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Analysis of investment strategies: a new look at investment returns

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Analysis of investment strategies: a new look at investment returns

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DEDICATION

To my family for all their support: To my grandparents, Jose and Maria Teresa, for always showing me that the most important thing in life is to be a good person; to my mother, Flor, for never once doubting in me and always, despite every concern, supporting each and every single one of my decisions; to my aunts, Yoli for taking care of me when I needed her the most, and Lali for always giving me her love and trust unconditionally. From the bottom of my heart, thank you.

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ABSTRACT

Chapter 1:

Intuition suggests that constraint investment strategies will result in losses due to a limited portfolio allocation. Yet prior research has shown that this is not the case for a particular set of constraint mutual funds so-called Socially Responsible Investing, SRI. In this paper I show that such assets do face loses to portfolio efficiency due to their limited asset universe. I contribute to the literature by employing two techniques to estimate asset performance. First, I estimate a DEA based efficiency score that allows for direct comparison between ex-post efficiency rankings and test the ex-ante relevance of such scores by including them into asset pricing models. Second, I further check if these results are consistent when comparing the performance of ethical funds based on the alphas of traditional asset pricing models even after adjusting for coskewness risk. Overall, the results suggest that ethical funds underperform traditional unconstraint investment assets.

Chapter 2:

Starting after the turn of the millennium, inflation has been persistently higher than the short term T-Bill rate. Following the traditional view, this will imply a negative real rates of return that have become commonplace in the US economy. This paper examines the possibility that if an inflation risk discount contained in nominal rates exist and can explain low or negative real rates, using consumption based asset pricing model. Evidence suggests using the traditional Fisher equation to calculate real rates leads to an overestimate of real rates due to a modest inflation risk premium. To achieve non-negative real rates in a consumption based asset pricing framework the covariance between consumption growth and inflation innovations would have to be at least thirty times larger than empirically found, and in opposite direction, for the Post-Volker era. Still, though the after 2000's covariance is positive, which suggest a discount on risk free, the magnitude is still too small to explain negativity of real rates.

JEL Classification	*:*	*E21, E31*
Key Words	*:*	Mutual Funds, Performance, Data Envelop Analysis, Coskewness, Risk Factors, Real Returns, Consumption Bases Asset Pricing Models*,* Inflation

1. Chapter 1: Performance of Socially Responsible Mutual Funds: Methodological Investigation

1.1. Introduction

The concept of social responsible investing (SRI) investing has been around for the last thirty years but little attention has been given to the performance of such assets. This type of investment imposes many restraints on the pool of firms, for the managers are highly concerned with the ethics and social responsibility of the business practices; for example, Northwest and Ethical Funds Investing limit their assets to only those which meet their rigorous standards on environmental risk, social risk, and governance risk. Depending on the fund manager, socially responsible investment can also limit holdings from business that engage in alcohol, tobacco, gambling, pornography, and weapons. Despite the restrictions, socially responsible investment has been increasing exponentially during the last decade according to the Social Investing Forum . This has caught the attention of the main stream literature.

Prior literature shows that there is not a consensus on the exact consequences of investing in ethical mutual funds. For example, it has been shown that volatility in said market is lower than the volatility of conventional funds (Bollen, 2007; Renneboog et al., 2005). But this does not include a discussion on the effects of reducing diversification; investing in a closed universe is expected to limit the power of diversification and thus it can result in lower risk-adjusted returns. Yet concise evidence of lower performance of SRI has been missing.

In this study I seek to provide further evidence of the performance of Socially Responsible Investing by using a larger data sample than in prior estimations as well as incorporating different measures of performance. I expand the literature of investments by first employing a non-parametrical measure of performance which measures the fund's relative efficiency in addition to traditional Jensen's alphas. In regards to the latter, I use traditional asset pricing models, as well as the inclusion of the newly incorporated coskewness factor, to explain differences in performance between size-adjusted portfolios of traditional investment assets and ethical investing.

I estimate the efficiency scores based on the data envelop analysis, DEA; DEA allows for multiple inputs and outputs to be included into a production framework while still offering a single, ex-post, performance index, thus allowing easy comparison between funds and thereby groups. In addition, I check if these results are consistent when using Jensen's alphas to rank performance. The results suggest that ethical funds do not seem to perform as good as traditional unconstrained investment funds.

Given an efficiency score, I rank funds in quintiles while differentiating between types of mutual funds. Cross-tabulations of efficiency score quintiles and whether the fund is ethical or not show that there are more ethical funds within the low efficiency quintiles compared to more traditional mutual funds on the efficiency quintiles. There are 4.27% more socially responsible mutual funds in Q1 and Q2 compared to traditional investing, while there are 3.75% more orthodox funds in Q4 and Q5 compared to ethical funds.

Given the ex-post nature of this efficiency score, from an investments framework, it is more interesting to know if efficiency has explanatory or predicting power of excess returns. I find that including the efficiency score in time series regressions decreases average mispricing errors. The magnitude of the averages alpha decreases from -23 to 11 basis points under a modified CAPM model and from -19 to 5 (non-statistically different from zero) basis points under a modified four factor model.

Going to cross-section regressions at t+1, however, the efficiency score does not seem to improve the results of other traditional models. In fact, the estimation of the risk premium is largely deviated from the ex-post realization. Further inclusion of an ethical dummy in these cross-section regressions shows that ethical funds can expect to receive a discount between 6 – 10 basis points in next period returns. Thought the parameter estimates are only significant at the 10% level. All in all, these results suggest initial evidence of underperformance of ethical investing.

The results are corroborated even by further including a coskewness risk factor to traditional asset pricing models. When comparing ethical investment to a size-adjusted portfolio of traditional mutual funds, the latter outperforms the former in 4/6 models; three of those four models include a coskewness factor. Quite remarkably, under the four factor model plus a factor of coskewness, socially responsible investment underperforms assets in the same category for 48 basis points, where the difference is highly statistically significant.

The remaining of this paper is structured as follows. Section 2 provides a summary of the literature on ethical investing. Section 3 explains the data collection and description. Section 4 develops the estimation of an efficiency score and its use under a investment strategy paradigm. Section 5 checks the results are consistent by employing traditional asset pricing models and a coskewness factor. Finally, section 6 provides concluding remarks.

1.2. Literature Review

Traditional modern portfolio theory develops in the idea that diversification (completely) removes the idiosyncratic risk, and thus no investment should compensate for bearing the extra risk of no diversification; i.e. investors should not be compensating for the firm specific risk, only for the market, as this risk could be fully eliminated by diversification (Markowitz, 1952 and 1959). In spite of this, ethical mutual funds have self-imposed constraints which limit their asset universe, thereby reducing the power of diversification. This is expected to have a direct impact on the performance of such mutual fund. For example, Geczy et al. (2003) show that investing only on ethical funds carry a significant financial cost for the period 1963-2001. Yet, Bollen (2007) argues that investors see beyond this traditional risk-reward optimization problem, as they may present a multi-attribute utility function which incorporates a set of personal and societal values; thus justifying the existence of ethical investments despite possible underperformance.

According to the Social Investment Forum in the U.S. (SIF), over the past 20 years, the total dollars invested in SRI has grown exponentially, as has the number of institutional, professional, and individual investors involved in the field. Between 1995 and 2010, total dollars under professional management in SRI grew from $639 billion to $3.07 trillion, outpacing the overall market. SRI investing has become part of the mainstream, and as a result, a number of conventional companies now offer SRI products to their clients; an increasing number of investors focus on ethical fund not only because the ethical aspect, but because returns are comparable to those of more conventional investments[1].

Ethical funds' mangers have to follow social responsible constraints on environmental risk, social risk, and governance risk. For example, they would not buy shares from the weapons, gambling, alcohol, and tobacco industries; nor would they buy shares from companies know from polluting the environment, using "sweatshops," discriminating employees, etc. On the other hand, said managers will increase the number of shares on ethical companies, philanthropic institutions, and firms well known for their social activities[2]. This is the social screening process. Barnett and Salomon (2006) find that when the number of social screens, positives and negatives, increases, the fund's annual return declines at first, but then rebounds as the number of screens reaches a maximum. Furthermore, managers also have to analyze the companies' financial statements; Goldreyer and Diltz (1999) find that the performance of ethical investment also depends on the level of financial screening.

The question still remains whether or not ethical investment reduces profitability, thereby efficiency. Said in another way, are the risk-adjusted returns of SRI portfolios higher than traditional investing. In lieu of this matter, Hamilton and Statman (1993) proposed three alternative hypotheses: (1) the risk-adjusted expected returns of socially responsible portfolios are equal to the risk-adjusted expected returns of conventional portfolios, as the social responsibility feature of stocks is not priced; (2) the risk-adjusted expected returns of socially responsible portfolios are lower than the expected returns of conventional portfolios, as the market prices the social responsibility characteristic by increasing the value of socially responsible companies relative to the value of conventional companies by driving down the expected returns and the cost of capital of socially responsible companies; and (3) (also suggested by Moskowitz, 1972), the risk-adjusted expected returns of socially responsible portfolios are higher than the expected returns of conventional portfolios, as the market prices social responsibility (incorrectly) in the case of "doing well while doing good."

In this regard, traditional numerical indexes used to measure the performance of mutual funds do not take into consideration the ethical aspect. Particularly, the Sharpe ratio (Sharpe, 1966), the reward-to-half-variance index (Ang and Chua, 1979) and the Treynor index (Treynor, 1965) are computed as ratios between the expected excess return and a risk indicator without considering additional features (Basso and Funari, 2003). Still, Goldreyer and Diltz (1999), compute Sharpe and Treynor ratios to show that social screening does not affect the investment performance of ethical mutual funds in any systematic way. Furthermore, Statman (2000) shows that the DSI index[3] (which is one of the most well-

[1] Abstract taken from SIF's Performance and SRI investments page: http://ussif.org/resources/performance.cfm; the full report on Sustainable and Responsible Investment trends can be downloaded from: http://ussif.org/resources/research/documents/2010TrendsES.pdf.

[2] See Basso and Funari, 2008 page 26 for further exemplification of social responsible screening.

[3] Domini 400 Social Index: A market cap weighted stock index of 400 publicly traded companies that have met certain standards of social and environmental excellence. Potential candidates for this index will have positive records on issues such as employee and human relations, product safety, environmental safety, and corporate governance. Companies engaged in the business of alcohol, tobacco, firearms, gambling, nuclear power and military weapons are automatically excluded. http://www.investopedia.com/terms/d/domini_400.asp#ixzz26NyXf2Ft

known SRI index) has a higher Sharpe ratio than the S&P 500, which implies that investors seeking to optimize the mean-variance would prefer the ethical investment.

Believers in the efficient market hypothesis argue that it is impossible that SRI funds outperform their conventional peers (Renneboog, Horst, and Zhang, 2008). At most, prior research has found that SRI performs at least as good as traditional investment portfolios.

