Predicting Return on Socially Responsible Investment Funds with Market Fundamental and Consumer Confidence

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In this paper, we examine how the market fundamental represented by dividend yield on S&P 500 index and consumer confidence as measured by the changes in consumer sentiment index (CSI) can predict future returns on a sample of mutual funds that comply with socially responsible investment (SRI) principles. Results reveal that both variables can predict SRI fund returns positively, while the coefficient on dividend yield is greater in magnitude than the coefficient on consumer sentiment. In addition, positive changes in consumer sentiment predict SRI return more strongly than negative changes in consumer sentiment. This finding can be interpreted as a rise in activism of SRI investors during period of high sentiment period and a fall in activism when sentiment is lower. The results hold for horizons of 3 to up to 12 months and are robust with different estimation specifications. Further, we find that flows of SRI funds do not predict the returns of these funds.

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1. Introduction

The rapid growth of socially responsible investment (SRI) funds since the 1990's has prompted researchers to investigate their performance in comparison to conventional funds and examine factors that affect SRI fund returns. [1] For example, Borghesi, et al (2014) identify factors that cause managers to promote socially responsible investments, and Ghoul and Karoui (2017) show the effects of the Corporate Social Responsibility score on fund performances of the U.S. equity funds. Riedl and Smeets (2017) provide comprehensive examinations of the possible reasons why and how investment decisions in SRI funds are made. Keen interest in the topic of socially responsible investments is also evidenced by various articles published in the mainstream financial news outlets.[2] A key question is whether promoting the

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[1] According to the Social Investment Forum (2010 and 2015), SRI funds have grown from $639 billion in 1995, $3.07 trillion in 2010, $13.3 trillion in 2012 to $21.4 trillion in 2014.
[2] For instance, the following articles have recently appeared in the *Wall Street Journal* (WSJ): "Sustainable Investing Goes Mainstream" January 13, 2016; "Does Socially Responsible Investing Make Financial Sense?" February 28, 2016; "How Much Do You Know About Ethical Investing" June 6, 2017; and "The Tricky Ethics of Socially Responsible Investing" September 4, 2017.

common interests of the society at large can be consistent with the corporate manager's goal of maximizing the wealth of the shareholders. From the investors' perspective, yet another related question is whether investment vehicles that are built upon the principles of social responsibility are responsive to movement in market fundamentals only or they are equally sensitive to fluctuations in sentiment as well. It is this second question that this paper attempts to address. The question can be rephrased as whether sentiment has predictive power for SRI funds future returns. If investors undergo some self-consciousness and emotional attachment to these SRI funds given their social preferences, then consumer sentiments could have a role in investing in these funds.

In this paper, we conjecture that both market fundamentals as well as consumer sentiment can predict the future returns on SRI funds. More specifically, we examine how the market fundamental represented by dividend yield and sentiment proxied by consumer sentiment index (CSI) can predict future returns on a sample of mutual funds that satisfy socially responsible investment principles. There may be different degrees of influence from these variables on the returns of SRI funds, where sentiments may reveal distinctive aspects of the predictability of SRI funds. There is little research on how consumer sentiment may affect the outcomes of SRI funds based on the use of predictable regression formats and different panel estimation settings. To the best of our knowledge, the current paper is the first to examine the predictive ability of the consumer sentiment for SRI fund returns and analyze the asymmetric responses of SRI fund returns on positive and negative changes in the sentiments over different investment horizons.

Bollen (2007) shows that cash flows of SRI funds are more sensitive to lagged positive returns and less volatile relative to conventional funds, and conjectures that the results can be attributed to differences in utility function rather than rational learning. Even during the financial crisis periods from 2007 to 2009, assets using SRI strategies experienced a healthy growth in their returns. Nolfsinger and Varma (2014) and Bechetti et al. (2015) find that SRI funds outperformed conventional funds during that financial crisis, possibly because investors perceive SRI funds to be safer, providing insurance against potential market downturns. The investors of SRI funds may not withdraw funds during the market downturn as much as investors in conventional funds do, and this could reduce the transaction costs of the investors as well as provide flexibility for fund managers. Riedl and Smeets (2017) document that social preferences and social signaling explain investing in SRI funds, and that financial motives play less of a role. They suggest that investors in SRI funds are willing to pay higher management fees even if they expect to earn lesser returns relative to conventional funds in order to satisfy their social preferences. In general, researchers document that SRI fund returns are at least as good as the aggregated investment returns (e.g., S&P500 index), and better than many mutual fund returns, and that they behave differently from conventional funds.[3]

