	0.1654	0.1343	0.0669	0.0399
p-value		0.0645		0.0869		0.0030

Using all observations to estimate volatility, the 25th, 50th, and 75th percentile values of the SR funds are all lower than the conventional funds, 7.72% versus 9.55% at the median, for example. The interpretation is that a $100 million fund experiences monthly flows with standard deviation of about $8 million for the SR funds and $10 million for the conventional funds. The sample means are higher than the medians, 11.74% for the SR funds versus 14.55% for the conventional funds, significantly different at the 10% level using a *t*-test for means. These findings indicate that SR fund flow is economically and statistically significantly less variable than that of conventional funds.

As mentioned in the prior subsection, Chevalier and Ellison (1997) and Sirri and Tufano (1998) both document life cycle effects in mutual fund flows. Younger funds feature stronger flow-performance relations and larger percentage fund flows than more mature funds. Consistent with the life cycle evidence, Table 4 shows for both SR and conventional funds, flow volatility for Mature funds is less than half the volatility of Young funds. Note also, however, that for both the Young and Mature subgroups, the SR funds have statistically significantly lower flow volatility than their conventional counterparts.

My analysis of monthly flow volatility suggests that SR investors move money in and out of their mutual funds at a significantly slower rate than investors in other funds. Furthermore the difference persists as funds age. Lower flow volatility may represent consumption smoothing on the part of SR investors. These results are inconsistent with Hypothesis 1 as well as the assumption of rational learning with diffuse prior beliefs. The results are consistent with the assumption of a multi-attribute utility function, however, which motivates Hypothesis 2 when the SR attribute is valued conditional on performance or motivates Hypothesis 3 when the SR attribute is valued unconditionally. In the next subsection, I investigate the flow-performance relation in SR funds to make the inference more precise.

D. Flow-Performance Relation

Analysis of the flow-performance relation requires specifying a response function; in particular, I need to specify how many lags of performance to include. This choice specifies the horizon over which investors measure performance. In order to avoid misspecifying the response function, I estimate the relation between annual fund flow and performance lagged one year. This can be viewed as the aggregate response over the course of a year to a fund's prior year performance.[16]

I estimate OLS parameters of the following flow-performance regression:

$$(7)\quad F_{i,t} \;=\; \alpha_0 + \alpha_1 S_i + \left(\beta_0 I^1_{i,t-1} + \beta_1 I^2_{i,t-1} + \beta_2 I^3_{i,t-1} + \beta_3 I^4_{i,t-1}\right) R_{i,t-1} + \varepsilon_{i,t},$$

where $F_{i,t}$ is the fund flow of fund i in year t, $S_i = 1$ if fund i is an SR fund and 0 otherwise, $I^1_{i,t-1} = 1$ if fund i is conventional and has a positive lagged return and 0 otherwise, $I^2_{i,t-1} = 1$ if fund i is SR and has a positive lagged return and 0 otherwise, $I^3_{i,t-1} = 1$ if fund i is conventional and has a negative lagged return and 0 otherwise, $I^4_{i,t-1} = 1$ if fund i is SR and has a negative lagged return and 0 otherwise, and $R_{i,t-1}$ is the lagged return. I frame the asymmetry around a 0 return for two reasons. First, a 0 return seems to be a reasonable quantitative anchor that might affect investor decision making. Second, coefficients in the flow-performance relation are easy to interpret in terms of inflows and outflows of investor capital. A positive coefficient on positive returns corresponds to a cash inflow, whereas a positive coefficient on negative returns corresponds to a cash outflow. Given the construction of the indicator variables, coefficients measure sensitivity of fund flow to lagged returns for the following subsets:

(8)

β_0 conventional funds following positive returns,

β_1 SR funds following positive returns,

β_2 conventional funds following negative returns, and

β_3 SR funds following negative returns.

To be included in the regression analysis, an observation of fund flow must be from a fund with at least \$10,000,000 of total net assets in the two successive years used to compute the flow, consistent with the procedure in Chevalier and Ellison (1997). This eliminates extremely small funds that may exhibit explosive growth and distort the results. I also discard observations of fund flow prior to 1980 since the number of funds in the pre-1980 time period is quite small. The results are robust to changes in this cutoff.

Table 5 lists the OLS parameter estimates. For the funds matched using the CAPM as listed in Panel A, cash inflows to conventional funds increase 0.6529% for every 1% increase in prior year return when the lagged return is positive.[17] In contrast, cash inflows to SR funds increase 1.4587% for every 1% increase in prior

[16]Gruber (1996) finds that fund flow is also related to performance lagged two years. I only include performance lagged one year to focus attention on the information provided by the most recent observation in the context of Bayesian updating.

