

Socially Responsible Investment in Good and Bad Times

Li Huimin

*Department of Accounting, Finance and Economics
Griffith University, Australia
E-mail: jane.li@griffith.edu.au
Tel: +61439785461*

Cheung Adrian Wai Kong

*Department of Accounting, Finance and Economics
Griffith University, Australia
E-mail: a.cheung@griffith.edu.au
Tel: +617 3735 7644*

Roca Eduardo

*Department of Accounting, Finance and Economics
Griffith University, Australia
E-mail: e.roca@griffith.edu.au
Tel: +61737357583*

Abstract

This paper investigates the financial performance difference between seven US Socially Responsible Investment (SRI) indices and their pair-wised corresponding benchmark indices across different stock market regimes. We employ the Markov Switching model to specifically divide the study period into three regimes. We then compare the risk, return and risk-adjusted-return of the SRI indices during each identified regime with their corresponding benchmark indices. We find that SRI has higher returns than non-SRI across three different regimes, but there is no difference in the risk-adjusted-return between SRI and non-SRI over time. Our study results imply that there is no sacrifice for SRI investors when market conditions change. We contribute to the literature by taking into consideration for the first time the effect of the stock market regimes on the financial performance comparison between SRI and non-SRI investments.

Keywords: Socially Responsible Investment; financial performance; Market regimes; Markov Switching model

1. Introduction

Socially Responsible Investment (SRI) is an investment that integrates social, environmental and/or ethical considerations into the investment “decision-making” process. The development of SRI is associated with the growing awareness among investors, companies and governments of the impact that social and environmental risks may have on long term issues ranging from sustainable development to long term corporate performance (Eurosif, 2008). During the last decade, SRI has grown rapidly worldwide. By the end of 2007, SRI represented 11 per cent (US\$2.71 trillion) of the US\$25.1 trillion total assets in the United States (US). In Europe, it was about €2.665 trillion during

the same period. Similar strength in SRI growth over the past decade has been also found in Australia, Canada, New Zealand and some Asian countries.

The fast development in SRI has attracted great attention from scholars, governments and investors. Numerous studies have been conducted on the financial performance of SRI. However, the findings from prior studies are rather inconclusive and contradictory. For example, some studies find that there is no difference between SRI and non-SRI (see Sauer, 1997; Fernandez-Izquierdo and Matallin-Saez, 2008; Mittal, Sinha, and Singh, 2008; Becchetti and Ciciretti, 2009; Cortez, Silva, and Areal, 2009), while some others report that SRI significantly outperformed non-SRI (see Guerard, 1997; Derwall, Guenster, Bauer, and Koedijk, 2005). Also, a large body of literature concludes that SRI has considerably underperformed non-SRI (see Luther and Matatko, 1994; Bauer, Koedijk and Otten, 2005; Luo and Bhattacharya, 2006; Jones, van der Laan, Frost and Loftus, 2008).

We argue that the traditional approach (a single period approach) of assuming that SRI performance remains constant over time can be misleading. This can explain the debate among the aforementioned studies. Proponents of positive SRI impact argue that SRI firms usually have sound managerial quality, which engenders “goodwill” and “moral capital”, builds stakeholder loyalty, and thus creates a sustainable competitive financial advantage (Barnett and Salomon, 2006; Hellsten and Mallin, 2006; Sauer, 1997; Shank et al., 2005; Becchetti and Ciciretti, 2009). Also, SRI screening criteria can effectively lower the firm risk by reducing operation induced litigation costs and alleviating the cost of capital (Renneboog, et al., 2008) On the other hand, the opponents of SRI’s positive effects, point out that the high risk that SRI produces is due to its additional costs, which include employee benefits costs, agency costs, and the information costs for social screening, performance evaluation, and disinvestment costs when exiting from SRI funds ((Luther, Matatko & Corner, 1992; Mittal et al., 2008; Jones et al., 2008; Becchetti & Ciciretti 2009).

Such mixed empirical evidence and endless arguments from these single-period studies provide no real indication to SRI investors, since none of them consider the market conditions. Based on Stakeholder Theory, SRI investors tend to be more loyal than non-SRI investors because of their specific social objectives. We should expect that when the market dives, SRI investors are expected to keep their investment, unlike non-SRI investors who tend to withdraw. Therefore, SRI may perform differently during different market conditions as compared to non-SRI. Shank, Manullang and Hill (2005) have realized the importance of market conditions. They examined the financial performance of 12 SRI mutual funds during three and five year bearish periods, and another ten year interval, respectively. While corporate social responsibility does not affect firm performance over the three or five year bearish periods, it improves firm performance considerably during the ten year period. In the same spirit, Hussein (2004) analysed the financial performance of the FTSE Global Islamic Index over a bullish period (July 1996 to March 2000) and a bearish period (April 2000 to August 2003). Despite the fact that the Islamic index yields statistically significant positive abnormal returns in the bull market period, it has performed poorly compared to the counterpart index during the bearish period. Their multiple-period approach is superior to prior single-period studies in explaining the stock returns over time. However, market conditions change dynamically and unpredictably and it is imprecise to assume the market was entirely bearish during either the period 1998 to 2003 or the period April 2000 to August 2003. We therefore argue that SRI literature is in need of new methodological approaches, which can define the discrete switching nature of market conditions that cannot be detected by simple single-period or multiple-period approaches.