Researchers have examined the predictive ability of consumer sentiments for the returns in equity markets. In the existing literature, the measure of consumer sentiments has been used as a proxy for the consumer confidence as well as investor confidence for the financial markets. For example, Schmeling (2009) uses consumer sentiment as a proxy for individual investor sentiment, and Akhtar et al. (2011) show that consumer sentiment is a good proxy for market sentiment. Lemmon and Portniaguina (2006) interpret consumer sentiment index as a measure for investors' optimism and show that this index can substitute for investor sentiment. Brown and Cliff (2004) and Schmeling (2009) find a negative relationship between the sentiment and aggregate stock market return. Chung et.al (2012) examine the asymmetry in the predictive power of investor sentiment on the cross–section of stock returns over different business cycles, and find strong evidence both in–sample and out–of–sample of the predictive power of investor sentiment. Akhtar et.al. (2012) examine the asymmetric announcement effects of consumer sentiment news on the US stock market and find that when there is an announcement for negative change in the sentiment index, the stock returns are influenced negatively. However, when the sentiment index is announced higher than the previous month, there is no significant effect on the stock returns. Johnson and Naka (2014) show that changes in CSI are able to forecast equity returns up to 24 months and that negative changes in sentiment have a greater impact on stock returns than positive changes in sentiment, attributing such discrepancy to the prospect theory.

This paper is expected to contribute to the literature by introducing consumer sentiment in the context of socially responsible investment. Although, consumer sentiment index has been used as a predictor in mutual funds and stock market literature, this paper introduces this variable to predict the SRI funds returns. More specifically, this research offers more comprehensive framework to understand predictability of future SRI fund returns by consumer sentiment as well as market fundamentals within the same model. Our sample, which includes periods of significant changes in sentiment such as the dot-com bubble and a financial crisis period, also enables us to better analyze the effect of positive and negative changes in sentiments on SRI fund returns. Additionally, we examine whether sentiments can forecast both short and long horizon SRI returns. The results would provide useful information to investors concerning how consumer sentiment affects the returns of SRI funds with different lengths of holding periods while controlling for the impact of market fundamentals on them. Therefore, it is expected that this paper would be a valuable addition to the SRI literature.

The sample of this paper provides a relatively long time-series data for SRI funds that includes the financial crisis periods, spanning from December 1990 to June 2014

[3] See Statman (2000, 2006), Greezy et al. (2003), Bauer et al. (2005), Bollen (2007), Gil-Bazo et al. (2010), and Leite and Cortez (2014), among others.

with monthly observations. There are 151 SRI mutual funds in this study with the total number of 18,503 observations. Dividend yield on S&P 500 index and changes in CSI are used to represent market fundamentals and consumer sentiment, respectively. Our results reveal that both variables can predict SRI fund returns positively and the estimated coefficients are statistically significant. In addition, positive changes in consumer sentiment predicts SRI returns more strongly than negative changes in consumer sentiment. This finding can be interpreted as a rise in activism of SRI investors during high sentiment period and a fall in activism during low sentiment period. The results also hold for longer horizons ranging from 3 to 12 months. This indicates that individual investors with different holding periods can use the information content of sentiment to forecast future SRI fund returns. The results are robust to orthogonalization of both dividend yield and sentiment variables with respect to a set of macroeconomic fundamentals. Further, we find that flows of SRI funds do not predict their returns, although the fundamental variable and sentiments are still statistically significant. The results indicate that investors of SRI funds are not return chasers and reveal prominent role of social preferences for predicating the returns as found by recent literature.

The rest of the paper is arranged as follows. The next section briefly reviews the relevant literate on socially responsible investments. Section 3 outlines the data and methodology while section 4 presents the empirical results. A final section concludes the paper.

2. Brief Review on Socially Responsible Investments

The studies on performance comparison among SRI funds and other assets are somehow mixed depending on the selection of funds, time periods, methodologies implemented, and countries studied. Statman (2000) presents that Domini Social Index (DSI), which is an index of socially responsible stocks, performs better than conventional mutual funds of equal asset size, as well as the S&P 500 Index. Furthermore, Statman (2006) shows that the returns of four socially responsible indexes, which are based on different social characteristics, generally perform better than the returns of S&P500 index. However, Bauer et al. (2005) find that there are no statistical differences in performance between SRI funds and conventional funds between 1990 and 2001 after controlling for investment style for countries including German, UK, and US. Gil–Bazo et al. (2010) show that the difference in the performance of SRI and conventional funds is statistically insignificant even after adjusting for fees. Leite and Cortez (2014) examine the performance of SRI mutual funds from eight European countries, in comparison with characteristics matched portfolios of conventional funds, and do not find statistical differences in performance between these SRI funds and their matched portfolios.

Nolfsinger and Varma (2014) present an asymmetric return pattern in SRI funds, where they outperform matched conventional mutual funds during the crisis periods, although SRI funds have tendency to underperform during the non-crisis periods using the data between 2000 and 2011. Henke (2016) investigates the performance of SRI bond mutual funds between 2001 and 2014 and finds that SRI bond funds outperformed against matched conventional bond funds during the crisis periods for the US and the Eurozone countries. The return differentials between SRI bond funds and conventional bond funds are statistically insignificant during the non-crisis periods. However, the outperformance of SRI bond funds arises from the sequences of three crisis periods: the burst of the dot-com bubble between 2001 and 2003; the financial crisis between 2008 and 2009; and the Eurozone sovereign debt crisis between 2011 and 2012.