Hamilton and Statman (1993) and Statman (2000) use a sample of SRI funds and non-SRI funds for the periods 1981-1990 and 1990-1998 respectively to estimate Jensen's alphas based on CAPM, using the DSI 400 index and the S&P500 index as the benchmark returns for SRI and Non-SRI. In the end, the authors did not find any statistical difference between the Jensen's alphas, thus favoring the first hypothesis. They results are consistent with Diltz (1995), Guerard (1997) and Sauer (1997).

This gave some initial insight regarding the performance of Socially Responsible Investing. Later attempts included the use of Fama and French's three factor model as well as the inclusion of Carhart momentum factor. Bauer, et al. (2005) finds no statistical difference in the performance of SRI for the overall period 1990-2001, but they do find a "catching up" period in their early life. Their results are consistent with Renneboog, et al. (2008a) who reiterate the study for the period 1991-2003. The latter also finds the catching up period in the sub-sample 1991-1995. Surprisingly, though, the authors also find that ethical funds outperform their counterparts for the sub-period 2001-2003 (not statistically significant).

Still using Carhart's four factor model, Gil-Bazo, Ruiz-Verdú and Santos (2010) compare the pre and after fees performance of ethical funds against non-ethical funds for the period 1997-2005. They find that ethical funds had better before and after fees performance when compared to non-ethical funds of the same characteristics.

Most of the literature, however, has focus on the social factor of ethical funds, and how SRI outperforms conventional investing due to said factor. Yet, several authors (see Kurtz and diBartolomeo, 1996; Guerard, 1997; and Kurtz, 1997; among others) report that the reason for the over performance of the DSI400 comes due to the large investing on growth stocks and not the social factor.

I extend prior studies by extending the data set and also accounting for different measurements of both performance and of risk-adjusted returns. The following section describes the data set.

1.3. Data Specification

The data comprises monthly returns from the Center of Research in Security Prices from January 1960 to September 2012. To identify SRI funds, I look for the keywords "Ethical", "Social", "Socially", and "SRI" within the fund name. This results in a reduction of the initial study period from 1960 to 1984. Furthermore, following Carhart (1997) I also omit sector funds, international funds, balanced funds, and money market funds[4]. This results in an asset universe of 43844 from which ethical funds account for only 142 funds. I do not impose any further immediate restriction on the data, but it is worth noting

[4] Regressions that include a market premium are considerably lower than prior studies show; I attribute this effect to an asset composition that relies heavily on debt instruments; this being the reason why to delete money market assets.

that all estimations rely on the existence of at least three continuous years' worth of data, and that will decrease the total number of estimations[5].

Socially responsible mutual funds are still relatively new financial products. While there were an average of 743 mutual funds in 1984, only 1 of those could be considered socially responsible constrained; even more so, the number of ethical mutual funds, as of September 2012, has not even reached 100 funds on average[6]. Moreover, while unrestricted mutual funds had total net asset value of up to 2.3 billion dollars by 1984, ethical investment did not surpass the 17.2 million dollars. This continues to be true even by 2012, where maximum total net assets of traditional investment reached 673 million dollars while ethical investment reached only about 74 million. Table I shows summary statistics regarding ethical funds and orthodox mutual funds from 1984 to 2012.

Simple inspection reveals that the returns of socially responsible investments are, on yearly average basis, never as large as orthodox funds as seen by their maximum returns. Further, looking at the average minimum return, ethical returns are also never as low as those of traditional funds. Intuition will suggest that this type of investment is less risky than traditional investment and thus their returns are less volatile. Table I shows that the standard deviation of returns for ethical investment is usually lower than that of traditional investment except for brief periods of time. Finally, generally speaking, average returns seem to be higher for ethical funds than for orthodox funds. But this is not risk adjusted.

1.4. Estimating Mutual Funds Efficiency: A DEA Approach

On the bases of portfolio performance, the literature has heavily relied on the mean-variance relationship. In this regard, portfolio performance is categorized in the bases or abnormal returns for unit of risk, where risk is proxy by the portfolio standard deviation (See Treynor, 1965; Lintner, 1965; Sharpe, 1966; and Jensen, 1968; among others). However, under non-normality of returns, variance should not be considered as the only proxy for risk. That is, the risk return relationship should incorporate higher moments. Thus I look into an operational model which allows for multiple parameters of risk.

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[5] Because of the extreme difference of number of funds between ethical and traditional mutual funds, prior versions of this paper included a size-adjusted one-to-one match of an ethical fund with a randomly selected traditional fund. That is, given an ethical fund, I look for a randomly selected traditional fund which falls in the same size category of average total net assets; this randomly selected traditional fund must have longer trading history than the ethical fund, from which I trim down observation to match exactly the trading period of the ethical fund. The resulting dataset contains a one-to-one match of ethical-to-traditional mutual funds which I use for the remaining of this paper. This methodology did not provide significant results when explaining both time-series and cross-sections returns because of the lack of sufficient observations to fit accurate regression lines. However, I am confident that BCC estimations reported in this paper are consistent with prior estimations.

[6] Though the sample includes 108 different funds, none of them have survived throughout the whole sample.

Table I: Descriptive Statistics of Mutual Funds

Table I shows monthly descriptive statistics of mutual funds. Panel A shows traditional mutual funds while Panel B shows ethical mutual funds.

Panel A: Traditional Mutual Funds											
		TNA					Return				
Year	Funds	Average	Median	Min	Max	Standard Deviation	Average	Median	Min	Max	Standard Deviation
1984	743	$22.13	$10.19	$0.53	$2,319.28	$112.53	0.30%	0.46%	-31.18%	33.17%	3.89%
1985	919	$23.08	$10.95	$0.54	$2,826.16	$119.13	1.88%	1.55%	-18.27%	59.77%	3.44%
1986	1202	$23.11	$11.64	$0.53	$3,641.44	$125.12	1.14%	1.06%	-23.24%	45.60%	3.80%
1987	1619	$20.25	$10.86	$0.62	$3,950.39	$112.65	0.22%	0.66%	-49.62%	45.20%	6.31%
1988	2005	$16.71	$10.28	$0.58	$3,044.52	$85.27	0.91%	0.60%	-20.73%	89.67%	2.60%
1989	2202	$17.70	$10.68	$0.34	$3,735.71	$94.03	1.21%	0.93%	-17.96%	28.30%	2.58%
1990	2402	$15.39	$10.24	$0.29	$3,235.57	$63.85	0.04%	0.47%	-29.79%	52.46%	4.00%
1991	2712	$15.03	$10.64	$0.57	$1,682.32	$50.15	1.65%	1.08%	-49.71%	101.62%	3.43%
1992	4355	$12.73	$10.82	$0.62	$1,033.32	$16.82	0.51%	0.50%	-40.59%	95.92%	2.41%
1993	5664	$12.87	$11.08	$0.80	$442.94	$11.39	0.88%	0.66%	-66.36%	34.96%	2.38%
1994	7260	$12.02	$10.37	$0.66	$458.74	$10.41	-0.33%	-0.09%	-51.08%	102.43%	2.60%
1995	8656	$12.54	$10.74	$0.59	$539.32	$11.27	1.46%	1.24%	-26.94%	39.75%	2.25%
1996	9550	$13.51	$11.29	$0.15	$596.12	$12.50	0.82%	0.66%	-33.44%	99.28%	2.89%
1997	10671	$14.57	$11.88	$0.14	$675.92	$15.22	1.04%	0.86%	-78.27%	532.64%	4.15%
1998	11776	$14.77	$11.69	$0.09	$725.36	$16.10	0.78%	0.60%	-60.64%	72.04%	5.71%
1999	12769	$15.25	$11.76	$0.13	$616.80	$13.65	1.29%	0.20%	-65.88%	169.89%	4.76%
2000	13918	$16.27	$11.93	$0.08	$620.78	$15.46	0.07%	0.30%	-86.97%	97.11%	6.34%
2001	15045	$13.50	$10.74	$0.05	$580.07	$12.33	-0.40%	0.36%	-87.25%	102.17%	6.20%
2002	15537	$12.24	$10.35	$0.05	$524.54	$10.79	-1.04%	-0.13%	-96.24%	861.54%	6.02%
2003	15902	$12.61	$10.63	$0.06	$493.87	$10.70	1.81%	1.14%	-33.33%	33.33%	3.41%
2004	16450	$14.54	$11.39	$0.06	$530.77	$12.65	0.80%	0.87%	-34.11%	30.00%	2.84%
2005	17048	$15.55	$11.92	$0.06	$547.80	$13.62	0.53%	0.39%	-46.56%	27.74%	2.72%
2006	18029	$16.51	$12.49	$0.06	$608.46	$14.65	0.89%	0.78%	-50.00%	29.64%	2.57%
2007	19021	$17.87	$13.12	$0.06	$685.23	$16.49	0.52%	0.50%	-33.43%	32.17%	2.92%
2008	20512	$14.64	$10.73	$0.06	$639.23	$14.21	-2.96%	-1.15%	-64.42%	378.94%	6.96%
2009	22519	$12.36	$9.82	$0.06	$551.97	$11.62	2.15%	2.25%	-67.84%	58.86%	6.03%
2010	22584	$14.82	$11.04	$0.06	$606.04	$13.61	1.15%	1.08%	-42.42%	43.84%	4.88%
2011	23465	$16.33	$11.75	$0.07	$647.37	$15.05	-0.04%	0.09%	-98.02%	134.21%	4.78%
2012	18288	$16.49	$11.84	$0.72	$673.47	$15.06	1.14%	1.33%	-69.96%	95.99%	3.70%