Earlier studies, such as Schaller and Van Norden (1997) and So, Lam, and Li (1998), documented the advantage of using the Markov Switching (MS) model to analyse the stock market returns. They said that the identification of occasional switching in the parameter values of the MS model provides a more appropriate estimate for the stock price returns and volatilities during different market regimes. This is because the MS model captures the different persistence of market shocks to affect stock returns under different market conditions by allowing sudden discrete shifts between regimes. The traditional single-period or multiple-period approaches do not allow regimes switching, therefore, are not able to identify the characteristics of each stock market regime (market volatility

states). Another advantage of the MS model is that it allows the time-varying parameters to switch endogenously, as it separates the equity market regimes based on the time series only (Krolzig, 1997).

In this paper we employ the MS model for the first time in SRI literature to identify the market regimes and their corresponding parameters precisely. We investigate the financial performance difference between SRI and non-SRI across different stock market conditions. In so doing, we provide evidence for investors and institutions on their investment decisions about whether to engage in SRI activities and to what extent during different market conditions.

We find three different volatility market regimes during our study period. SRI return is always superior to non-SRI across the three regimes. However, unfortunately, SRI also carries higher risks compared to its conventional counterparts, no matter in which market regime. Overall, we find there is no difference in the risk-adjusted-returns between SRI and non-SRI across the three market regimes. Our findings have important implications for potential SRI investors who are in fear of stock market downturns. Moreover, our study indicates that SRI might be a good choice for risk-taking investors due to its unique characteristics of the risk-return relationship. We conclude that market conditions have no obvious impact on the total-risk-adjusted-returns of SRI compared to non-SRI. However, we recommend future studies to conduct more thorough analysis on the SRI specific risk component in order to be able to precisely determine the difference in the risk-return relationship between SRI and non-SRI, based on the study of Li, Cheung, and Roca (2010).

The rest of the paper is organized as follows. Section 2 describes data characteristics and collection techniques. Methods used in this study are explained next in Section 3. In Section 4 we present our empirical results and finally, Section 5 concludes the paper.

2. Research Data

We investigate seven equity indices from the most well developed US SRI market. These indices have been constructed and published by 3 different suppliers. They are the well known SRI index families - KLD Research & Analytics Inc. (KLD), Calvert and Financial Times Stock Exchange (FTSE). For the purpose of examining the SRI risk-return relationship, studying at index level has significant advantages over studying at fund level. For example, the SRI effect can be measured without being confounded by other issues such as specific screening aims and objectives, transaction costs and funds managers' timing skills and stock picking skills (Schroder, 2007; Statman & Glushkov, 2009).

The seven SRI indices have different asset sizes. Included are three large caps, two mixed caps, one medium cap and one small cap. Panel A of Table 1 presents the included SRI indices, the benchmark indices, the abbreviation and the SRI index's launching date. Each SRI index is benchmarked by a closely approximated conventional index based on their investment universe. Panel B of Table 1 presents the investment universe for the SRI indices and their benchmark indices.

Table 1: Characteristics of SRI and Benchmark Indices

<i>Panel A: Description of the SRI-Equity Indices</i>				
Index Name	Abbrev.	Launch Date	Benchmark	Abbrev. of Benchmark
FTSE4Good US	FUS	7/2001	FTSE Local USA	FTSE
KLD Domini 400 Social Index	DSI	5/1990	S and P 500	S&P
KLD Broad Market Social Index	USSA	1/2001	Russell 3000	R3000
KLD Large Cap Social Index	USSL	1/2001	Russell 1000	R1000
Calvert Social Index	CAL	6/2000	Russell 1000	R1000
KLD Small Cap Social Index	USSS	1/2001	Russell 2000	R2000
KLD Mid Cap Social Index	USSM	1/2001	S and P Mid Cap 400 Index	S&PM
<i>Panel B: Indices Investment Universe</i>				
Index	Index's Universe	Benchmark	Benchmark's Universe	
DSI	250 S&P and 100 Large and Mid Cap, 50 Small Cap	S&P	500 large cap US equities	
CAL	1000 Largest US Equities	R1000	1000 Largest US Equities	
USSL	400 Largest US Equities	R1000	1000 Largest US Equities	

FUS	100 Largest Equities	FTSE	100 Largest Equities
USSA	3000 Largest US Equities	R3000	3000 Largest US Equities
USSM	600 Mid-Cap US equities	S&PM	Medium-sized 400 US Equities
USSS	2000 Small Cap US Equities	R2000	2000 Small Cap US Equities

We choose the study period from June 2001 to December 2009 to make sure the time interval is long enough to include as many US SRI indices with full data history record as possible. Also, we aim to include part of the recession that occurred from March 2001 to October 2001, and the one that began in December 2007. Including these two recessions allows more opportunities for testing the variation of SRI indices performance during different market volatility conditions, since most recessions overlap market downturns (Gonzalez et al., 2006).