Bollen (2007) compares the flow and return relations of SRI funds to matched conventional funds in the US, and finds that SRI funds have significantly lower monthly fund flow volatility than conventional funds and US SRI fund flows are less sensitive to past negative returns than conventional funds, but the flows of SRI funds are more sensitive to past positive returns. Benson and Humphrey (2008) compare the determinants of fund flows for SRI funds and conventional funds. Their results show that SRI fund flows are less sensitive to returns than conventional funds, and that SRI investors are more likely to invest in a fund they already own. Renneboog et.al (2011) analyze the predictive power of money flows for future fund returns and show that the investors of SRI funds from various countries (US, UK, Continental Europe, and Asia and the Pacific Rim region) are less sensitive about past negative returns than investors in conventional funds. Their findings suggest that SRI investors may take into account nonfinancial attributes in their investment decisions.

Liston (2016) examines the impact of investor sentiment on a portfolio formed of sin stocks and shows that both individual and institutional investor sentiments have a positive impact on these sin stock returns. Further, after controlling for the effects of investor sentiment on the sin portfolio, the paper presents that the abnormal returns (Jensen's alpha) found in previous studies vanish, and argues that investor sentiment would be driving the large risk-adjusted returns found in the literature for sin stocks. Ghoul and Karoui (2017) examine the effects of CSR (Corporate Social Responsibility) score on fund performances and flows using U.S. equity funds over the period of 2003 to 2011, and find that CSR score negatively predicts next year's fund performance, and funds with a high CSR score exhibits performance persistence relative to funds with a low CSR score. An increase in CSR score may attract socially conscious investors and prevent performance or return chasing investors. Further, they show that the flow-performance relationship becomes weaker as the level of CSR score increases and high CSR funds tend to attract investors who are less sensitive to performance.

Riedl and Smeets (2017) provide possible reason that investors hold SRI funds by utilizing three unique data sets, which are the administrative investor data from the mutual fund providers in the Netherlands between 2006 and 2012, measure of social preferences based on experiments, and large numbers of survey data. Their administrative investor data include variety of socially responsible and conventional mutual funds. Further, they document that both social preferences and social signaling explain investors' decision of holding SRI funds, where socially responsible investors expect lower returns on SRI funds than on conventional funds and pay higher management fees. Riedl and Smeets (2017) state that "This suggests that investors are willing to forgo financial performance in order to invest in accordance with their social preferences, which indicates that socially responsible investors have a longer investment horizon."

3. Data and Methodology

3.1 Data

We obtain the list of the socially responsible mutual funds from the website of the Forum for Sustainable and Responsible Investment (USSIF) to identify these funds.4 Following the relevant literature, we focus on the equity funds only and exclude balanced and bond funds (Bollen 2007; Renneboog, Ter Horst and Zhang, 2011; Nofsinger and Varma, 2014). Our sample includes 151 SRI funds for which monthly data on total net asset (TNA), return (R), and net asset value (NAV) are obtained from the CRSP survivorship bias free database. The data spans from December 1990 to June 2014.

Table 1: Distribution of Descriptive Statistics

Percentile	Months	$\overline{TNA}$	$\overline{Ret\ (\%)}$	$\overline{NAV}$	$\overline{Flow}$	$\alpha(3F)$	$\alpha(4F)$
Minimum	12	0.17	–1.60	7.13	–2.92	–0.37	–0.38
25th pcnt	97	16.54	0.45	10.61	0.10	–0.17	–0.17
Median	178	56.41	0.61	15.69	0.35	–0.12	–0.12
75th pcnt	244	198.47	0.80	19.98	0.82	–0.01	–0.01
Maximum	283	1400.29	2.06	40.06	14.66	0.01	0.01
Mean	173	181.51	0.60	16.86	0.78	–0.11	–0.11
St. Dev.	79	306.93	0.30	7.58	2.03	0.09	0.09
Skewness	–0.10	2.53	–1.31	1.14	4.68	–0.45	–0.456
Kurtosis	1.65	8.83	14.41	3.73	31.82	2.18	2.24

Note: This table presents distribution of fund level summary statistics. $\overline{TNA}$ is monthly average of total net asset (in millions of dollar), $\overline{Ret\ (\%)}$ is monthly percentage excess return on SRI funds, $\overline{NAV}$ is monthly average net asset value for each fund and $\overline{Flow}$ is average net flow to each fund (in millions of dollar). $\alpha(3F)$ and $\alpha(4F)$ are constants obtained from a three–factor and four–factor regressions for individual fund. The sample period is from December 1990 to June 2014. Total observation in the sample is 18,503.