Panel B: Ethical Mutual Funds											
Year	Funds	TNA					Return				
		Average	Median	Min	Max	Standard Deviation	Average	Median	Min	Max	Standard Deviation
1984	1	$16.59	$16.74	$15.74	$17.21	$0.46	0.56%*	0.79%	-2.54%	4.15%	1.85%
1985	1	$19.17	$19.27	$18.17	$20.61	$0.75	2.04%*	2.15%	-2.63%	5.58%	2.72%
1986	1	$23.58	$23.56	$20.92	$25.19	$1.16	1.47%*	2.07%	-6.74%	6.44%	3.96%
1987	3	$18.65	$15.25	$11.90	$27.61	$5.87	-0.39%	0.60%	-17.29%	8.11%	5.64%
1988	4	$17.10	$14.94	$13.02	$25.28	$4.48	1.02%*	0.42%	-2.22%	7.07%	2.26%
1989	4	$18.72	$16.43	$14.74	$27.79	$4.66	1.56%*	1.13%	-1.71%	6.06%	1.84%
1990	4	$17.88	$15.87	$10.00	$27.44	$5.02	0.07%	0.01%	-7.81%	7.36%	3.26%
1991	5	$18.83	$17.39	$9.68	$29.22	$5.44	1.60%*	1.48%	-4.22%	11.40%	3.21%
1992	6	$16.80	$16.81	$5.96	$29.86	$7.07	0.75%	1.26%	-2.97%	5.54%	1.87%
1993	8	$17.75	$17.57	$6.69	$31.17	$6.56	0.74%	0.86%	-4.40%	4.09%	1.77%
1994	13	$15.50	$15.92	$4.41	$30.84	$7.00	-0.19%	-0.03%	-6.72%	4.29%	2.45%
1995	15	$16.27	$16.27	$4.47	$32.91	$7.18	2.05%*	1.98%	-2.46%	8.34%	1.73%
1996	15	$17.76	$17.52	$6.20	$33.12	$6.63	1.07%*	1.14%	-5.84%	8.39%	2.84%
1997	19	$17.99	$17.61	$6.84	$35.79	$7.29	1.92%*	2.43%	-6.10%	10.27%	4.14%
1998	29	$21.29	$20.26	$7.56	$40.21	$8.33	1.55%*	2.45%	-20.10%	9.05%	6.21%
1999	42	$22.54	$24.04	$8.98	$41.89	$8.02	0.97%*	0.69%	-9.26%	8.94%	3.31%
2000	51	$20.85	$19.77	$8.34	$43.03	$8.85	-0.45%	-0.49%	-30.47%	13.42%	5.13%
2001	64	$16.11	$13.40	$3.86	$36.09	$8.10	-0.68%	0.00%	-34.54%	30.61%	7.06%
2002	63	$14.68	$12.93	$2.37	$42.90	$8.06	-1.55%*	-0.95%	-19.94%	19.08%	6.06%
2003	59	$15.53	$14.51	$5.62	$41.77	$7.87	1.77%	1.06%	-4.77%	12.45%	3.03%
2004	57	$17.05	$15.90	$7.38	$45.21	$8.51	0.65%	0.88%	-5.44%	5.69%	2.03%
2005	51	$16.94	$15.63	$7.45	$53.24	$8.72	0.43%*	0.10%	-6.42%	6.63%	2.25%
2006	52	$17.88	$15.68	$8.30	$59.02	$9.28	0.98%	0.92%	-6.74%	8.32%	1.88%
2007	57	$19.00	$15.83	$8.86	$64.33	$10.86	0.30%*	0.48%	-8.32%	10.44%	2.56%
2008	66	$15.43	$12.56	$1.25	$58.57	$9.32	-3.53%	-1.63%	-29.06%	11.01%	6.40%
2009	87	$13.45	$11.41	$1.15	$60.93	$8.37	2.39%*	3.22%	-13.07%	19.70%	5.80%
2010	86	$16.27	$14.11	$1.50	$66.82	$9.70	1.18%*	1.68%	-10.21%	12.02%	5.01%
2011	85	$18.25	$15.48	$1.67	$71.96	$11.09	-0.02%	-0.09%	-17.12%	17.52%	4.41%
2012	63	$18.89	$15.85	$1.81	$74.01	$11.57	1.33%*	2.05%	-15.24%	11.69%	3.39%

*Represents higher average return

Data Envelop Analysis (DEA), as proposed by Charnes, Cooper and Rhodes (1978, 1979), focuses in an operational research methodology which allows to measure the relative efficiency of decision making units in the presence of multiple inputs and outputs. DEA ranks the efficiency of said decision making process and it yields a single number which can be easily assigned to a particular unit. In fact, with DEA, one can estimate a time specific score and assign it to a process as a characteristic of said process, which I call efficiency. In terms of investment assets, one can estimate monthly efficiency scores of each mutual fund and then compare over time.

Several studies have followed to analyze the performance of mutual funds using DEA (see: Murthi et al. (1997), McMullen and Strong (1998), Morey and Morey (1999), Choi and Murthi (2001), Basso and Funari (2001, 2003, 2005), Galagedera and Silvapulle (2002), Gregoriou (2003, 2006), Haslem and Scheraga (2003), Chang (2004), Darling et al. (2004), Gregoriou and McCarthy (2005), Gregoriou, Roush, Satchel, & Diz (2005), Gregoriou and Chen (2006), Eling (2006), among others). My study extends their findings by using the efficiency scores to create a Fama-French type risk factor; I use the fund's subjective performance index as a proxy for risk which, assuming that investors value efficiency, should reduce asset pricing errors.

I expect DEA to give a sound estimation of a performance index by incorporating multiple inputs and outputs simultaneously: DEA assumes a production framework on which one uses inputs to produce outputs where inputs are defined as bearers of risk while outputs are bearers of wealth. Under normality of returns, only the mean return and its standard deviation would suffice as measurements for risk and wealth. However, if distributions are non-normal, as it is often the case, then higher moments should be required (Glawischnig and Sommersguter-Reichmann, 2010).

It is expected that different assets will have different statistical properties, such as skewed return distributions with fat tails, which makes relevant the inclusion of, at least, the third moment when characterizing the relationship between risk and return; thus the need to check for normality of returns.

1.4.1. Normality Testing

In order to measure normality, I use the Jarque Bera (JB) test statistic (Jarque and Bera, 1980, 1981, 1987), formally:

$$JB_j = \frac{T}{6}\left[S_j^2 + \frac{K_j^2}{4}\right] \sim \chi^2(k)$$

where:

$$S_j = \frac{E_j(r_t - r_d)^3}{\sigma_j^3}, \text{ the skewness of monthly returns of fund } j \tag{4.1}$$

$$K_j = \frac{E_j(r_t - r_d)^4}{\sigma_j^4} - 3, \text{ the excess kurtosis of monthly returns of fund } j$$

r_t, monthly return

r_d, average returns

σ_j, standard deviation

Normality is rejected when JB_j is larger than 5.99 for the 5% significance level and 9.21 for the 1% significance level. I find that, at the 5% level, 20839 funds are non-normally distributed. This is, about 69.2% of ethical funds and only about 50.4% of traditional funds can be considered normally distributed. These results are summarized in Table II Panel A.

It is expect that the results in Table II Panel A would be biased towards non-normality due to sample interdependence[7] Thus I bootstrap the returns to check how many funds will reject true normality under traditional χ^2 values. I estimates a three year rolling period betas which I used to create normal returns that mimic fund performance. That is, given the fund's specific $\beta_{i,t}$, I estimate normally distributed returns given by $r_{i,t} = \alpha + \beta_i(r_m - r_f) + \varepsilon$ where $r_m \sim N(\mu, \sigma_m^2)$ and $\varepsilon \sim N(0, \sigma_r^2)$.

Table II: Normality Testing

Table II shows JB statistics for the fund universe accounting the sample period from January 1984 to September 2012.

	Rejection Rule for JB Statistic			
	Panel A: Standard χ^2		Panel B: Bootstrapped χ^2	
	5% Significance	1% Significance	5% Significance	1% Significance
Traditional Funds	21563	18865	18388	11616
	69.57%	60.86%	59.32%	37.48%
Ethical Funds	61	52	43	31
	52.14%	44.44%	36.75%	26.50%

Using standard χ^2 values, I find that about 10% of funds reject normality under a 5% confidence level and 6% of funds reject normality under a 1% confidence level, proving the need to estimate sample specific cut-off values. After bootstrapping, I find the sample specific χ^2 values to be 9.83 for the 5% level and 24.83 for the 1% level. Given a 5% confidence level, normality is then rejected for a total of 18431 funds, which accounts for 59.32% of traditional funds and 36.75% of ethical funds.

The results are consistent with prior findings (as early findings as Mandelbrot, 1963; Fama, 1965; Press, 1967; Praetz, 1972; Blattberg and Gonedes, 1974; Simkowitz and Beedles, 1980; Smith, 1981; Ball and Torous, 1983; Kon, 1984; So, 1987; Gray and French, 1990). The results thus suggest that a large number of funds do not follow normality, creating a bias on the description of the risk and return relationship based solely on a mean-variance frontier. This suggests the need to use a DEA model that that incorporates such further moments.

1.4.2. The DEA Model

Given non-normality of returns, I estimate a fund specific relative performance score which allows for ex-post ranking of funds based on Data Envelop Analysis. This index is estimated based on a 3-year monthly-rolling window starting on January 1984; this results in the first efficiency score corresponding to the time window January 1984 – December 1986. The resulting score is then recorded as the fund's efficiency corresponding to December 1986; this becomes the first valid observation.

The literature shows that the input-oriented BCC[8] with radial[9] inputs is the dominating method to

[7] This is expected because funds invest in a finite number of assets. In fact, the pool of ethical assets is even smaller and thus this is expected to be significantly more important for ethical funds.

[8] Banker, Charnes, and Cooper (1984).

estimate fund performance. According to Glawischnig and Sommersguter-Reichmann (2010), the use of the BCC model can be justified because (1) as the CCR[10] model and the output-oriented BCC[11] model are not translation invariant[12] towards outputs, the input-oriented BCC model is often the metric of choice; (2) the assumption of variable returns to scale is justified by the fact that alternative investment funds might operate in regions of increasing or decreasing return to scale due to, for example, minimum investment requirements or fixed cost digression; and (3) the use of the BCC model is advisable whenever ratios are used as inputs or outputs.

DEA estimates a frontier (the production possibility frontier, PPF) to the production possibility set (PPS) that envelops the PPS as tightly as possible. When comparing the DEA frontier with standard portfolio theory (the Markowitz portfolio theory) the DEA frontier is essentially the same but with a different approach: the DEA frontier is the resulting from the convex combination of the best practices[13] followed by the industry given the multiple hyperplanes resulting from the use of multiple inputs and outputs. Based on said frontier, one can estimate a performance index based on the distance between a specific fund and said frontier.

Formally, given $j = 1, \dots, N$ funds where each uses $x_m \ \forall\, m = 1, \dots, M$ inputs to produce $y_r \ \forall\, r = 1, \dots, R$ outputs. Then the performance estimate for the k^{th} fund, P^{BCC}, is given by the solution to the linear programming problem:

$$
\begin{aligned}
P^{BCC} &= \min \theta \quad s.t. \\
\sum_{j=1}^{N} x_{mj}\lambda_j &\leq \theta \cdot x_{mk} \ \ \forall\ m = 1, \dots, \mathrm{M} \\
\sum_{j=1}^{N} y_{rj}\lambda_j &\geq y_{rk} \quad \forall\ r = 1, \dots, \mathrm{R} \\
\sum_{j=1}^{N} \lambda_j &= 1 \ \ with\, \lambda_j \geq 0 \ \ \forall\, j
\end{aligned}
\tag{4.2}
$$

The LP given in 4.2 represents the percentage of efficiency of each particular fund *k*. Equation 4.2 minimizes the equiproportionate (radial) contraction θ of the inputs produced by unit *k*. The performance index, P^{BCC}, satisfies $0 \leq P^{BCC} \leq 1$ where $P^{BCC} = 1$ represents a fund which is 100% efficient. That is, given the input-output combination which characterizes the best practice frontier,

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[9] Given the inputs $(x_1, x_2, \dots, x_n)$, they are consider radial if they increase proportionally given an $\alpha > 0$, such that the inputs increase as $(\alpha x_1, \alpha x_2, \dots, \alpha x_n)$ (Cooper, Seiford, Tone, 2000)

[10] Charnes, Cooper, and Rhodes, 1978.