[17]Del Guercio and Tkac (2002), for comparison, include lagged raw and abnormal returns simultaneously as independent variables and estimate coefficients of 0.45 and 3.24, respectively.

year return when the lagged return is positive. This result shows that investors in SR funds are more sensitive to positive returns than conventional investors. The heightened sensitivity to positive returns is consistent with both assumptions motivating Hypothesis 2, rational learning with diffuse priors and a conditional utility function, but inconsistent with the assumption of an additive utility function underlying Hypothesis 3. As discussed in the prior subsection, I can rule out rational learning with diffuse priors due to the lower fund flow volatility of SR funds, hence, the conditional utility function seems to capture the salient features of the data the best. Now consider the sensitivity to performance following negative returns. Cash outflows from conventional funds increase by 0.5360% for every 1% decrease in prior year return when lagged returns are negative. SR outflows increase by just 0.3207% for every 1% decrease in prior year return when lagged returns are negative. Furthermore, the coefficient on negative lagged returns is not statistically different from zero for SR funds. This result indicates that investors in SR funds are *less* sensitive to negative returns than conventional investors.

TABLE 5

OLS Regression Results

Listed are OLS parameter estimates of the β coefficients of the following regression:

$$F_{i,t} \quad = \quad \alpha_0 + \alpha_1 S_i + \left(\beta_0 I^1_{i,t-1} + \beta_1 I^2_{i,t-1} + \beta_2 I^3_{i,t-1} + \beta_3 I^4_{i,t-1}\right) R_{i,t-1} + \varepsilon_{i,t},$$

where F is fund flow as a percentage of beginning-of-year total net assets, $S_i = 1$ if fund i is SR and 0 otherwise, $I^1_{i,t-1} = 1$ if fund i is conventional and has a positive lagged return and 0 otherwise, $I^2_{i,t-1} = 1$ if fund i is SR and has a positive lagged return and 0 otherwise, $I^3_{i,t-1} = 1$ if fund i is conventional and has a negative lagged return and 0 otherwise, $I^4_{i,t-1} = 1$ if fund i is SR and has a negative lagged return and 0 otherwise, and R is return. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "All" shows results when observations are included from a fund's entire life, "Young" shows results when only observations for fund age five years or less are included, and "Mature" shows results when only observations for fund age six years or greater are included. Panel A shows results when each annual observation of an SR fund is matched to annual observations of three conventional funds where the match is based on age, start date, size, and CAPM β. Panel B shows the results when the match is based on age, start date, size, and the four β coefficients from the four-factor model.

Panel A. CAPM Match

	All Funds (N = 2,696)			Young Funds (N = 912)			Mature Funds (N = 1,784)		
		t-Stat.	*p*-Value		*t*-Stat.	*p*-Value		*t*-Stat.	*p*-Value
R^2	0.0579			0.0434			0.0723		
β_0	0.6529	6.4302	0.0000	0.6887	3.2610	0.0012	0.5666	5.4872	0.0000
β_1	1.4587	8.0376	0.0000	1.8922	3.6405	0.0003	1.2577	7.7575	0.0000
β_2	0.5360	2.4420	0.0147	0.3543	0.7484	0.4544	0.6673	3.0667	0.0022
β_3	0.3207	0.7212	0.4709	0.3807	0.3239	0.7461	0.2019	0.4946	0.6209

Panel B. Four-Factor Match

	All Funds (N = 2,836)			Young Funds (N = 952)			Mature Funds (N = 1,884)		
		t-Stat.	*p*-Value		*t*-Stat.	*p*-Value		*t*-Stat.	*p*-Value
R^2	0.0572			0.0583			0.0609		
β_0	0.7102	7.1396	0.0000	1.1778	4.7588	0.0000	0.4751	5.1368	0.0000
β_1	1.4186	7.9447	0.0000	1.8149	3.5770	0.0004	1.2382	7.7734	0.0000
β_2	0.4894	2.2161	0.0268	0.3788	0.7173	0.4734	0.5194	2.4907	0.0128
β_3	0.3117	0.7084	0.4788	0.4353	0.3773	0.7060	0.2027	0.5020	0.6157

The asymmetric difference between SR funds and conventional funds is not consistent with any of the three hypotheses discussed in Section II. All of the motivating assumptions predict a symmetric difference: either the flow-performance relation would be stronger or weaker in SR funds than conventional funds for both positive and negative performance. Prior research has documented similar asymmetries. As mentioned in Section II, a standard result in the flow-performance literature is that poor performers are not punished with outflows to the same extent that superior performers are rewarded with inflows. Kahneman and Tversky's (1979) prospect theory provides one explanation for the asymmetric response to performance by assuming that investor attitudes are described as risk seeking in the region of losses and risk averse in the region of gains. Alternatively, Lynch and Musto (2003) argue that investors may expect that management companies will replace managers of poorly performing funds, and may anticipate expected returns to increase as a result.