Table 1 presents the distributions of the numbers of SRI funds, the overall statistics of these funds, and estimated Jensen's alpha (e.g., risk-adjusted performance measure). The funds in the sample have a minimum of 12, a median of 178 and a maximum of 283 consecutive months of data. These descriptive statistics are obtained

4 http://www.ussif.org/.

by first taking time series averages of each mutual fund, and then, creating their distribution across all funds in the sample. Columns 3 through 6 describe variations in TNA, return, NAV, and fund flows that show nature of asset holdings across mutual funds in our sample. The funds included in the sample vary considerably in size, based on average TNA, which is distributed with a positive skewness. The SRI funds in our sample vary greatly in terms of size and flows. The flow variable for each fund is constructed as:[5]

$$Flow_{it+1} \equiv \{TNA_{it+1} - [TNA_{it} \times (1 + R_{it+1})]\} \div TNA_{it},$$

where all variables are defined previously.

The overall average of TNA is $181.51 million with a standard deviation of $306.93 million. Bailkowski and Stark (2016) find similar result for SRI funds' average monthly TNA. The column indicates that some funds are very large and attract investors significantly, while some are small and not as successful. Distribution of average performance or return across the funds is reported in the next column. Average excess return, where the average of risk free rate is 0.016%6, is distributed with mean of 0.48% per month with the standard deviation of 0.08%. The excess return distribution is not much skewed and there is little evidence of excess kurtosis. As for NAV, which is the market price per share of open–ended mutual funds, variation across the funds is lower compared with TNA and flow of funds, with smaller standard deviation and skewness. A possible explanation may be based on the underlying asset holdings by the funds. All SRI funds, regardless of size and age, would face a similar asset universe that is constrained by some socially responsible investment principles. We observe that considerable variation exists in the average net flow to the funds with positive skewness. Average net flow of funds is 0.78 million per month with a standard deviation of 2.03 million, reflecting significant growth for some SRI funds over the sample period.

The last two columns of Table 1 present the distribution of estimated Alpha from the three and four factors Asset Pricing Models. These factors are market premium, SMB (small market capitalization minus big market capitalization), HML (high book-to-market ratio minus low book-to-market ratio), and momentum factor. 7 The results are very similar with a mean of –0.11 % and standard deviation of 0.09% for models. Alphas estimated from individual fund level regressions have low negative skewness but they have no excess kurtosis. Overall, Table 1 indicates that although the funds included in the sample vary greatly in terms of size and flow of funds, they are relatively homogeneous in terms of returns and performances measured by estimated Alphas from multi–factor asset pricing models. Ghoul and Karoui (2017) document that while the average fund return is positive, the annualized risk-adjusted return (alpha) is negative. Also, Becchetti et.al (2015) also find the negative alpha for SRI funds in North America.

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[5] This construction is commonly used. See for example, Bollen (2007).

[6] 1–month US Treasury Bill yield is used as the risk free rate of return.

[7] All variables are obtained from Professor French's web site.

Table 2: Descriptive Statistics

Variable	Mean	St. Deviation	Minimum	Maximum
Total Net Assets (TNA)	181.51	464.15	0.20	7263.20
Net Asset Value (NAV)	16.87	8.64	4.05	77.63
Net Flow of Funds	0.90	19.19	–361.13	1970.90
Monthly Return	0.61	0.44	–0.37	0.31
Monthly Excess Return	–0.15	0.18	–0.78	0.30
Dividend yield	0.02	0.01	0.01	0.04
Consumer Sentiment	81.62	13.04	55.30	112.00
Changes in Sentiment	0.20	0.05	–0.18	0.26

Table 2 reports the summary statistics of the variables used for regression analysis. They are the excess returns, dividend yield, CSI, and changes in CSI. Dividend yield on S&P 500 index is collected from Robert Shiller's Data Library[8] and Consumer Sentiment Index d is downloaded from the University of Michigan Surveys of Consumers website.[9] The CSI compiled by the University of Michigan is the most established data set that represents the consumer confidence on assessing the economic conditions by general household, and widely employed by researchers (Lemmon and Portniaguina, 2006; Schmerling, 2009; Chen, 2011; Johnson and Naka, 2014; among others). The mean of dividend yield is 0.02% per month and its standard deviation is 0.01% in our sample. The mean of the changes in CSI is positive of 0.20 with the standard deviation of 0.054. The descriptive statistics for consumer sentiment are similar with findings of Johnson and Naka (2014), and other researchers although their observations are different from this study.

3.2 Predictive Regression Models

To examine the predictive ability of dividend yield and consumer sentiment for SRI fund returns, we specify the following baseline predictive regression model:

$$Ret_{i,t+k} = \alpha_{it+k} + \beta DY_t + \gamma\, \Delta Sent_t + e_{i,t+k}, \tag{1}$$

where Ret is excess return on an SRI mutual fund, i, at month $t+k$, DY is dividend yield on S&P 500 index, $\Delta Sent$ is the monthly change in CSI[10] and e is the contemporaneous error term. In order to ensure correct level of significance of estimated coefficients, clustered standard errors are implemented. This method is used to correct for possible correlation within a cluster (Rogers, 1993; and Petersen, 2009). In our case, this translates into corrections of correlations across mutual funds at any given month. A particular problem with estimating a predictive panel regression is Stambaugh (1999) bias that was originally discussed in the context of

[8] www.econ.yale.edu/~shiller/data.htm
[9] http://www.sca.isr.umich.edu/
[10] We use change in CSI and many other papers also use this specification. Akhtar, Faff, Oliver and Subrahmanyam (2011) employ ratio of current and past level of CSI.

time series regressions. As for panel data, estimation of predictive regressions using fixed effects method may result in this bias in the estimates (e.g., Mark and Sul, 2001). However, Hjalmarsson (2010) analyzes the bias in the panel context and demonstrates that it is not a serious issue for pooled estimates.