Our main data source is the suppliers of the indices. We also use the database of Thomson Reuters Tick History (TRTH) to collect some of the index series. We calculate the monthly returns based on the discrete return formula $R_t = (P_t - P_{t-1})/P_{t-1} \times 100$

The systematic risk (Beta Coefficient) and the unsystematic risk (Standard Error of the Regression) during different market regimes are obtained directly from the output of the Markov Switching model. Following the studies of Jobson & Korkie (1981) and Sauer (1997), we assess the risk-adjusted-return by the transformed difference of the Sharpe Ratio (SI_{ab}), which is superior to the traditional Sharpe Ratio for being able to test the statistical significance of the transformed difference of the Sharpe Ratio. It is computed by

$$SI_{ab} = S_b \bar{r}_a - S_a \bar{r}_b \tag{1}$$

where S_b is the Sharpe Ratio for the benchmark index (b), S_a is the Sharpe Ratio for the SRI index (a), \bar{r}_a and \bar{r}_b are the average excess return for the SRI index (a) and the corresponding benchmark (b) respectively. The average excess return is calculated as:

$$\bar{r} = \frac{1}{T} \sum_{t=1}^T (r_t - r_{ft}) \tag{2}$$

where, r_t represents the individual index return, during month t, r_{ft} represents the risk free rate during month t, T is the number of the observations during one period. The asymptotic distribution of the transformed difference of the Sharpe Index is normal with mean SI_{ab} , and variance given by:

$$\varphi = \frac{1}{T} \left[2\sigma_a^2\sigma_b^2 - 2\sigma_a\sigma_b\sigma_{ab} + \frac{1}{2}\mu_a^2\sigma_b^2 + \frac{1}{2}\mu_b^2\sigma_a^2 - \frac{\mu_a\mu_b}{2\sigma_a\sigma_b}(\sigma_{ab}^2 + \sigma_a^2\sigma_b^2) \right] \tag{3}$$

where, μ_a and μ_b are the mean returns for SRI index (a) and its corresponding benchmark (b), respectively, and σ_{ab} is the covariance of returns from the SRI index (a) and the benchmark index (b). We examine each SI_{ab} by testing the null hypothesis of equal risk-adjusted performance $H_0: SI_{ab} = 0$. We then test the significance of each SI_{ab} by analysing the approximate Sharpe Ratio Z statistics, which is computed as:

$$Z = \frac{SI_{ab}}{\sqrt{\varphi}} \tag{4}$$

If an approximate Sharpe Ratio Z statistic exceeds the critical value at 5 per cent level, it will result in a rejection of the null hypothesis of equivalent Sharpe performance between the SRI index and its corresponding benchmark index.

¹ Although using monthly data provides us with only 102 observations for the MS model, our data are still reasonable for the MS model as compared to Guo, Brooks & Shami (2010), and Marco, Zacharias & Martin (2003), which have used 124 and 89 observations for the MS model respectively.

3. Research Methodology

We apply the Markov Switching (MS) model to decompose the index time series into a finite sequence of regimes. Each of the processes is linear, but their combination is non-linear. This creates a combination of variables with a model, which describes the stochastic process that determines the switch from one regime to another by means of the Markov Chain. A Markov Chain has the probability of P_{ij} , which can be defined as:

$$P_{ij} = P_r(S_{t-1} = i | S_t = j), \sum_{j=1}^M P_{ij} = 1 \quad \forall i, j \in \{1, \dots, M\} \tag{5}$$

P_{ij} indicates the probability that a variable S_t in state i is followed by state j . $P_{i1} + P_{i2} + P_{i3} + \dots + P_{in} = 1$. A transition matrix p produced from the stochastic process can be computed as follows:

$$p = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{bmatrix} \tag{6}$$

Each regime is the realization of a first-order Markov chain, and the state S_t is unobservable.

Following the studies of Krolzig (1997), Roca and Wong (2008), and Guidolin and Hyde (2009), we estimate the regression model underlying the MS model as:

$$Y_t = v_{(s_t)} + \sum_{k=1}^p \beta_k \cdot X_{t-k} + \sum_{j=1}^6 \alpha_j \cdot Z_{jt} + \mu_{s_t} \tag{7}$$

Where, $Y_t = [R_{it} - R_{ft}]$, $i = \text{index } i$, v_{s_t} is a vector of intercepts in state s_t , β_k is the coefficient of market risk premium $X_t = [R_{mt} - R_{ft}]$ at lag k . $Z_{jt} = [R_{jt} - R_{ft}]$ $j \neq i$, k stands for the lag length, α is the coefficient parameters for SRI indices other than index i and R_{ft} is the rate of the US three month Treasury bill. $\mu_{s_t} (0, \sum S_t)$ is the residual.

To be precise, we can rewrite this general model in seven different regression equations, based on the choice of the dependent variable of the SRI index. For example, we can form the regression model for index DSI as follows:

$$R_{DSI} - R_{ft} = v_{(s)} + \sum_{j=1}^q \beta_{j,s_t} [(R_{S\&P} - R_{ft})_{t-j}] + \alpha_1 \cdot (R_{CAL} - R_{ft})_t + \alpha_2 \cdot (R_{USSA} - R_{ft})_t + \alpha_3 \cdot (R_{USSL} - R_{ft})_t + \alpha_4 \cdot (R_{USSM} - R_{ft})_t + \alpha_5 \cdot (R_{USSS} - R_{ft})_t + \alpha_6 \cdot (R_{FUS} - R_{ft})_t + \varepsilon_{S_t} \tag{8}$$

We adopt the returns of SRI indices other than the dependent variable index as control variables. This is because they have unspecified and unobservable common factors, which might affect the returns of the dependent variable. Adding those indices returns as control variables can effectively improve the regression explanatory power. Meanwhile, we do not use book-to-market ratio (HML), the momentum (MOM), and the size ratio (BMS) as control variables of our model because we can capture the effects of HML, MOM and BMS on the SRI return simply by comparing with their closely approximated benchmark index (Schroder (2007)).