As listed in Table 5, three results stand out when observations are split by fund age. First, for both young funds and mature funds, the sensitivity of SR fund flow to positive lagged returns is still approximately twice that of conventional fund flow. This supports the assumption of a conditional utility function because a utility-based explanation predicts differences between SR funds and their conventional counterparts persist over time. Second, for mature funds, the sensitivity of SR fund flow to negative lagged returns is insignificantly different from zero, whereas the sensitivity of conventional fund flow to negative lagged returns is a statistically significant 0.6673. Both these results are consistent with the full sample. Third, for young funds, the sensitivities of SR and conventional funds to lagged negative returns are similar in magnitude and neither is significantly different from zero.

Panel B lists results for the four-factor match. In all cases, the coefficients' magnitudes and significance levels are consistent with the CAPM match. This result indicates that the differences between SR funds and their conventional counterparts cannot be explained by any differences in risk exposure.

E. Robustness Tests

In unreported analysis, I rerun the flow-performance tests on subsets of the data split two ways. First, to determine whether SR investors in aggregate have changed behavior over time, I split the observations into an early period from 1980 to 1993 and a later period from 1994 to 2002. In both periods, coefficients on lagged positive returns are statistically significant, and the sensitivity of SR fund flow to lagged positive returns is approximately double that of conventional funds. For the 1980 to 1993 period, the sensitivity of fund flow to lagged negative returns is not statistically significant for either group of funds. For the 1994 to 2002 period, the sensitivity of fund flow to lagged negative returns is substantially smaller for SR funds than conventional funds. In sum, the results across the subsets indicate that preferences of SR investors are persistent and do not indicate that behavior is explained by a model of rational learning.

Second, to determine whether SR investors distinguish between types of SR funds as measured by the extent of their screening activity, I collect information from mutual fund company Web sites regarding the number and types of SR screens employed. I construct two subsets, one for funds that exclude only "sin" companies such as tobacco or alcohol producers, and the other for funds

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with multiple concerns. The coefficient estimates are qualitatively robust across the subsets, suggesting that investors behave similarly regardless of the extent of portfolio screening. These results should be interpreted with caution, however, because the limited size of the subsamples likely reduces the statistical power of the test.

As noted earlier, the CRSP data contain a number of extreme observations of fund total net assets. Even after excluding observations of fund flow below -90% or above 1,000%, analysis of the regression residuals suggests the presence of outliers that might be influencing the results. Both the Jarque-Bera and Kolmogorov-Smirnov tests for normality reject the null hypothesis that the residuals are Gaussian, primarily due to excess kurtosis. To ensure that the conclusions are robust to the presence of outliers, I reestimate the coefficients of the regressions in (7) by minimizing the sum of absolute errors, rather than the sum of squared errors. The LAD regression places less weight on outliers. I use the IMSL routine DRLAV to estimate parameters. As described in Birkes and Dodge (1993), standard errors of the estimates are approximately equal to OLS standard errors scaled by $\tau/\sigma_{\mathrm{OLS}}$, where σ_{OLS} is the standard deviation of residuals from OLS and

$$\tau = \frac{\sqrt{N-2}[\varepsilon_{k_2} - \varepsilon_{k_1}]}{4}, \tag{9}$$

where N is the number of observations, ε are residuals from the LAD regression sorted in ascending order, and $k_{1,2}$ are the two integers closest to $(N-1)/2 \pm \sqrt{(N-2)}$. Table 6 shows the results. In almost all cases, the coefficients are smaller, which is consistent with the procedure putting less weight on the tails, but the qualitative inference is the same as in the OLS analysis.