We also use an asymmetric specification, which allows us to see whether positive and negative changes in consumer sentiment predict future returns differently. The predictive regression model is modified as:[11]

$$Ret_{i,t+k} = \alpha_{it+k} + \beta\, DY_t + \gamma^+ \Delta Sent_t^+ + \gamma^- \Delta Sent_t^- + e_{it+k}, \qquad (2)$$

where $\Delta Sent^+$ and $\Delta Sent^-$ are the positive and negative changes in CSI, respectively, γ^+ and γ^- are their associated coefficients and the other variables are as defined before. A test is conducted under the null hypothesis of no difference between γ^+ and γ^-, rejection of which would justify this asymmetric specification.

4. Empirical Results

4.1 Baseline Predictive Regression

Table 3 presents the empirical results of the base line predictive regression model. We estimate the model by using both pooled and fixed effect panel regressions, but repot only the results based on pooled regressions since the estimated results using fixed effect panel regressions are qualitatively the same and the estimated coefficients are very close. We find that both dividend yield and changes in sentiment are significant and positive. Both variables have predictive ability for future returns on SRI funds, where the coefficient on dividend yield is larger than the coefficient on consumer sentiment. To assess how this predictability changes over different holding period returns, we estimate long horizon regressions with holding periods of 3, 6 and 12 months. Both predictive variables are significant and coefficients on dividend yield are greater than coefficients on changes in sentiment index at all investment horizons. Consistent with Johnsen and Naka (2014) that show a positive change in CSI resulting in positive future excess stock returns for subsequent holding period returns, we find the positive relation between the changes in CSI and future returns of SRI funds. We observe that the R^2 increases as the horizon periods increase as expected. This is well documented in the literature, and in our case, both the results from short and long horizons are significant in our regression model. However, interpreting the goodness of fit based on R^2 in long horizon regressions is not straightforward and requires further analysis.[12]

In order to gain additional insight on the comparative magnitude of dividend yield and sentiment, we utilize the "standardized beta coefficients" and report them in brackets in Table 3.[13] The standardized beta coefficients will enable us to compare

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[11] This specification is also called the "Asymptotic Response Model" in literature.

[12] Valkanov (2003) presents theoretical discussion regarding the goodness of fit and the standard errors for long horizon regressions.

[13] Standardized beta coefficients are obtained by running the regressions on standardized values of the independent variables, i.e. right hand side variables (See STATA manual for additional details).

estimated coefficients within the same regression directly. More specifically, we measure changes in the dependent variable in units of standard deviation per one standard deviation change in an independent variable. For instance, for k = 1, a one standard deviation increase in DY would predict a 0.333 standard deviation increase in next period return, whereas, a one standard deviation increase in ΔSent would predict only a 0.049 standard deviation increase in next period return. These findings indicate that market fundamentals have more predictive ability for future returns on SRI funds than sentiment. This trend remains similar over longer horizon as well. However, as the size of the regression coefficients increases over longer horizon, so does the standardized coefficients. In line with Brown and Cliff (2004) and others, we document that sentiment indicates the predictability in different horizon and is significantly related to the long horizon returns, and the value of coefficient increases with the length of the horizon. The results suggest that the information about the predictive power of sentiment for SRI fund future returns could be beneficial for investors regardless of their investment horizon.

Table 3: Pooled Predictive Regressions

$Variable$	$k = 1$	$k = 3$	$k = 6$	$k = 12$
DY	12.823***	26.747***	37.418***	45.808***
	[0.333]	[0.361]	[0.401]	[0.445]
$\Delta Sent$	0.162***	0.302***	0.462***	0.568***
	[0.049]	[0.047]	[0.057]	[0.062]
α	−0.400***	−0.834***	−1.142***	−1.374***
R^2	0.1151	0.1338	0.1664	0.2048

Note: This table presents results of the pooled predictive regressions at various horizons for the following specification: $Ret_{i,t+k} = \alpha_{it+k} + \beta DY_{t+k-1} + \gamma\ \Delta Sent_{t+k-1} + e_{it+k}$, where, Ret is excess return on a mutual fund, i, in month, t, DY is dividend yield on S&P 500, $\Delta Sent$ is the change in CSI, and e_{it+1} is the error term. The prediction horizon is denoted by k, which can be 1, 3, 6 or 12 months. The sample period is from December 1990 to June 2014. Standardized beta coefficients are reported in brackets. The significance of coefficients is based on Rogers standard errors (robust to within cluster correlation). ***, **,and * indicate significance at the 1%, 5% and 10% level, respectively.