[11] Banker, Charnes, and Cooper (1984).

[12] Translation invariance is meant by the fact that dealing with alternative investments is likely that some of the outputs, such as average and minimum return, are negative. Translation invariance of the respective DEA model towards outputs therefore becomes an issue because DEA cannot handle negative data.

[13] Best practices, in this context, refer to those funds with the highest level of outputs given the prevailing level of inputs.

$P^{BCC} = 1$ represents the k^{th} fund which is on the actual frontier and thus the fund is fully efficient. Any deviation from the PPF, given by $P^{BCC} < 1$, will result in inefficiencies. Furthermore, the linear programme uses exogenous weights, λ_j, to fit the best linear combination of all funds given an specific input-output combination; $\lambda_j \neq 0$ represents the best practice units that delimit the frontier. That is, the process only uses those inputs and outputs delimiting the frontier and disregards everything else.

1.4.2.1. Inputs and Outputs Description

The specification of the input-output model is given by the risk-return relationship. In this case, all risk measures are considered as inputs while all return measurements will be considered outputs. Following the literature, initial input candidates are given by the fund's standard deviation, the lower partial moments *(LPM)*, and maximum drawdown periods, while the output candidates are the expected returns, the upper partial moments *(UPM)* and the maximum consecutive gain.

$$LPM_{j,m} = \frac{1}{T}\sum_{t=1}^{\tilde{T}}\left(r_{min} - \underline{r}_{t,j}\right)^m \quad \forall \ m = 0, \dots, 4$$

$$UPM_{j,m} = \frac{1}{T}\sum_{t=1}^{\hat{T}}\left(\overline{r}_{t,j} - r_{min}\right)^m \quad \forall \ m = 0, \dots, 4$$

where (4.3)

r_{min}, target rate

$\underline{r}_{t,j}$, monthly return of fund j below target rate

$\tilde{T}$, number of returns of fund j below target rate

$\overline{r}_{t,j}$, monthly return of fund j above target rate

$\hat{T}$, number of returns of fund j above target rate

The partial moments, both upper and lower, are estimated as the m^{th} root of the *LPMs* and *UPMs* described by equation 4.3, in percentages. While the *LPMs* capture the downside or risk of holding a specific investment asset, the *UPMs* will capture the upside or benefit of the investment. I use r_{min} as the mean return to differentiate between the downside and the upside of the investment strategy.

It is worthwhile noting that *LPM0* accounts for the percentage of funds below the target rate and *LPM1* accounts for the percentage of funds above it, and thus using both *LPM0* and *UPM0* will result redundant. [14] Thus only one of them is sufficient. LPM0 is preferred to UPM0 because the risk measurement is regarded as more important[15].

Finally, the maximum drawdown period (*MDP*) is estimated as the maximum number of months that fund *j* has been below historically high net asset value (NAV). And the maximum consecutive gain is the maximum number of months fund *j* has been above the minimum target rate.

---

[14] $LPM0_j = \frac{1}{T}\sum_{t=1}^{\tilde{T}} 1 \ ; LPM0_j = 1 - UPM0_j$

[15] Looking at the correlation between I/O also supports choosing *LPM0* instead of *UPM0.*

Basso and Funari (2003, 2008) further includes an output measurement that takes positive values from 0 … 3 based on the degree of ethical exposure. But this imposes an extra bonus for ethical investment which could bias the results in their favor. Thus such measurement is rather avoided.

Table III: Inputs and Outputs Description for DEA

Summary statistics of the proposed input-output specification used to estimate the DEA performance index under BCC. All inputs and outputs are estimated based on the prior three years. Since the first 36 observations are lost due to estimations, results are the average based on 309 months.

Panel A: Traditional Mutual Funds

	Inputs					Outputs		
	MDP	LPM0	LPM1	LPM2	LPM3	UPM1	UPM2	UPM3
Mean	16	48.720%	1.467%	2.755%	3.714%	1.468%	2.452%	3.132%
Median	14	47.222%	1.207%	2.354%	3.173%	1.367%	2.263%	2.865%
Minimum	1	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
Maximum	36	100.000%	14.378%	22.766%	29.137%	17.397%	88.715%	16.100%
Standard Deviation	13	14.484%	1.020%	1.875%	2.551%	1.073%	1.834%	2.419%

Panel B: Ethical Mutual Funds

	Inputs					Outputs		
	MDP	LPM0	LPM1	LPM2	LPM3	UPM1	UPM2	UPM3
Mean	15	47.291%	1.569%	2.927%	3.922%	1.523%	2.559%	3.260%
Median	11	47.222%	1.610%	3.081%	4.155%	1.503%	2.571%	3.277%
Minimum	1	2.778%	0.005%	0.029%	0.052%	0.001%	0.003%	0.006%
Maximum	36	97.222%	3.589%	6.996%	9.968%	4.422%	7.159%	9.027%
Standard Deviation	12	10.058%	0.750%	1.385%	1.880%	0.746%	1.206%	1.528%

Consistent with prior studies, a production framework that provides higher rewards for taking extra levels of risk is chosen, thus requiring inputs and outputs to be positively correlated. The correlation table (not reported) shows that only the inputs *LPM0-LPM4 and MDP* as well as the outputs *UPM1-UPM4* are positively correlated. Further, the forth moments, *LPM4* and *UPM4,* are disregarded due to the extreme high correlations; *LPM3* and *LPM4* as well as *UPM3* and *UPM4* show a correlation greater than 0.999.[16] Still, using the third moment is enough to apply an extra penalty (bonus) to funds with extremely low (high) returns –high negative or positive skewness.

[16] Just like Glawischnig and Sommersguter-Reichmann (2010), the results show high correlation among *LPM2* and *LPM3* (*UPM2* and *UPM3*), as well as *LPM2* and *LPM4* (*UPM2* and *UPM4*). Despite that high correlation, they are still incorporated into the model to apply an extra penalty/ benefit for higher moments due to non-normality of returns.

All inputs and outputs are estimated on a three year rolling window basis. I impose a restriction that each fund has to have full history in NAV and returns to estimate its corresponding inputs and outputs. Since the first 36 observations are lost due to estimations, future results are the average based on 309 months. Table III summarizes the descriptive statistics of the input-output specifications considered for the production framework used in further tests.

Except for MDP, simple inspection shows that all inputs and outputs are higher for ethical funds. This is statistically significant only for LPM0 – LPM2 at the 10% level[17]. This shows that ethical investment relies more on inputs without producing, on average, higher outputs. This is the first evidence I find that socially responsible investment does not seem to be more efficient than the unconstrained universe.

It is worthwhile mentioning that it is striking that only orthodox funds achieve an average 100% on *LPM0*. That means that, every month, there are funds that have had only below average returns ($LPM0 = 1$) during the prior 36 months. Furthermore, the opposite is also true; there are funds only within traditional investment which only had above average returns during the prior 36 months. Generally speaking, traditional investing seems perhaps more volatile than SRI.

The following subsection provides further analysis of each fund's monthly relative efficiency, as given by its BCC score.

1.4.3. Estimating the Efficiency Scores

Since the number of mutual funds has increase overtime, finding a feasible solution for all funds might be impossible. And thus values of $BCC = 1$ might be misleading. This is corrected by setting the linear program with two passes; each pass has a different starting value and the BCC score is recorded only if the solution is the same regardless of the starting value; i.e. BCC score converges to the same numeric value regardless of its initial seed.

I estimate equation 4.2 based on the inputs and outputs discussed in prior sections. I estimate monthly BCC scores only when a fund has no missing observation during the immediate past three years. This gives a panel with monthly BCC rankings.

In order to differentiate between performances, I rank funds based on their BCC score into quintiles where Q1 is the smallest. Every month I compute a cross-tabulation between the Funds monthly BCC score and whether the fund is cataloged as socially responsible investment or not. Every time I run a cross-tabulation I also perform a chi-square test for difference between groups (not reported). I store the number of funds per category and I estimate a time series average number of funds per category. Table IV reports the results.

As expected, the number of traditional funds far outweighs that of ethical funds. Thus direct comparisons of the percentage number of funds per quintile are irrelevant to conclude difference in efficiency rankings. I, thus, look at the conditional probabilities of each quintile. It seems that traditional investment achieves the highest levels of efficiency. There is an average of 2.42% more

[17] A test of differences in means was estimated but, for simplicity, it is not reported.

traditional funds in the high efficiency quintile, Q5, than there are ethical funds.[18] Though traditional investments have a higher amount of funds in the lowest BCC quintile, Q1, when Q1 and Q2 are taken together, socially responsible investment has 4.27% more funds in those categories than orthodox investments, mainly from an average 5.39% more ethical funds in the low efficiency quintile, Q2.

Table IV: Efficiency Comparison Between Mutual Funds

Table IV reports the Cross-Tabulation of average monthly BCC scores for both ethical and unrestricted mutual funds. I report estimations based on the average number of monthly funds. Chi-square tests were conducted based on monthly cross-tabulations as well as the overall sample; the results are not reported but the P values are estimated as less than 0.001, which rejects the null that the percentage among groups are equal.

		Quintile Distribution of BCC Score					
		LOW				HIGH	Total
		Q1	Q2	Q3	Q4	Q5	
Traditional	Funds	1626	1564	1580	1642	1286	
	%Total	21.03%	20.23%	20.43%	21.23%	16.63%	99.55%
	%Row	21.12%	20.32%	20.52%	21.33%	16.71%	
	%Column	99.57%	99.43%	99.56%	99.58%	99.61%	
Ethical	Funds	7	9	7	7	5	
	%Total	0.09%	0.12%	0.09%	0.09%	0.06%	0.45%
	%Row	20.00%	25.71%	20.00%	20.00%	14.29%	
	%Column	0.43%	0.57%	0.44%	0.42%	0.39%	
Total		21.12%	20.34%	20.52%	21.32%	16.69%	1

Unlike Hamilton et al. (1993); Diltz (1995); Guerard (1997), Sauer (1997); Bauer et al. (2005); Goldreyer et al. (1999), who have shown that ethical investing is not different than traditional investing, I find that SRI is more heavily distributed towards the low efficiency scores. These results suggest that traditional mutual funds are more efficient than socially responsible investments[19]. However, a word of caution is advised given the presence of traditional funds in the very lowest quintile.