In order to determine the appropriate MS model to use, we conduct a number of diagnostic tests. We use the Augmented Dickey Fuller (ADF) test to examine stationarity of the data. We also identify the parameters to switch, the optimal number of regimes and the number of lags for the model based on the Schwarz Information Criterion (SIC). After that, we will estimate the parameters of the model developed by Krolzig (1997).

4. Empirical Results

4.1. Diagnostic Test Results

The ADF test for the null hypothesis of non-stationary (unit root) against the alternative hypothesis of stationary (no unit root) is carried out in the original form with trend and intercept². We use a data-driven automatic lag length selection procedure in E-View to select the number of lagged difference terms (or lag length).

The ADF test rejects the null hypothesis of a unit root at 1% level of significance for all the index time series, since the ADF test t-statistics are all less than -7.3978, while the test critical value at 1 per cent is -4.0515. Hence we conclude that the excess returns of the SRI indices and their benchmarks are all stationary and no further differencing or testing for co-integration is needed.

4.2. Model Selection Process

To decide the appropriate Markov Switching process to use, we apply the SIC to determine the switching parameters, the proper number of regimes, and the appropriate lag length to apply. The reason for using the SIC test other than the usual Likelihood ratio or the Akaike Information Criterion (AIC) is due to the introduction of a stronger penalty term for the number of parameters in the SIC criteria, which makes its application more efficient (Sylvain, 2009).

Now we apply a computationally intensive approach to run each regression 36 times by adjusting the number of lags and regimes and choosing the different switching parameters in use. By doing this, we are able to find the model with the lowest SIC value for each SRI index. We restrict the number of regimes and lags to three, since including more regimes and lags would pose extreme computational problems and make the number of parameters difficult to estimate. The parameters such as intercept term (I), beta coefficient (β), and variance of the error terms (H) can be either state dependent (switching) or remain constant (non-switching). Table 2 shows the models selected for the individual SRI indices. Except DSI, which fits the model MSIH (3)-(3), the other six SRI indices fit the model MSH (3)-(2). The MSIH model allows switches in both the intercept term and the variance of the error terms, and the MSH model only switches in the variance of error terms. For both MSH and MSIH models, the Beta coefficients do not switch across regimes (see also Hamilton, 1989; Schwert, 1989; Payaslioglu, 2008).

Table 2: MS Models for Each Index Groups

Index	Benchmark	Markov Switching Model	SIC
DSI	S&P	MSIH(3)-(3)	13.9715
USSA	R3000	MSH(3)-(2)	11.6511
USSL	R1000	MSH(3)-(2)	13.9186
CAL	R1000	MSH(3)-(2)	13.9186
USSS	R2000	MSH(3)-(2)	17.7568
USSM	S&PM	MSH(3)-(2)	15.8371
FUS	FTSE	MSH(3)-(2)	14.0393

Notes: The first number in the brackets is the number of regimes, and the second one is the number of lags. In this study, all of the models have 3 regimes and 2 lags, except for DSI which has 3 lags.

4.3. Transition Probabilities and Characteristics of Market Regimes

Table 3 presents the transition probabilities, the number of observations, duration and Ergodic probability for the seven indices in each of the three identified regimes.

² By plotting the excess return data series, we see a clear trend of these series. Therefore, we apply unit root test in the original form with trend and intercept (the plotting charts can be provided as requested).

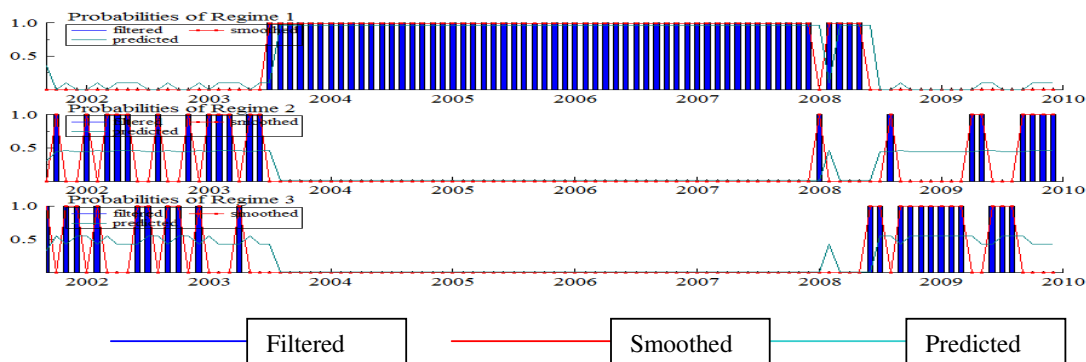
Table 3: Transition Probabilities and Characteristics of MS Models