4.2 Asymmetric Specifications

Table 4 presents the results of asymmetric specification, where positive and negative changes in sentiment are treated as separate variables. The purpose of this specification is to see whether they have differing degrees of predictive ability for future returns. Both negative and positive changes in consumer sentiment can predict future returns significantly. As in the previous tables, coefficient on dividend yield is greater than the sentiment, both positive and negative changes. The sign on the coefficient of positive changes in sentiment (γ^+) is positive but the sign on the coefficient on the negative changes in sentiment (γ^-) is negative. This implies that on average a positive (negative) change in the consumer sentiment will predict future positive (negative) returns. The coefficients on positive changes are greater in absolute magnitude than those on negative changes. The net effect of the two coefficients is therefore positive which can be seen in the results of baseline symmetric equation in Table 3. Both negative and positive changes in sentiment have significant degree of predictability for future SRI fund returns with stronger influence of positive changes in sentiment on SRI fund returns. This finding is in line with Jonson and Naka (2014) and Charoenrook (2002) for the asymmetric influence of the sentiment on stock market returns. Akhtar, et.al (2012) find similar result for negative changes in sentiment but they find no significant effect on the stock returns when change in sentiment is positive.

Table 4: Predictive Regressions with Asymmetric Specification

$Variable$	$k = 1$	$k = 3$	$k = 6$	$k = 12$
DY	12.266*** [0.319]	25.416*** [0.342]	35.726*** [0.383]	43.640*** [0.424]
$\Delta Sent^+$	0.527*** [0.094]	1.179*** [0.108]	1.592*** [0.116]	2.014*** [0.129]
$\Delta Sent^-$	–0.188*** [–0.034]	–0.535*** [–0.050]	–0.611*** [–0.046]	–0.774*** [–0.052]
α	–0.405***	–0.844***	–1.156***	–1.391***
R^2	0.1198	0.1411	0.1740	0.2144
$F(\gamma^+ = \gamma^-)$	22.30***	34.17***	33.97***	50.94***

Note: This table presents results of the pooled predictive regressions at various horizons for the following specification: $Ret_{i,t+k} = \alpha_{it+k} + \beta\ DY_{t+k-1} + \gamma^+ \Delta Sent^+_{t+k-1} + \gamma^- \Delta Sent^-_{t+k-1} + e_{it+k}$, where, Ret is excess return on a mutual fund, i, in month, t, DY is dividend yield on S&P 500, $\Delta Sent^+$ and $\Delta Sent^-$ are the positive and negative changes in CSI, respectively, and e_{it+1} is the error term. The prediction horizon is denoted by k, which can be 1, 3, 6 or 12 months. The sample period is from December 1990 to June 2014. Standardized beta coefficients are reported in brackets. $\mathrm{F}(.)$ is the test statistics for the null hypothesis that there is no asymmetric impact of investor sentiment. The significance of coefficients is based on Rogers standard errors (robust to within cluster correlation). ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

This relationship remains unchanged in longer horizon regressions as well. As expected, the value of coefficient increases with the length of horizon, the sign and comparative magnitudes remain unchanged. This is an indication of consistent nature of predictive ability of sentiment for fund returns over longer horizons. The Wald statistics for the significance of the difference between the positive and negative changes in sentiment are reported in the last row of the table. As they are all significant, positive and negative changes in sentiment predict return differently. For one month ahead return regression, (i.e. K=1), a one standard deviation changes in the DY predicts 0.319 standard deviation changes in return. On the others hand, a one standard deviation positive (negative) changes in *ΔSent* predicts only 0.094 (0.034) standard deviation in return. These results are consistent with our previous findings.

4.3 Robustness Issues

It is possible that the predictor variables in the previous regressions are both influenced by the prevailing macroeconomic condition. Following Baker and Wurgler (2006), Lemmon and Portniaguina (2006), and McLean and Zhao (2014), we orthogonalize changes in CSI with respect to the key macroeconomic variables: 1) growth in industrial production, 2) real growth in durable consumption, 3) nondurable consumption, 4) services consumption, 5) growth in employment, and 6) NBER recession indicator. First, we regress both dividend yield and change in CSI, separately on the above macroeconomic variables and save the residuals. These residuals can be interpreted as the level responsiveness of future returns on SRI funds to the predictor variables over and above, justified by the prevailing economic fundamentals. Then, these newly formed series are used as the regressors to estimate equations (1) for symmetric case and (2) for asymmetric case, respectively. The results for the two specifications are presented in Tables 5 and 6.

In Table 5, coefficients on both dividend yield and consumer sentiment are significant with the same positive sign as before. The magnitude of the coefficients are smaller after orthogonalization, and the coefficient on dividend yield is still larger than that on consumer sentiment. This trend remains unchanged over longer horizons as well. As for Table 6, the results are qualitatively similar to those reported in Table 4. However, magnitudes of the coefficients on the consumer sentiment in Table 6, both positive and negative changes, are larger compared to the coefficients in Table 4. In sum, the predictive ability of dividend yield and consumer sentiment remain significant even after the effects of macroeconomic elements are removed from their time series.