In this section I estimate an ex-post realization of efficiency. But it remains unknown if investors take this in consideration when assessing their required rate of return. Though it is expected that highly efficient funds will have higher returns, it is uncertain if the efficiency score can be used as a predictor of future fund performance. Moreover, if efficiency scores can indeed help explain returns, then a risk

[18] The difference is expected to be statistically significant given close inspection of monthly chi-square tests, but the test results are not reported for simplicity.

[19] Earlier estimates looked at the monthly distribution of BCC scores based on a 1-1 match between ethical and traditional investment for a 3000-iteration bootstrap. Results were congruent with these findings: ethical funds appear less efficient than traditional investment assets, consistently after 1990. Results are available upon request.

factor could be created to account for the underlying risk of holding underperforming mutual funds. The following sections look at BCC scores and it plausible use as a proxy for risk.

1.4.4. The Efficiency Score Explanatory Power in Time Series Regressions:

Since ex-post estimations can still have an element of luck, I need to test whether knowing the funds efficiency score can produce a feasible investment strategy. If investors care about fund efficiency, then it will become a valid component of a security pricing. Intuition will suggest that investors will require a higher rate of return for holding under performing funds, implying that BCC scores would have explanatory power in a time series regression. I thus include the estimated BCC score into CAPM and Carhart's four-factor model which should help explain excess returns and reduce average mispricing error.

The literature on asset pricing shows that CAPM should generate R^2 values around 90% while Carhart's Four Factor Model should improve those estimates to around 97%. Earlier attempts to fit such models (not reported) resulted on R^2 values of 50% for CAPM and 55% for Carhart's model. By the same token, the market beta was also well below 1, suggesting a small correlation between mutual fund returns and the market excess returns. Further inspection revealed that a large number of small market beta funds rely on debt instruments[20]. Therefore, I include two bond factors two help explained the returns. These factors are constructed based on Fama and French (1993) suggested bond factors.

First, $TERM_t$ is expected to capture the term structure of bond yields, defined as the 10-year treasury security minus the 1- year treasury security. $DEFAULT_t$ is set to capture the default premium of bond yields, measured as the spread between BAA and AAA corporate bonds.

Finally the efficiency score should enter the regression as a proxy for risk rather than a characteristic. Because $BCC = 1$ represents a fund which is fully efficient, it does not measure the individual riskiness of the fund. But because *0 < BCC < 1*, one can define *BCC' = 1-BCC* which will thus measures total efficiency deviations. In other words, BCC' can be regarded as an efficiency discount measured as the percentage deviation from full efficiency. This specification of BCC', which should account for risk rather than a characteristic, guarantees that no penalty will be given for fully efficiency, but inefficient funds will receive a 100% penalty. The equations are thus:

$$R_{i,t} - r_{f_t} = \hat{\alpha}_t + \hat{\beta}_{1,t}(R_{m_t} - r_{f_t}) + \hat{\beta}_{2,t}TERM_t + \hat{\beta}_{3,t}DEFAULT_t \tag{4.4}$$

$$R_{i,t} - r_{f_t} = \hat{\alpha}_t + \hat{\beta}_{1,t}(R_{m_t} - r_{f_t}) + \hat{\beta}_{2,t}TERM_t + \hat{\beta}_{3,t}DEFAULT_t + \hat{\beta}_{4,t}(BCC'_t) \tag{4.5}$$

$$R_{i,t} - r_{f_t} = \widehat{\hat{\alpha}_t} + \hat{\beta}_{1,t}(R_{m_t} - r_{f_t}) + \hat{\beta}_{2,t}TERM_t + \hat{\beta}_{3,t}DEFAULT_t + \hat{\beta}_{5,t}SMB_t + \hat{\beta}_{6,t}HML + \hat{\beta}_{7,t}MOM_t \tag{4.6}$$

$$R_{i,t} - r_{f_t} = \hat{\alpha}_t + \hat{\beta}_{1,t}(R_{m_t} - r_{f_t}) + \hat{\beta}_{2,t}TERM_t + \hat{\beta}_{3,t}DEFAULT_t + \hat{\beta}_{5,t}SMB_t + \hat{\beta}_{6,t}HML + \hat{\beta}_{7,t}MOM_t + \hat{\beta}_{4,t}(BCC'_t) \tag{4.7}$$

[20] Even after deleting all money market mutual funds, the possibility of large debt holding is not removed. CRSP only reports the latest objective, and thus the fund could have historically had money market instruments. Furthermore, many funds rely in bonds.

Table V: Descriptive Statistics of Parameters

Panel A summarizes statistical information on the proposed repressors. Panel A shows the descriptive statistics and Panel B shows the different correlations between them. The correlation on BCC is the pooled correlation estimation based on the fund specific scores and the time series of the proposed factors.

	Panel A: Descriptive Statistics					Panel B: Correlations						
	Mean	Median	Standard Deviation	Minimum	Maximum	BCC	$R_m - R_f$	TERM	DEFAULT	HML	SMB	Mom
BCC	0.5628	0.6121	0.3068	0	1	1.0000						
$R_m - R_f$	0.43%	1.09%	4.72%	-23.24%	12.46%	0.0993	1.0000					
TERM	1.57%	1.78%	1.15%	-0.41%	3.40%	-0.5513	-0.0038	1.0000				
DEFAULT	1.09%	0.95%	0.49%	0.55%	3.38%	-0.4562	-0.0559	0.2957	1.0000			
HML	0.22%	0.17%	3.17%	-12.60%	13.84%	0.0127	-0.3027	0.0402	-0.0844	1.0000		
SMB	0.27%	-0.03%	3.26%	-16.39%	22.00%	-0.0485	0.2284	0.1255	0.0296	-0.3279	1.0000	
Mom	0.32%	0.59%	5.59%	-34.74%	18.39%	0.1491	-0.1874	-0.0826	-0.1979	-0.1303	0.0358	1

The betas are estimated based on a rolling window of 36 months. This imposes a further reduction of the asset universe, for a total of 72 observations per fund which reduces the number of valid funds. The monthly market premium, $(R_{m_t} - r_{f_t})$; the monthly size factor, SMB_t; the monthly book to market factor, HML; the monthly momentum factors, MOM_t; as well as the monthly risk free rate all come from Kenneth French's website. I also estimate monthly excess returns based on their risk free rate. Table V, Panel A, summarizes the descriptive statistics.

As expected, there are funds which are completely efficient and those which are completely inefficient. The median efficiency score is 61.2% which is about 6% higher than the average score. This suggests a negative skewness of efficiency scores. As for the risk factors, TERM and DEFAULT are rather higher than all others, but also less volatile. All of Carhart's four factors seem small on average, but highly volatile. Surprisingly, SMB has a negative median which suggest that the return of big firms are larger than those of small firms. A positive average momentum factor suggests that prior winners continue to outperform prior losers.

Table V, Panel B, shows the cross-correlations of the proposed factors. Since BCC is fund specific, its correlation with all factors is estimated based on the pooled sample. One can immediately notice the moderate negative correlation between BCC scores and the two bond factors, $\rho_{BCC,TERM} = -0.5513$ and $\rho_{BCC,DEFAULT} = -0.4562$. This suggests that bond yields decrease as BCC scores increase. This could be due to investors requiring higher rates of return for holding inefficient bonds. This in turn should pass onto mutual funds in the same manner. This is more attenuated for long term debt of efficient assets requiring lower compensation than long term debt of the less efficient assets. Moreover, both bond factors are positively correlated as expected.

Table VI, Panel A, shows the time-series monthly average mutual fund beta, as well as the time-series t-stat, for the period from December 1989 to September 2012. Though the small R^2 values remain a problem even after including both bond factors, all regressions are improved. The use of BCC seems to slightly increase the fit of the models, regardless of the original specification. R^2 increases in both cases by about 2 percentage points. Further analysis between regressions shows that all factors are statistically significant, except for the maturity premium, which is only significant under the four factor model. Consistently with prior research, the use of the four factor model improves CAPM results. In one hand the value of R^2 increases from 54.6% to 65.61% and, on the other, the average mispricing error, α, decreases from -0.23% to -0.19%.

After including the efficiency penalty, I find that the beta on BCC' is highly significant even at the 1% level. The net effect of a score increase is lower efficiency deviations and higher returns. By definition, efficient funds are those which achieve more outputs, wealth, given the same level of inputs, risk. According to the model, an average efficiency fund will expect to receive about 72 basis points less than a fully efficient fund (*BCC=1*) under MCAPM, and about 55 basis points less under the four factor model. More importantly, a one standard deviation increase in BCC score will result in an increase of almost 1.14 percentage points under MCAPM and 87 basis points under the modified four factor model.

Moreover, Looking at Jensen's alphas, it is surprisingly how the average mispricing errors decrease when BCC is included to explain mutual fund returns. Under the MCAPM model, alpha decreases from -22.7 to 22.5 basis points, while the difference is statistically significant (*t=12.04*), it is of no economic significance. However, under the modified four factor model, the decrease is of 5.1 basis points which is of both statistical (*t=11.34*) and economic significance.

Table VI: Time Series Regressions with Efficiency Score

Comparison between time-series CAPM, Carhart's Four Factor Model, and subsequent models than includes a fund specific characteristic, BCC Score, which measures its relative efficiency from December 1989 – September 2012. All models include two bond factors, TERM which is the ten year minus the one year return in government securities and DEFAULT which is the AAA minus BAA corporate spread, to account for mutual funds with small correlation with equity markets. I estimate monthly betas based on a three year rolling window and report the average time series betas of said monthly betas. T-statistics are in parenthesis.