		Transition Probabilities: (%)			Obs	Duration	Ergodic Prob.
		Regime 1	Regime 2	Regime 3			
USSM	Regime 1	83.52	9.83	6.66	61	6.07	60.90
	Regime 2	24.80	61.99	13.22	17	2.63	18.17
	Regime 3	26.44	4.41	69.15	22	3.24	20.93
USSL CAL	Regime 1	91.91	1.64	6.45	62	12.36	62.10
	Regime 2	16.20	51.39	32.41	19	2.06	18.98
	Regime 3	10.29	43.40	46.31	19	1.86	18.92
USSS	Regime 1	92.16	6.25	1.59	64	12.76	65.81
	Regime 2	23.36	64.24	12.40	18	2.8	18.50
	Regime 3	5.32	15.97	78.71	18	4.7	15.68
USSA	Regime 1	94.74	0.00	5.26	58	19.02	58.56
	Regime 2	15.52	51.74	32.74	20	2.07	19.84
	Regime 3	0.00	44.33	55.67	22	2.26	21.60
FUS	Regime 1	96.52	1.724	1.754	58	28.75	58.54
	Regime 2	10.29	46.31	43.40	20	1.86	19.78
	Regime 3	0.00	44.33	55.67	22	2.26	21.68
DSI	Regime 1	82.18	2.27	15.55	45	5.61	28.15
	Regime 2	11.68	68.86	19.46	26	3.21	45.33
	Regime 3	17.69	25.68	56.62	28	2.31	26.52

Notes: Obs stands for the number of observations in a regime. Ergodic prob. stands for the ergodic probability, which detects the aperiodicity and the irreducibility of the regime for the Markov Chain.

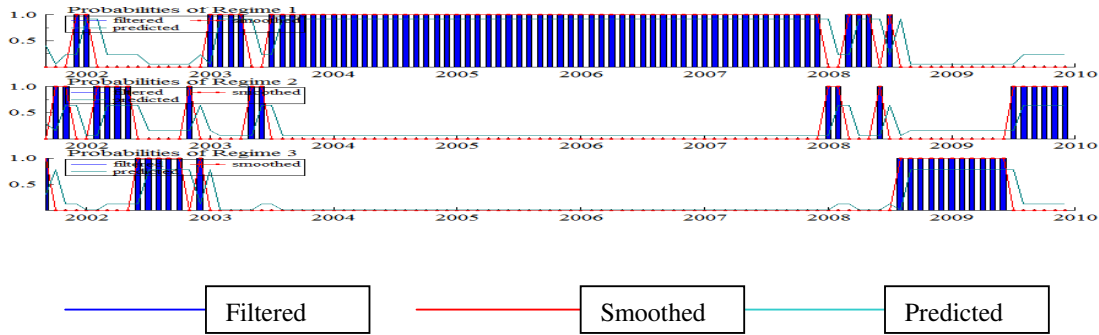
It can be seen that Regime 1 is the most persistent one with the longest duration and is characterized by low volatility and moderate return. It represents the state that no abnormal market boom occurred and shares are valued at their “fair price”. This regime represents most of the study period extending from 2003 to 2007. Regime 3 is corresponding to the highest volatility and the lowest return state. It coincides with the periods over which stock markets distress events occurred, such as the September 11 attacks in 2001, the Adelphia bankruptcy in 2002, the WorldCom bankruptcy in 2003, and the subprime crisis in 2008. Regime 2 on the other hand, is associated with speculative bubbles or government intervention. It is generally displayed by the disassociation between price and value (overvalued share price) and is characterized by medium volatility and high return state. Both Regimes 2 and 3 fall between 2001 to 2003 and 2008 to 2009 and switch rapidly between each other, as illustrated in Figures 1 to 6. Table 4 represents the empirical results of the excess return and total risk, which is mixed by the variance of the excess return during the three different market regimes.

Figure 1: Probabilities of Regimes for the FUS



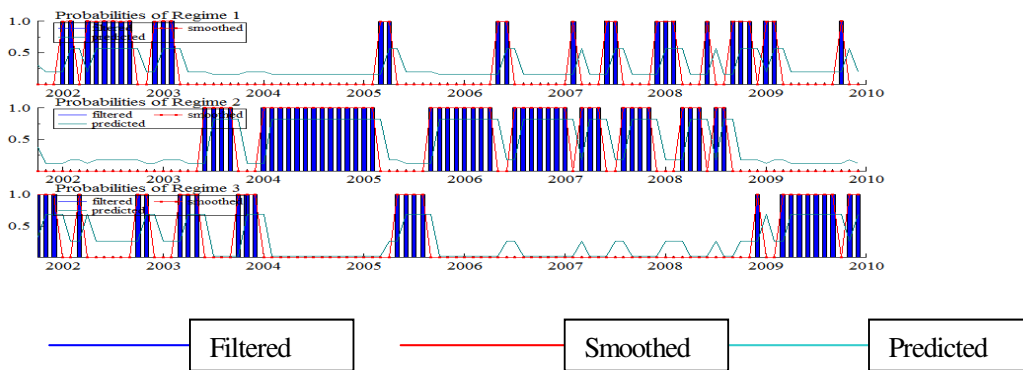
Notes: 1.FUS stands for FTSE4Good US.

Figure 2: Probabilities of Regimes for the USSS



Notes: 1.USSS stands for KLD Small Cap Social Index.