Our sample include a period of financial crisis that affected the US economy in general and the financial markets in particular. Here, we exclude the observations for year 2007 and 2008 and re-estimate the regressions specifications in equations (1) and (2) to examine the impact of the financial crisis. Table 7 reports the results for the one month ahead predictive regression. For easy comparison, we reproduce the previously reported results for the full sample. The coefficients for the sample excluding the crisis period are similar to the full sample period in sign and magnitude, and the standardized beta coefficients reported in the brackets are also very similar. An exception is the size of coefficient on dividend yield, which becomes smaller in the sample excluding the crisis period along with the beta coefficient. This indicates that during the financial crisis, the predictive power of dividend yield was larger than in the rest of the sample period. We do not reject the difference between the coefficients with and without the observations belonging to the financial crisis period based on the *p*-values reported in the last column. Overall, results reported earlier are qualitatively same with or without the financial crisis period data included in the regressions.

Table 5: Predictive Regressions with Orthogonalized Predictors

Variable	$k=1$	$k=3$	$k=6$	$k=12$
DY	9.590*** [0.210]	19.253*** [0.218]	26.278*** [0.237]	32.200*** [0.0371]
$\Delta Sent$	0.099*** [0.029]	0.157*** [0.024]	0.279*** [0.034]	0.338*** [0.262]
α	–0.149***	–0.309***	–0.405***	–0.471***
R^2	0.0455	0.0488	0.0581	0.0711

Note: This table presents results of the pooled predictive regressions for each SRI mutual fund sample at various horizons for the following specification: $Ret_{i,t+k} = \alpha_{it+k} + \beta DY_{t+k-1} + \gamma\, \Delta Sent_{t+k-1} + e_{it+k}$, where, Ret is excess return on a mutual fund, i, in month, t, DY is dividend yield on S&P 500, $\Delta Sent$ is the change in CSI, and e_{it+1} is the error term. The predictor variables are orthogonalized to a set of macroeconomic variables. The prediction horizon is denoted by k, which can be 1, 3, 6 or 12 months. The sample period is from December 1990 to June 2014. Standardized beta coefficients are reported in brackets. The significance of coefficients is based on Rogers standard errors (robust to within cluster correlation). ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6: Predictive Regressions with Asymmetric Specification and Orthogonalized Predictors

Variable	$k=1$	$k=3$	$k=6$	$k=12$
DY	9.247*** [0.202]	18.471*** [0.209]	25.152*** [0.227]	30.566*** [0.249]
$\Delta Sent^+$	0.638*** [0.111]	1.390*** [0.125]	1.999*** [0.142]	2.648*** [0.166]
$\Delta Sent^-$	–0.392*** [–0.073]	–0.959*** [–0.092]	–1.268*** [–0.097]	–1.688*** [–0.115]
α	–0.170***	–0.358***	–0.475***	–0.563***
R^2	0.0558	0.0631	0.0753	0.0951
$F(\gamma^+ = \gamma^-)$	59.92***	87.84***	107.34***	185.99***

Note: This table presents results of the pooled predictive regressions for each SRI mutual fund sample at various horizons for the following specification: $Ret_{i,t+k} = \alpha_{it+k} + \beta\, DY_{t+k-1} + \gamma^+ \Delta Sent^+_{t+k-1} + \gamma^- \Delta Sent^-_{t+k-1} + e_{it+k}$, where, Ret is excess return on a mutual fund, i, in month, t, DY is dividend yield on S&P 500, $\Delta Sent^+$ and $\Delta Sent^-$ are the positive and negative changes in CSI, respectively, and e_{it+1} is the error term. The predictor variables are orthogonalized to a set of macroeconomic variables. The prediction horizon is denoted by k, which can be 1, 3, 6 or 12 months. The sample period is from December 1990 to June 2014. Standardized beta coefficients are reported in brackets. $\mathrm{F}(.)$ is the test statistics for the null hypothesis that there is no asymmetric impact of investor sentiment. The significance of coefficients is based on Rogers standard errors (robust to within cluster correlation). ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7: Financial Crisis and Predictive Regressions

Variable	**Full Sample**	**Excluding Crisis Period**	**p-value of Difference**	**Decision**
Panel A: The Baseline Predictive Regression				
DY	9.590*** [0.210]	7.432*** [0.164]	0.203	No Difference
$\Delta Sent$	0.099*** [0.029]	0.100*** [0.028]	0.559	No Difference
α	−0.149***	−0.143***	0.660	No Difference
R^2	0.0455	0.0280		
Panel B: The Asymmetric Predictive Regression				
DY	9.247*** [0.202]	7.122*** [0.157]	0.205	No Difference
$\Delta Sent^+$	0.638*** [0.111]	0.685*** [0.113]	0.696	No Difference
$\Delta Sent^-$	−0.392*** [−0.073]	−0.466*** [−0.079]	0.227	No Difference
α	−0.170***	−0.166***	0.597	No Difference
R^2	0.0558	0.0392		
$F(\gamma^+ = \gamma^-)$	59.92***	74.57***		