Panel A: Average Monthly Betas for Full Sample

$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	$1 - BCC$	R^2
-0.227%	0.58243	0.004	0.190					54.60%
(-4.196)*	(98.096)*	(0.304)	(3.433)*					
-0.225%	0.5665	-0.004	0.271				-0.0164	57.26%
(-3.535) *	(94.788)*	(-0.247)	(4.881)*				(-20.413)*	
-0.188%	0.5813	-0.032	0.160	0.074	0.028	0.005		65.61%
(-4.404)*	(115.212)*	(-2.248)*	(3.625)*	(41.821)*	(4.256)*	(2.176)**		
-0.137%	0.57117	-0.005	0.196	0.071	0.026	0.001	-0.0125	67.54%
(-2.503)**	(113.135)*	(-0.29)	(4.083)*	(37.333)*	(4.013)*	(0.618)	(-21.654)*	

Panel B: Average Monthly Betas before December 1999

$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	$1 - BCC$	R^2
-0.28%	0.549	-0.009	0.291					52.74%
(-3.392)*	(96.793)*	(-0.427)	(2.939)*					
-0.53%	0.53109	-0.004	-0.048				-0.018	56.05%
(-6.044)*	(93.207)*	(-0.187)	(-0.497)				(-18.972)*	
-0.16%	0.55459	-0.043	0.180	0.052	0.044	0.019		65.31%
(-2.115)**	(117.105)*	(-2.798)*	(2.149)**	(26.323)*	(6.223)*	(6.761)*		
-0.46%	0.54211	-0.011	-0.077	0.050	0.041	0.015	-0.014	67.76%
(-6.108)*	(115.574)*	(-0.649)	(-0.908)	(22.339)*	(5.539)*	(5.904)*	(-19.598)*	

Panel C: Average Monthly Betas after January 2000

$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	$1 - BCC$	R^2
-0.18%	0.6087	0.014	0.111					56.07%
(-2.577)*	(66.951)*	(0.724)	(1.83)***					
-0.019%	0.59432	-0.004	0.522				-0.015	58.21%
(-0.218)	(65.345)*	(-0.173)	(9.154)*				(-12.459)*	
-0.21%	0.60229	-0.024	0.144	0.091	0.014	-0.006		65.86%
(-3.61)*	(77.085)*	(-1.067)	(3.314)*	(51.097)*	(1.438)	(-1.625)		
-0.12%	0.59401	0.000	0.410	0.088	0.015	-0.009	-0.011	67.38%
(-1.690)***	(76.556)*	(0.014)	(8.594)*	(42.284)*	(1.457)	(-2.674)*	(-13.27)*	

***** Significant at the 10% 1.65; ** Significant at the 5% level 1.96; * Significant at the 1% level 2.57**

It is worthwhile noting that, as expected given the correlation between BCC score and the bond factors, including the BCC score in the regression has a direct effect on the betas for both bond factors. The Beta for the term structure decreases from 0.0043 to -0.0038 under CAPM, while increasing from -0.032 to -0.005 under the four factor model; the beta for the default premium increases from 0.19 to 0.27 and from 0.160 to 0.196 for both CAPM and Carhart's model respectively. While beta increases are expected due to the correlations previously reported, the decrease under CAPM is quite puzzling. It appears that including a efficiency score to CAPM captures the combined effect of size, book to market, and momentum factors.

Having established the appropriate use of the efficiency score as a factor of mutual fund returns, I check whether the effect is time specific. Table VI, Panel B, shows the time series average monthly betas from December 1989 to December 1999 and Table VI, Panel C, shows the betas for the period from January 2000 to September 20012. T-statistics are also reported in parenthesis.

Overall, the direction of the factors' effects remains mostly unchanged, though the magnitude of the effects has shifted significantly. Only the beta for momentum seems to have a different sign for the period after 2000. A possible explanation could be that mutual funds are following a reversal after the dot com bubble. Moreover, R^2 values remain mostly unchanged regardless of the period of study.

All and all, prior results continue to hold true. Regardless of the time period, BCC score has both statistical, as well as economical, significance; though the efficiency beta is quite lower after January 2000. Comparing the same models across time, the effect of efficiency is 3 basis points lower after 2000 regardless of the model used.

It seems that the explanatory power of the efficiency scores is time subjective. During the pre-2000's era, using BCC in the regression does not reduce average mispricing errors. Under MCAPM, the alpha increase from -28 basis points to -53 basis points, while under the four factor model the alpha increases from -16 to -46 basis points. On the other hand, during the 2000's, the explanatory power of the models is heavily improved by including an efficiency score. The value of the alphas decreases from 18 basis points to 1 basis point (statistically insignificant) under the MCAPM specification, and from 21 to 12 basis points under the four factor model.

1.4.5. The Cross-Section of Mutual Funds Returns: Is BCC Significant at Pricing Future Returns?

An important aspect of asset pricing is whether a specific model can accurately predict future returns. In such case, the model underlies a feasible investment strategy. That is, conditional on efficiency, can the model predict mutual fund's future excess returns. In lieu of this question, I estimate the Fama-MacBeth second pass regressions at t+1 based on the factor loadings from the prior 3 years.

Given an asset pricing model $R_{i,t} = r_{f_t} + \hat{\beta}_t \mathbf{X_t}$ where $\mathbf{X_t}$ is a vector of risk factors, if the model has explanatory power, the returns at t+1 will be given by $R_{i,t+1} = r_{f_{t+1}} + \delta_{t+1}\widehat{\boldsymbol{\beta}}_{\boldsymbol{t}}$, where δ_{t+1} is the risk premium at $t+1$. Also, the risk premium δ_{t+1} should be equal to $\mathbf{X_{t+1}}$. I thus estimate the empirical models:

$$R_{i,t+1} - r_{f_{t+1}} = \hat{\alpha}_{t+1} + \widehat{\lambda}_{1,t+1}\hat{\beta}_{1,t} + \widehat{\lambda}_{2,t+1}\hat{\beta}_{2,t} + \widehat{\lambda}_{3,t+1}\hat{\beta}_{3,t} \tag{4.8}$$

$$R_{i,t+1} - r_{f_{t+1}} = \hat{\alpha}_{t+1} + \widehat{\lambda}_{1,t+1}\hat{\beta}_{1,t} + \widehat{\lambda}_{2,t+1}\hat{\beta}_{2,t} + \widehat{\lambda}_{3,t+1}\hat{\beta}_{3,t} + \widehat{\lambda}_{4,t+1}\hat{\beta}_{4,t} \tag{4.9}$$

$$R_{i,t+1} - r_{f_{t+1}} = \hat{\alpha}_{t+1} + \hat{\lambda}_{1,t+1}\hat{\beta}_{1,t} + \hat{\lambda}_{2,t+1}\hat{\beta}_{2,t} + \hat{\lambda}_{3,t+1}\hat{\beta}_{3,t} + \hat{\lambda}_{5,t+1}\hat{\beta}_{5,t} + \hat{\lambda}_{6,t+1}\hat{\beta}_{6,t} + \hat{\lambda}_{7,t+1}\hat{\beta}_{7,t} \quad (4.10)$$

$$R_{i,t+1} - r_{f_{t+1}} = \hat{\alpha}_{t+1} + \hat{\lambda}_{1,t+1}\hat{\beta}_{1,t} + \hat{\lambda}_{2,t+1}\hat{\beta}_{2,t} + \hat{\lambda}_{3,t+1}\hat{\beta}_{3,t} + \hat{\lambda}_{5,t+1}\hat{\beta}_{5,t} + \hat{\lambda}_{6,t+1}\hat{\beta}_{6,t} + \hat{\lambda}_{7,t+1}\hat{\beta}_{7,t} + \hat{\lambda}_{4,t+1}\hat{\beta}_{4,t} \quad (4.11)$$

Table VII shows the time-series averages of the slopes of the month my month Fama-MacBeth type regression. Consistent with prior research, the average mispricing of future returns decrease under the four factor model. But the use of an efficiency factor does not seem to improve results. The problem of low R^2 values is persistent throughout all cross-section regressions.

Across models, it can be seen that both bond factors have no predictive power for excess returns. This is somehow expected for the maturity premium, since its beta is statistically insignificant. Yet the insignificance of the default premium is surprising. Also, it seems that the only useful factors are the market, the size factor, and the efficiency premium. The estimation of the first two are close to the average actual factors, average market risk premium is 0.43% and average $\hat{\lambda}_1 = 0.48\%$ for the four factor model with BCC and the average size factor is 0.22% compared to $\hat{\lambda}_5 = 0.26\%$ under the same model. On the other hand, $\hat{\lambda}_4$ is not even close to the average value of *BCC';* average *BCC'=3.8* and average $\hat{\lambda}_4 = 0.0184$, significant at the 5% level, under the MCAPM specification and average $\hat{\lambda}_4 = 0.0028$, statistically insignificant, under the modified Carhart's specification.

Further analysis of different time periods provide interesting results. While alphas are small and insignificant for the pre-2000's period, they are large and highly significant after January 2000. This suggests difficulty pricing future returns under the rapid expansionary period following the dot com bubble and subsequent 2007 financial crisis. Positive alphas after 2000 suggest that mutual funds systematically outperformed the market.

More surprisingly, the market does not seem to have any predictive power during said period regardless of the model specification. Quite conversely, size and book to market are the only significant predictors during this period. Perhaps, after the dot com bubble, investors stop basing their decisions based on historical market performance and started paying closer attention to size: the too big to fail argument.

Moreover, it seems that the net effect of the book to market ratio, though insignificant for the full sample, is significant for the individual samples. Given that their effects are opposite depending on the period of time, $\hat{\lambda}_6$ is negative before 2000 and positive afterwards, the overall effect is nullified.

1.4.6. Socially Responsible Investing Future Performance

In prior sections I discuss that ethical funds do not seem to be as efficient as traditional unconstrained investing. However, it remains unknown if investors use this information to value ethical funds future returns. If they do, it is expected that the returns of ethical funds will be lower, on average, than those of orthodox mutual funds. That is, a relative underperformance of ethical investing.

Table VII: Cross-sectional Regressions with Efficiency Score

Comparison between the cross-section performance at time $t+1$ of CAPM, Carhart Four Factor Model, and the funds relative efficiency score given by the individual factor loadings estimated at time t given three years of prior information. All models include the factor loadings of two bond factors, TERM which is the ten year minus the one year return in government securities and DEFAULT which is the AAA minus BAA corporate spread, to account for mutual funds with small correlation with equity markets. Table VII reports the time-series averages of the slopes of the month my month Fama-MacBeth cross-section regression. Finally, the regression includes a dummy variable to capture the effect of Socially Responsible Investing in future returns.