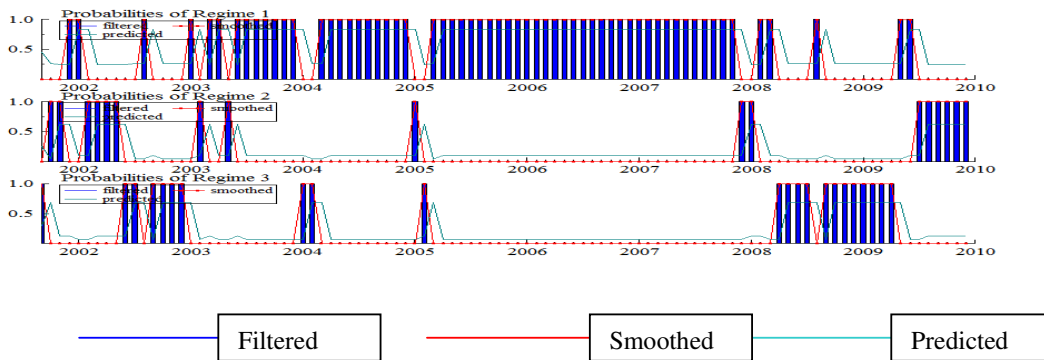
Figure 3: Probabilities of Regimes for the DSI



Notes: 1.DSI stands for KLD Domini 400 Social Index.

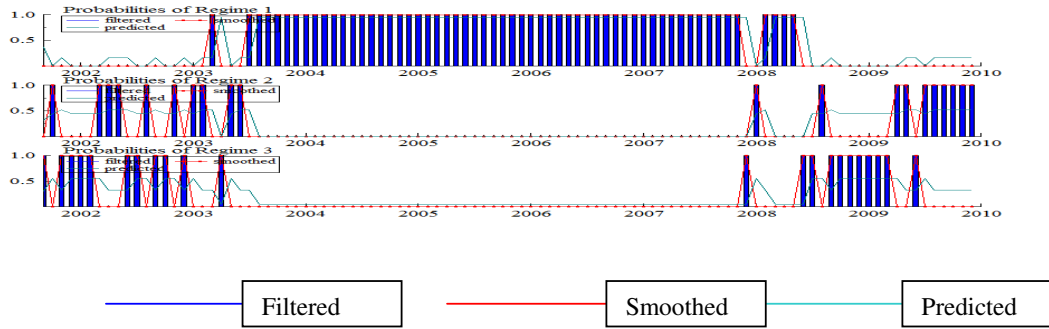
2. Regime 2 denotes the stable state with moderate return and low volatility, Regime 3 denotes high return and medium volatility, and Regime 1 represents the low return and high volatility state. Therefore, the regime numbers here are different from the ones in the body of the text.

Figure 4: Probabilities of Regimes for the USSM



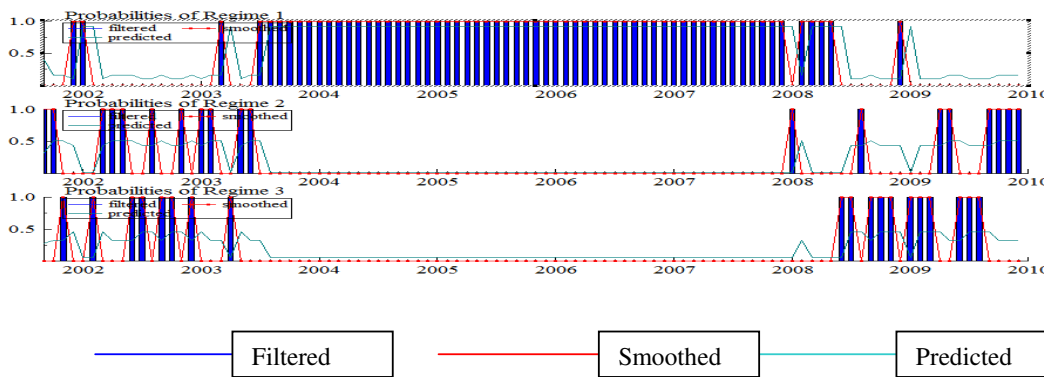
Notes: 1.USSM stands for KLD Mid Cap Social Index.

Figure 5: Probabilities of Regimes for the USSA



Notes: 1.USSA stands for the KLD Broad Market Social Index.

Figure 6: Probabilities of Regimes for the CAL & the USSL



Notes: 1.CAL stands for the Carvel Social Index, and USSL stands for the KLD Large Cap Social Index.

Table 4: Estimated Excess Return and Variance across Regimes

	DSI	CAL	USSA	USSL	USSM	USSS	FUS
<i>Panel A: Regime 1</i>							
μ_1	1.18	0.61	0.96	0.82	1.25	1.25	0.74
μ_{BK1}	1.05	0.79	0.86	0.79	1.12	1.25	1.00
σ_1^2	4.07	6.43	7.10	5.99	10.24	15.71	6.95
σ_{BK1}^2	3.83	5.30	5.95	5.30	9.32	15.68	5.95
<i>Panel B: Regime 2</i>							
μ_2	3.91	1.15	2.36	1.13	2.61	2.29	1.45
μ_{BK2}	3.58	0.99	1.99	0.99	2.16	2.18	1.54
σ_2^2	17.76	25.72	20.62	24.70	27.73	44.94	18.23
σ_{BK2}^2	14.58	22.57	18.81	22.57	22.64	38.94	17.81
<i>Panel C: Regime 3</i>							
μ_3	-4.67	-2.56	-3.21	-2.57	-2.37	-3.68	-2.39
μ_{BK3}	-4.82	-2.88	-3.38	-2.88	-2.37	-3.97	-2.57
σ_3^2	14.86	79.62	59.96	72.87	79.87	98.77	71.44
σ_{BK3}^2	17.03	64.38	52.26	64.38	77.52	90.6	58.99

Notes:

1.BK denotes corresponding value for the relative benchmarks.