An analysis of the demographic characteristics of SR investors, and a comparison to the demographics of investors in conventional funds, may provide additional insight regarding the behavior of SR investors. While I am unaware of any published research concerning the demographics of SR investors, private conversations with the research staffs at two large SR fund companies revealed that SR mutual fund investors are significantly more likely to be female, highly educated, and have lower income than investors in conventional funds. To the extent that one expects educated female investors to be less prone to an overconfidence bias than other investors (see Barber and Odean (2001)), one may expect them to trade less, thereby generating lower fund flow volatility. Unfortunately, investment companies are reluctant to reveal information regarding their shareholders, so I am unable to generate and test empirically more detailed hypotheses regarding investor behavior. However, even with the observable aggregate flow data, significant differences between SR and conventional investors are apparent.

V. Conclusions

This paper analyzes the dynamics of investor fund flows in a sample of socially screened equity mutual funds. SR funds feature significantly lower monthly fund flow volatility than conventional funds. This result suggests that the extra-

TABLE 6

LAD Regression Results

Listed are LAD parameter estimates of the β coefficients of the following regression:

$$F_{i,t} = \alpha_0 + \alpha_1 S_i + \left(\beta_0 I^1_{i,t-1} + \beta_1 I^2_{i,t-1} + \beta_2 I^3_{i,t-1} + \beta_3 I^4_{i,t-1}\right) R_{i,t-1} + \varepsilon_{i,t},$$

where F is fund flow as a percentage of beginning-of-year total net assets, $S_i = 1$ if fund i is SR and 0 otherwise, $I^1_{i,t-1} = 1$ if fund i is conventional and has a positive lagged return and 0 otherwise, $I^2_{i,t-1} = 1$ if fund i is SR and has a positive lagged return and 0 otherwise, $I^3_{i,t-1} = 1$ if fund i is conventional and has a negative lagged return and 0 otherwise, $I^4_{i,t-1} = 1$ if fund i is SR and has a negative lagged return and 0 otherwise, and R is return. "SR" refers to those funds identified as socially responsible by the Social Investment Forum. "All" shows results when observations are included from a fund's entire life, "Young" shows results when only observations for fund age five years or less are included, and "Mature" shows results when only observations for fund age six years or greater are included. Panel A shows results when each annual observation of an SR fund is matched to annual observations of three conventional funds where the match is based on age, start date, size, and CAPM β. Panel B shows the results when the match is based on age, start date, size, and the four β coefficients from the four-factor model.

Panel A. CAPM Match

	All Funds (N = 2,696)			Young Funds (N = 912)			Mature Funds (N = 1,784)		
		t-Stat.	*p*-Value		*t*-Stat.	*p*-Value		*t*-Stat.	*p*-Value
β_0	0.3355	10.7113	0.0000	0.3852	4.2745	0.0000	0.2884	6.2440	0.0000
β_1	0.8654	15.4567	0.0000	1.1117	5.0120	0.0000	0.6431	8.8685	0.0000
β_2	0.4451	6.5720	0.0000	0.4694	2.3238	0.0204	0.5253	5.3976	0.0000
β_3	0.2053	1.4967	0.1346	0.4023	0.8024	0.4226	0.3062	1.6774	0.0936

Panel B. Four-Factor Match

	All Funds (N = 2,836)			Young Funds (N = 952)			Mature Funds (N = 1,884)		
		t-Stat.	*p*-Value		*t*-Stat.	*p*-Value		*t*-Stat.	*p*-Value
β_0	0.4122	10.8687	0.0000	0.6815	6.4689	0.0000	0.2780	9.3042	0.0000
β_1	0.8547	12.5553	0.0000	1.0942	5.0658	0.0000	0.6247	12.1414	0.0000
β_2	0.3485	4.1394	0.0000	0.3402	1.5134	0.1305	0.3875	5.7517	0.0000
β_3	0.1797	1.0710	0.2842	0.4401	0.8962	0.3704	0.3269	2.5066	0.0123

financial SR attribute serves to dampen the rate at which SR investors trade mutual funds.

I also compare the relation between annual fund flows and lagged performance in SR funds to the same relation in a matched sample of conventional funds. For the 1980 through 2002 period, SR investors exhibit a significantly larger response to positive returns than investors in conventional funds, but a smaller response to negative returns than investors in conventional funds. Furthermore, the differences between SR funds and their conventional counterparts are robust over time and persist as funds age. Taken together, the evidence suggests that preferences of SR investors can be represented by a conditional multi-attribute utility function in the sense that they appear to derive utility from being exposed to the SR attribute, especially when SR funds deliver positive returns.

Mutual fund companies, which continually compete to offer new funds in an effort to attract investor capital, can expect SR investors to be more loyal than investors in ordinary funds. My results should extend to other sectors of the mutual fund industry characterized by specific extra-financial attributes—I leave tests of generality to future research.

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