Note: This table presents results of the pooled predictive regressions for each SRI mutual fund sample at various horizons for both the base line and asymmetric specifications as outlined in the text. The predictor variables are orthogonalized to a set of macroeconomic variables. The significance of coefficients is based on Rogers standard errors (robust to within cluster correlation). The prediction horizon is denoted by k, which is 1 for this table. "Full Sample" period is from December 1990 to June 2014 and observations pertaining to year 2007 and 2008 are deleted in the sample "Excluding Crisis Period". Standardized beta coefficients are reported in brackets. F(.) is the test statistics for the null hypothesis that there is no asymmetric impact of sentiment. The last column reports the p–value associated with the null hypothesis of no difference between coefficients obtained from two different samples. ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Empirical evidences document that in general mutual fund flows are positively related to their returns, and also flows predict future performances. In general, investors chase positive returns while making decision on funds investment resulting in positive relationship between fund performances and their returns, supporting the hypothesis of such as smart-money effect. For example, Del Guercio and Tkac (2002) find significant relationship between flow of funds and returns for two different groups of funds, namely, retail mutual funds and pension funds. Bollen (2007) reports lower monthly volatility of investor cash flows in to SRI funds compared to conventional funds, while significant funds flow in SRI funds following positive returns. Jiang and Yuksel (2017) find positive relationship between fund flows and their performances using the different classes of US equity mutual funds between 1993 and 2014. On the other hand, Renneboog, Ter Horst, and Zhang (2011) do not find significant relationship between the fund returns and flows based on SRI funds. We re-examine this issue in our sample to see whether such investor behavior is particular to the SRI funds.

Table 8: Flow of Fund as an Additional Predictor

Variable	$k = 1$	$k = 3$	$k = 6$	$k = 12$
DY	9.594***	19.234***	26.247***	32.172***
$\Delta Sent$	0.098***	0.158***	0.280***	0.338***
$Flow$	0.032*	0.046	0.047	0.047
α	–0.148***	–0.308***	–0.405***	–0.471***
R^2	0.0456	0.0487	0.0580	0.0710

Note: This table presents results of the pooled predictive regressions for each SRI mutual fund sample at various horizons for the following specification: $Ret_{i,t+k} = \alpha_{it+k} + \beta DY_{t+k-1} + \gamma\, \Delta Sent_{t+k-1} + \delta\, Flow_{i,t+k-1} + e_{it+k}$, where, Ret is excess return on a mutual fund, i, in month, t, DY is dividend yield on S&P 500, $\Delta Sent$ is the change in CSI, *flow* is net flow of funds, and e_{it+1} is the error term. The predictor variables are orthogonalized to a set of macroeconomic variables. The prediction horizon is denoted by k, which can be 1, 3, 6 or 12 months. The sample period is from December 1990 to June 2014. The significance of coefficients is based on Rogers standard errors (robust to within cluster correlation). ***, **, and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8 presents the predictive regression results with flow of funds as an additional predictor. The flow variable is constructed using formula presented in the Data and Methodology section. We find that the flow variable is insignificant, though positive, in all horizons. Our results support the findings of Renneboog, Ter Horst and Zhang (2011). This indicates absence of return chasing behavior in our sample, which may be explained with investors' commitment to socially responsible investment. The fund flows are expected to be insensitive or independent of returns on SRI funds, and the motive of investing in SRI funds is more than economic reasons, but more for social preferences. Our results are agreeable with Riedl and Smeets (2017), who argue that social preferences and social signaling explain investing in SRI funds rather than financial inspirations. Other predictive variables such as dividend yield and changes in CSI are still significant for all horizons, and the magnitude and size of these two predictors are very similar to the results found earlier.

5. Concluding remarks

This paper aims to examine the ability of both market fundamentals and consumer sentiments to predict future returns on a sample of mutual funds that comply with Socially Responsible Investment (SRI) principles. Our results reveal that both dividend and consumer sentiment can predict SRI funds return positively, while the coefficient on dividend yield is greater in magnitude than coefficient on consumer sentiment. In addition, positive changes in consumer sentiment predicts SRI return more strongly than negative changes in consumer sentiment. This finding could be interpreted as a rise in activism of SRI investors during high sentiment period and a fall in activism during low sentiment period. This relationship remains unchanged in longer horizon regressions as well. The value of coefficient increases with the length of horizon, but the sign and comparative magnitude remain unchanged. This is an indication of consistent nature of predictive ability of sentiment for fund returns over horizons. Further, we find that flows of SRI funds do not predict the returns of these funds. This indicates absence of return chasing behavior in our sample, which may be explained with investors' commitment to socially responsible investments. The results support the significant findings of a recent paper by Riedl and Smeets (2017).

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