Panel A: Average Monthly Cross-Section Slopes for Full Sample

$\hat{\alpha}_{t+1}$	$\hat{\beta}_{1,t}$	$\hat{\beta}_{2,t}$	$\hat{\beta}_{3,t}$	$\hat{\beta}_{5,t}$	$\hat{\beta}_{6,t}$	$\hat{\beta}_{7,t}$	$\hat{\beta}_{4,t}$	Ethical	R^2
0.097%	0.0052	0.0002	-0.0001					-0.0010	44.710%
(1.619)	(1.894)***	(0.386)	(-0.385)					(-2.032)**	
0.104%	0.0048	-0.0001	0.0001				0.0184	-0.0008	46.060%
(1.817)***	(1.69)***	(-0.161)	(0.397)				(1.801)***	(-1.729)***	
0.068%	0.0049	0.0002	-0.0001	0.0028	0.0015	-0.0001		-0.0006	56.930%
(1.292)	(1.767)***	(0.414)	(-0.493)	(1.542)	(0.85)	(-0.03)		(-1.596)	
0.083%	0.0046	-0.0001	0.0000	0.0027	0.0010	-0.0003	0.0028	-0.0006	57.140%
(1.616)	(1.657)***	(-0.275)	(-0.285)	(1.438)	(0.549)	(-0.115)	(0.34)	(-1.558)	

Panel B: Average Monthly Cross-Section Slopes before December 1999

$\hat{\alpha}_{t+1}$	$\hat{\beta}_{1,t}$	$\hat{\beta}_{2,t}$	$\hat{\beta}_{3,t}$	$\hat{\beta}_{5,t}$	$\hat{\beta}_{6,t}$	$\hat{\beta}_{7,t}$	$\hat{\beta}_{4,t}$	Ethical	R^2
-0.026%	0.0092	0.0005	0.0001					-0.0008	40.230%
(-0.284)	(2.447)**	(0.711)	(0.631)					(-1.178	
0.005%	0.0091	0.0001	0.0001				0.0117	-0.0007	41.020%
(0.056)	(2.407)**	(0.164)	(0.903)				(0.919)	(-1.027)	
0.000%	0.0090	0.0005	0.0000	0.0006	-0.0045	0.0023		-0.0012	51.110%
(-0.002)	(2.481)**	(0.869)	(0.021)	(0.275)	(-1.962)**	(0.83)		(-1.861)***	
0.033%	0.0087	0.0001	0.0000	0.0002	-0.0054	0.0022	0.0073	-0.0012	51.630%
(0.458)	(2.377)**	(0.152)	(-0.015)	(0.102)	(-2.336)**	(0.822)	(0.62)	(-1.921)***	

Panel C: Average Monthly Cross-Section Slopes after January 2000

$\hat{\alpha}_{t+1}$	$\hat{\beta}_{1,t}$	$\hat{\beta}_{2,t}$	$\hat{\beta}_{3,t}$	$\hat{\beta}_{5,t}$	$\hat{\beta}_{6,t}$	$\hat{\beta}_{7,t}$	$\hat{\beta}_{4,t}$	Ethical	R^2
0.206%	0.0017	0.0000	-0.0002					-0.0012	48.630%
(2.666)*	(0.435)	(-0.018)	(-0.69)					(-1.656)***	
0.191%	0.0010	-0.0002	0.0000				-0.0448	-0.0009	50.480%
(2.578)*	(0.234)	(-0.349)	(0.006)				(-2.93)*	(-1.408)	
0.128%	0.0013	-0.0001	-0.0001	0.0048	0.0068	-0.0021		-0.0001	62.040%
(1.695)***	(0.311)	(-0.202)	(-0.546)	(1.69)***	(2.621)*	(-0.508)		(-0.231)	
0.127%	0.0011	-0.0003	-0.0001	0.0048	0.0067	-0.0025	-0.0116	0.0000	61.970%
(1.747)***	(0.255)	(-0.503)	(-0.313)	(1.673)***	(2.476)**	(-0.585)	(-1.019)	(-0.099)	

*** Significant at the 10% 1.65; ** Significant at the 5% level 1.96; * Significant at the 1% level 2.57

To capture the effect of Socially Responsible Investing in future returns, I include a dummy variable to the estimations proposed in equations 8-11. The dummy takes the value of 1 if a fund can be regarded as ethical and 0 otherwise. Thought the number of ethical observation is small, the dummy is statistically significant for the most part. Including the ethical dummy can help explain the nature of any decrease (increase) of risk-adjusted excess returns compared to traditional investments. On one hand, if ethical funds loose returns because off a performance decrease, then the slope on the ethical dummy should be statistically insignificant but the slope for the efficiency score should not. On the other hand, if ethical funds have systematically lower returns because of their ethical status alone, then the BCC factor will not capture any of the dummy explanatory power; that is, both slopes will be statistically significant. I find supporting evidence of the latter.

Under MCAPM, ethical investment receives, on average, 10 basis points less than traditional mutual funds. This shows that investors who hold ethical mutual funds receive lower average expected returns even without considering their lower efficiency ranking. Including BCC to the model decreases the net effect to minus 8 basis points which is still significant; even more so, the difference is not statistically significant. This shows that ethical fund will not only receive lower returns for their lower efficiency scores, but also because they are, in fact, ethical funds. In other words, the fact that they trade in a constrained universe signals investors to expect lower average returns.

These results are somewhat consistent with the use of Carhart's model. Though ethical funds receive the same discount regardless of the existence of an efficiency proxy, the efficiency proxy is not statistically significant. In other words, when Carhart's model is employed, there is no extra penalty for being inefficient and ethical; the whole penalty comes from being ethical.

Deeper analysis of the individual sub periods shows that the effect is somehow persistent through time. According to the MCAPM specification, average excess returns for ethical investment are 8 basis points lower for the pre-2000's era (not statistically significant), and its effect attenuates to an average of 12 basis points lower returns after the year 2000. According to the four factor model, however, the returns of ethical funds are only lower, for about 12 basis points, before the year 2000. When analyzing both models, one can see that the significance of ethical investment is not consistent through time and the model employed.

Consistently with the whole sample, the efficiency loading is never statistically significant regardless of the period of time used. Which suggest that any impact of socially responsible investment in mutual fund returns might be a timing feature.

So far, I have shown that investors seem to keep efficiency in mind when setting their implicit required rates of return. As seen by the decrease of average mispricing errors in time series regressions. However, I do not find conclusive evidence that such feature can be used to predict future mutual fund performance. Perhaps developing a efficiency risk measurement can provide light to this issue. In the following section I discuss the creation of a BCC efficiency factor which will capture the underlying risk of holding underperforming securities.

1.4.7. Robustness Check: Creating a BCC Factor

Following Fama and French (1992-1993) and Carhart (1997), I create a BCC risk factor based on the specification of *BCC'* from the prior section. At the end of each month, I sort mutual funds based on current BCC score from the highest efficiency deviation to the lowest. I then group mutual funds into deciles, and estimate the average BCC score of the decile; these are ten portfolios created based on efficiency. The efficiency factor is defined as far deviation from the efficiency frontier minus close deviations from the efficiency frontier: $FMC = BCC'^{+} - BCC'_{-}$. Since BCC' is always positive, this definition guarantees positive risk premium estimates. It is expected that while the BCC score is a fund specific characteristic, FMC will capture the risk on the spread between the highest performing funds and the lowest performing funds. As the spread increases, so will risk.

Table VIII reports the explanatory and forecasting power of the efficiency factor. Panel A shows the average slopes of time series regressions of mutual fund's excess returns on a market premium, two bond factors, Fama and French's size and book to market factors, Carhart's momentum factor, and an efficiency factor. The betas are estimated at the end of each month based on the mutual fund past three year excess returns. Further, Panel B reports the risk premia estimate of the cross-sectional regression of future stock returns on the fund-specific factor loadings.

Rapid inspection of Panel A shows that the use of an efficiency factor does not really increase the explanatory power of the regression as compared to the characteristics regression. All R-squared values continue to be as low as before, and no significant improvement can be seen.

As expected given the correlation between efficiency and the bond factors, using FMC has a stronger impact on their factor loadings than any other factors. In fact, the market factor does not even change when FMC is incorporated. More importantly, however, is the effect on the overall specification rather than individual factors.

Surprisingly, the power of the efficiency factor to reduce average mispricing error is reduced under the risk factor specification. While using the efficiency factor by itself reduced the overpricing of mutual funds, including it as a risk factor increases the mispricing error. Under CAPM, FMC suggest an increase in overpricing of 25 basis points while the four factor model suggests an overpricing of 30 basis points[21].

Regarding the factor loading of FMC, it is consistent with the paradigm of higher risk being compensated with higher returns. Under the MCAPM, when efficiency deviation are low, $FMC_{\_} = 0.1593$, mutual fund returns will be compensated 9 basis points, but in times when funds are highly segregated on the basis of efficiency, $FMC_{\_} = 0.9735$, returns will increase by 46 basis points. By the same token, under the four factor model, returns under the lowest efficiency risk will be compensated with 11 basis points and it will increase by 59 basis points when efficiency risk increases to its maximum. All estimations are statistically significant even at the 1% level.

With the factor loading of FMC, I estimate the risk premium based on the cross-section of future returns. The results are consistent with prior findings. R-squared values are highly similar to those from the characteristics regression. Under MCAPM + FMC R^2 increases from 46.06% to 48.02% while under the modified four factor model + FMC R^2 increases from 57.14% to 58.24%. Also, the risk premia from all factors, except off course FMC which is statistically indifferent from zero, continue to be the same.

[21] Different attempts were made to reduce mispricing by changing the specification of the FMC factor, but the higher mispricing error is persistent. Neither increasing nor decreasing the spread between high and low efficiency rankings can improve results.

Table VIII: Feasibility of an Efficiency Factor

Comparison between CAPM, Carhart's Four Factor Model, and an efficiency factor from December 1989 – September 2012. The efficiency factor is defined as far deviation from the efficiency frontier minus close deviations from the efficiency frontier: $FMC = BCC'^{+} - BCC'_{-}$ where $BCC'^{+}$is the portfolio of the top 10% deviations from efficiency and BCC'_{-} represents the lowest 10% portfolio of deviations from efficiency. All models include two bond factors, TERM which is the ten year minus the one year return in government securities and DEFAULT which is the AAA minus BAA corporate spread, to account for mutual funds with small correlation with equity markets. I estimate monthly betas based on a three year rolling window and report the average time series betas of said monthly betas. T-statistics are in parenthesis.

Panel A: Descriptive Statistics of FMC

Min	Max	Mean	Median	Standard Deviation
0.1593	0.9735	0.4844	0.4737	0.1234

Panel B: Average Monthly Time Series Slopes Excess Returns on Risk Factors

$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	FMC	R^2
-0.227%	0.5824	0.0043	0.1900					54.600%
(-4.196)*	(98.096)*	(0.304)	(3.433)*					
-0.480%	0.5798	-0.0138	0.1742				0.0057	56.580%
(-6.175)*	(99.611)*	(-0.868)	(2.934)*				(5.85)*	
-0.188%	0.5813	-0.0325	0.1599	0.0740	0.0276	0.0052		65.610%
(-4.044)*	(115.212)*	(-2.248)**	(3.625)*	(41.821)*	(4.256)*	(2.176)**		
-0.490%	0.5796	-0.0205	0.0986	0.0772	0.0318	0.0043	0.0072	67.390%
(-7.588)*	(118.743)*	(-1.276)	(2.178)**	(41.127)*	(4.993)*	(1.76)***	(7.862)*	

Panel C: Average Monthly Cross-Section Slopes of Excess Returns at $\boldsymbol{t+1}$

$\hat{\alpha}_{t+1}$	$\hat{\beta}_{1,t}$	$\hat{\beta}_{2,t}$	$\hat{\beta}_{3,t}$	$\hat{\beta}_{5,t}$	$\hat{\beta}_{6,t}$	$\hat{\beta}_{7,t}$	$\hat{\beta}_{4,t}$	Ethical	R^2
0.097%	0.0052	0.0002	-0.0001					-0.0010	44.710%
(1.619)	(1.894)***	(0.386)	(-0.385)					(-2.032)**	
0.100%	0.0050	0.0003	0.0001				-0.0015	-0.0011	48.020%
(1.677)***	(1.792)***	(0.548)	(0.427)				(-0.168)	(-2.482)**	
0.068%	0.0049	0.0002	-0.0001	0.0028	0.0015	-0.0001		-0.0006	56.930%
(1.292)	(1.767)***	(0.414)	(-0.493)	(1.542)	(0.85)	(-0.03)		(-1.596)	
0.063%	0.0048	0.0002	0.0001	0.0028	0.0013	-0.0004	0.0028	-0.0006	58.240%
(1.21)	(1.76)***	(0.397)	(0.691)	(1.522)	(0.738)	(-0.153)	(0.417)	(-1.626)	

*** **Significant at the 10% 1.65;** ** **Significant at the 5% level 1.96;** * **Significant at the 1% level 2.57**

Moreover, the use of this specification of efficiency risk factor does not seem to reduce mispricing errors of future stock returns. The estimation under FMC of the MCAPM model's alpha is only 0.4 basis points lower than the characteristics estimation while the alpha under the four factor FMC model is 2 basis points lower than under the characteristics model. The latter is insignificantly different than the alpha of the modified four factor model with no efficiency factor.