2. μ_1 , μ_2 and μ_3 stand for the mean excess return in Regime 1, 2, and 3 respectively, and σ_1^2 , σ_2^2 and σ_3^2 stand for the variance of the excess return in Regime 1, 2, and 3 respectively.

Five SRI indices perform better than their counterparts in Regime 1, while six SRI indices have outperformed the benchmarks in Regime 2. Also in Regime 3, six SRI indices have higher mean excess

returns, and another one is equal to its benchmark; whereas for the variance, most SRI indices are higher than their benchmarks in all regimes, except DSI in Regime 3, where the benchmark excess return is higher. This implies that a higher return may commensurate with the higher risks that SRI bears. This result is consistent with earlier studies, such as Schroder (2007), which suggested that the higher return of SRI indices mainly stems from higher risk as compared to conventional indices.

4.4. Systematic Risk (Beta Coefficient)

As mentioned in section 4.2, Beta coefficients in MSH or MSIH models are identified as regime-invariant. Panel A of Table 5 presents the estimated results of the Beta coefficients. All Beta coefficients in this study are significantly different from 1 and 0. Therefore, SRI indices have a different and meaningful systematic risk exposure against their benchmark indices. At lag 1, the Beta coefficient of five SRI indices is negative. The negative Beta coefficients indicate that the excess returns of SRI indices move in an opposite direction to their benchmarks over one month. This result is consistent with the findings of Potterba and Summers (1986), which stated that negative information from shocks on stock market volatility does not persist for long periods and usually lasts less than one month. On the contrary, at lag 2 and lag 3, most Beta coefficients are positive, which suggests that the market risk premium has a positive effect on the SRI index returns for two or three months after the shock happened. These results agree with the conclusion of Brennan, Chordia, and Subrahmanyam (1998), who found a significant positive effect of the market risk premium on the two months' lagged market returns. The rationale is that the market is generally inefficient, and investors normally wait until they realize the real effect of the changes to understand the stability of the changes. Therefore, it takes over one month for them to respond to market changes (Günsel and Çukur, 2007). Overall, the absolute value of most Beta coefficients is less than 1, which implies that SRI has a lower systematic risk than conventional benchmarks.

4.5. Unsystematic Risk

Panel B of Table 5 presents the empirical results of SRI unsystematic risk across the three market regimes.

Table 5: Estimated Systematic and Unsystematic risk

<i>Panel A: Estimated Systematic Risk (Beta Coefficients)</i>							
	DSI	CAL	USSA	USSL	USSM	USSS	FUS
β_{t-1}	1.08***	-0.54***	-0.75***	-0.35***	-0.69***	1.10***	-2.06***
t-value	6462	-5745	-23809	-6281	-26101	15.15	-34242
β_{t-2}	0.44***	0.04***	0.31***	0.27***	-0.36***	0.40***	0.73***
t-value	3492	537	4708	4351	-6412	5.54	6077
β_{t-3}	0.12***						
t-value	-677						
<i>Panel B: Estimated Unsystematic Risk (Standard Error of Regression Residuals)</i>							
	DSI	CAL	USSA	USSL	USSM	USSS	FUS
σ_1	1.88	2.66	2.74	2.60	2.96	3.37	3.32
σ_2	3.13	4.60	4.45	4.59	5.95	5.58	3.47
σ_3	2.29	8.88	8.49	8.49	8.30	9.76	9.93

Notes:

1. Asterisks *, **, *** = H_0 rejected at a significance level of 10%, 5% and 1%, respectively.
2. β_{t-1} , β_{t-2} and β_{t-3} denote Beta coefficient for lag 1, 2 and 3 of benchmark excess return respectively.
3. σ_1 , σ_2 , and σ_3 stand for the standard error of regression in Regime 1, 2, and 3 respectively.

The unsystematic risk for most of the SRI indices increases when the market moves from a low volatility state (Regime 1) to a medium volatility state (Regime 2), and then to a high volatility state

(Regime 3). This result indicates that the market cycles have an impact on the unsystematic risk in the same way as on the total risk. This is reasonable because the systematic risk remains constant during the three regimes for both MSIH and MSH models applied.

The question to ask is why SRI unsystematic risk is so highly regime-dependent. Possible explanations at the firm level are as follows. Firstly, the SRI corporations usually change their objectives according to market conditions. For example, SRI firms tend to focus more on social objectives during low volatility states and less during high volatility states. During high volatility states, SRI firms with increasing survival and competitive stress have to shift some of their attention from social goals to financial objectives. Secondly, for the same reason, SRI firms tend to be involved in socially responsible innovation more during low volatility states and less during high volatility states, if they are involved in socially responsible activities. Therefore, SRI unsystematic risk tends to increase when market volatility increases.

This phenomenon can also be explained at the portfolio level. Firstly, when the market dives, social screening enables SRI index providers to select firms that have performed financially well. Secondly, social screening provides flexibility to the SRI indices suppliers or funds managers to add more weight to preferred industries, while avoiding poorly performing ones, although the investors tend to be loyal to SRI funds. These facts enlarge the asset allocation inequality, and therefore increase unsystematic risk. Also, rising unsystematic risk may come from the fact that some social investors withdraw their investments from certain industry sectors or SRI companies during the down market.

4.6. Risk Adjusted Return

The transformed difference of the Sharpe Ratio (SI_{ab}) during the three different regimes is presented in Table 6.

Table 6: Transformed Difference of the Sharpe Index and Significance

	DSI	CAL	USSA	USSL	USSM	USSS	FUS
<i>Panel A: Regime 1</i>							
$SI_{ab} S_1$	-0.66	-0.61	0.03	-0.04	0.21	-4.45	-0.82
$Z S_1$	-0.17	-0.63	0.01	-0.05	0.12	-1.64	-0.73
Prob. S_1	0.43	0.26	0.50	0.48	0.45	0.05	0.23
<i>Panel B: Regime 2</i>							
$SI_{ab} S_2$	0.19	0.45	1.22	0.46	1.06	-13.18	-0.44
$Z S_2$	0.19	0.06	0.18	0.06	0.12	-0.94	-0.08
Prob. S_2	0.42	0.48	0.43	0.48	0.45	0.17	0.47
<i>Panel C: Regime 3</i>							
$SI_{ab} S_3$	-0.03	5.11	2.98	3.94	-0.29	35.92	3.39
$Z S_3$	0.00	0.22	0.14	0.18	-0.01	1.12	0.17
Prob. S_3	0.49	0.41	0.44	0.43	0.50	0.13	0.43

Notes:

1. SI_{ab} stands for the transformed difference between the SRI and the non-SRI for the Sharpe Index.
2. Z stands for the Z-test for the difference between the Sharpe Index of the SRI indices and the corresponding benchmarks.
3. s_1, s_2 and s_3 stand for state 1, 2 and 3 respectively.

During Regime 1, SI_{ab} of five SRI indices is negative. During Regime 2, five SRI indices have a positive SI_{ab} , while six SRI indices generate a positive SI_{ab} during Regime 3. This implies that SRI industries have generated lower total-risk-adjusted-returns compared to non-SRI during the low volatility market state. But with the increase in the market volatility, the total-risk-adjusted-return of most SRI indices is higher than non-SRI indices. However, most of the Sharpe Z statistics (with only one exception) do not show any powerful ability to distinguish the differences in performance between SRI and non-SRI across the three regimes. In other words, the use of social responsibility screens does

not necessarily have an adverse impact on the total-risk-adjusted-return. This result is in line with the findings of Sauer (1997) and Schroder (2007), who concluded that SRI investors do not make more financial sacrifices than conventional investors, based on their risk-adjusted-return.

5. Conclusion

In this paper, we analysed the effect of stock market regimes on the financial performance of seven US SRI indices as compared to their pair-matched conventional benchmark indices for the period between June 2001 and December 2009.

We determine the stock market regimes precisely by applying the Markov Switching (MS) model based only on our time series data. We identify three market regimes during our study period. These regimes are Regime 1, which is the low volatility and medium return states, Regime 2 which is the medium volatility and high return states, and Regime 3 which is the high volatility and low return states.

Generally, the total risk of SRI indices is higher than non-SRI, which is consistent with the total returns of SRI as compared to non-SRI during each of the three market regimes. However, the systematic risk for SRI indices is constantly lower than non-SRI. Also, we find that market premium has a negative effect on one-month-lagged returns, whilst it has a positive effect on two and three months lagged returns. This implies that the negative effect of stock market shocks does not last longer than one month and that investors normally need two or three months to recognise whether their returns tend to be stable or temporary. It is worth noting that the unsystematic risk of SRI indices increases when market volatility rises.

Finally, based on the Sharpe ratio, we cannot find any significant difference in the total risk adjusted return between SRI and non-SRI across the three market regimes. This implies that market condition changes do not affect the financial rewards of SRI investors based on the total risk they bear as compared to non-SRI investors. Although our study has similar findings to many previous studies, it does provide an interesting indication that SRI unsystematic risk plays a major role in SRI higher total risk. Since the systematic risk is lower, the expected return on the systematic risk should be lower, according to modern portfolio theory. Hence, the higher returns of SRI can only be explained by the higher unsystematic risk of SRI under different market conditions. As the unsystematic risk is changing when the market either dives or rises, further research on the changing pattern of the unsystematic risk premium across stock market regimes could prove very interesting.

Biographical Notes

Li Huimin is a Research High Degree student at Griffith University, Australia.

Dr. Cheung Adrian Wai Kong is a finance lecturer in the Griffith Business School at Griffith University.

Dr. Roca Eduardo is an Associate Professor of Finance and the acting head of the Department of Accounting, Finance and Economics in the Griffith Business School at Griffith University.

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