Still, these results are taken as evidence that efficiency should be incorporated into asset pricing models. Though I fail to produce a risk factor that explains excess returns, I find an efficiency measurement that works as a characteristic which helps decrease average mispricing errors present in other models. As for the performance of socially responsible investments, the results consistently show that ethical investing receives lower average returns. This decrease in returns comes from two parts: a loss in efficiency and also from being cataloged as ethical funds. In the following section I further evaluate the underperformance of ethical funds.

1.5. Estimating Mutual Funds Efficiency: A Coskewness Approach

Markowitz modern portfolio theory (1952) suggests that the intercept of a regression between excess returns and the market risk factors should be zero, which is the basic principle behind Jensen's alphas as a measurement of performance. Portfolios which outperform the market will have a positive alpha, and those which underperform the market will have a negative alpha. In other words, performance is measured by the distance between the asset's return and a (market) portfolio's mean-variance frontier.

Asset performance has typically been measured on the bases of Jensen's alphas. In this regard, ranking assets in the bases of alphas can show their difference in performance. Alphas closer to zero imply good performance, while deviations from zero, positive and negative, represent under and over pricing respectively. However, this requires the asset pricing model to be well specified. Recent asset pricing studies demonstrate that systematic skewness of return is a necessary factor in explaining excess returns (see Klemkosky, 1973; Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Moreno and Rodriguez, 2009). I expect that using the latter factor will significantly increase explanatory power of the model, thereby making asset comparison unbiased.

Intuition suggest that if assets' excess returns are non-normal, that is fatter tails, the risk-returns relationship will be undermined or strengthened, depending on the side of the tail, compared to the traditional explanation given by the mean-variance frontier. In other words, holding average return and variance constant, a positive skewed asset should be regarded as riskier than a negative skewed asset. That is because the downside risk is higher for positively skewed assets, while the upside reward is also higher for negatively skewed assets.

In this regard, Kraus and Litzenberger (1976) extended the classical asset pricing model to account for the effect of systematic skewness. The three-moment conditional CAPM takes the form:

$$R_i - R_f = \lambda_1 \beta_i + \lambda_2 \gamma_i \tag{5.1}$$

where

R_i is one plus the expected return of a risky asset

R_f is defined as one plus the return of a risk-free asset

β_i is the systematic risk

γ_i denotes the systematic skewness

λ_i denotes the risk premium, respectively

Then, from an empirical standpoint, Harvey and Siddique (2000) developed a standardized unconditional coskewness measurement as:

$$S_i = \frac{E\left(\varepsilon_{i,t+1}\varepsilon_{M,t+1}^2\right)}{\sqrt{E\left(\varepsilon_{i,t+1}^2\right)}E\left(\varepsilon_{M,t+1}^2\right)} \tag{5.2}$$

where $\varepsilon_{i,t+1} = r_{i,t+1} - \alpha_i - \beta\left(r_{m,t+1}\right)$; that is, the residuals from the regression of the excess return on the contemporaneous market excess return. $\varepsilon_{M,t+1}$ then represent the residuals from the regression of the excess returns over their mean. Negative measures mean that the security is adding negative skewness. The authors explain that according to the utility assumptions, a stock with negative coskewness should have a higher expected return which implies a negative premium.

Since the unconditional skewness by itself cannot be cataloged as a risk factor, prior literature shows that a Fama and French like transformation should be employed. That is, sorting the assets based on the proposed measurement and creating three portfolios: the top 30% (S_i^+), the middle 40% $\left(S_i^0\right)$, and the bottom 30% (S_i^-); the risk premia factor will then be defined as $CSK = S_i^- - S_i^+$. By construction, the coskewness factor is negatively defined so that increases in coskewness exposure will increase returns.

Following the literature, I compared the overall effect of adding a coskewness factor to prior asset pricing model, namely CAPM, Fama and French three factor model, and Carhart's four factor model. The models are thus,

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^m\left[R_{M,t} - R_{f,t}\right] + e_{i,t} \tag{5.3}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^m\left[R_{M,t} - R_{f,t}\right] + \beta_i^{smb}SMB_{i,t} + \beta_i^{hml}HML_{i,t} + e_{i,t} \tag{5.4}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^m\left[R_{M,t} - R_{f,t}\right] + \beta_i^{smb}SMB_{i,t} + \beta_i^{hml}HML_{i,t} + \beta_i^{wml}WML + e_{i,t} \tag{5.5}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^m\left[R_{M,t} - R_{f,t}\right] + \beta_i^{CSK}CSK_{i,t} + e_{i,t} \tag{5.6}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^m\left[R_{M,t} - R_{f,t}\right] + \beta_i^{smb}SMB_{i,t} + \beta_i^{hml}HML_{i,t}\beta_i^{CSK}CSK_{i,t} + e_{i,t} \tag{5.7}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^m\left[R_{M,t} - R_{f,t}\right] + \beta_i^{smb}SMB_{i,t} + \beta_i^{hml}HML_{i,t} + \beta_i^{wml}WML + \beta_i^{CSK}CSK_{i,t}e_{i,t} \tag{5.8}$$

For comparison purposes, I rank mutual funds based on size and match traditional investing with ethical investment. Ethical funds have an average size of 69.8 million dollars while unconstrained funds have an average size of 178.6 million. This shows that ethical investment is roughly one third of traditional funds based on average total net assets. I rank funds into 3 portfolios where the small portfolio is match to ethical funds. In this way, I can directly compare the size-adjusted performance of ethical investment.

Table X summarizes the results. As expected from prior research, including more factors increases the explanatory power of the regression. But the R-squares continue to be lower than previously reported, as in the prior section. Results suggest that, except for the estimation under CAPM, the models fit large size portfolios better than the small ones. Remarkably, the models seem to always explain ethical funds better than any of the traditional size-sorted portfolios. A feasible explanation can arise due to the fact that ethical investment relies heavily on stocks rather than debt, as the latter has to go through further scrutiny to prove its social responsibility.

Table IX: Coskewness of Mutual Funds

Performance comparison between Social Responsible Investment and orthodox funds based on CAPM, Fama and French's Three Factor Model, Carhart's Four Factor Model, their interacting with an unconditional skewness factor from December 1989 – September 2012. Table IX also reports the intercepts for three size adjustments of ethical funds, on which the small portfolio allows for a direct comparison. The coskewness risk factor is created by subtracting the lowest 30% of portfolios ranked on unconditional skewness minus the highest 30%.

Panel A: CAPM									
$\overline{TNA}$	$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	CSK	R^2
Small	-0.340%	0.5574	-0.0659	0.1178					50.63%
	(-4.26)*	(50.503)*	(-3.616)*	(1.367)					
Medium	-0.200%	0.5154	-0.0172	0.0897					49.94%
	(-3.486)*	(65.599)*	(-1.069)	(1.474)					
Large	-0.220%	0.6066	0.0126	0.2111					56.38%
	(-3.986)*	(116.939)*	(0.891)	(3.843)*					
Ethical	-0.100%	0.6849	-0.0973	0.0573					79.65%
	(-1.951)***	(110.824)*	(-4.196)*	(0.791)					

Panel B: CAPM + CSK									
$\overline{TNA}$	$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	CSK	R^2
Small	0.110%	0.5530	-0.0765	-0.1658				0.0029	52.70%
	(0.94)	(51.656)*	(-3.354)*	(-1.679)***				(3.02)*	
Medium	0.060%	0.5108	0.0256	-0.0638				0.0041	52.04%
	(0.774)	(67.581)*	(1.397)	(-0.885)				(4.32)*	
Large	0.070%	0.6015	0.0434	0.1436				0.0055	58.31%
	(0.909)	(124.378)*	(2.62)*	(2.354)*				(5.81)*	
Ethical	0.060%	0.6809	-0.0630	0.2508				0.0066	80.36%
	(0.972)	(115.058)*	(-2.515)**	(2.923)*				(7.37)*	

Panel C: Fama and French									
$\overline{TNA}$	$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	CSK	R^2
Small	-0.110%	0.5536	-0.1101	-0.0847	0.0886	0.0200			58.96%
	(-1.586)	(51.799)*	(-6.225)*	(-1.146)	(23.974)*	(3.41)*			
Medium	-0.200%	0.5219	-0.0507	0.1183	0.0629	0.0420			59.04%
	(-3.86)*	(74.459)*	(-3.152)*	(2.298)**	(23.87)*	(7.35)*			
Large	-0.210%	0.6124	-0.0294	0.2241	0.0783	0.0367			65.30%
	(-4.131)*	(134.028)*	(-2.159)**	(4.766)*	(43.282)*	(6.27)*			
Ethical	-0.140%	0.7066	0.0016	0.0243	-0.0455	0.0121			83.73%
	(-2.908)*	(108.74)*	(0.112)	(0.374)	(-14.59)*	(2.58)*			

Table IX –Continued

Panel D: Fama and French + CSK									
$\overline{TNA}$	$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	CSK	R^2
Small	0.410%	0.5519	-0.1333	-0.3770	0.0864	0.0236		0.0035	60.65%
	(3.621)*	(52.9)*	(-5.983)*	(-4.221)*	(23.069)*	(4.061)*		(4.153)*	
Medium	0.080%	0.5196	-0.0260	-0.0460	0.0596	0.0439		0.0038	60.76%
	(0.984)	(77.658)*	(-1.361)	(-0.708)	(22.437)*	(7.951)*		(4.525)*	
Large	0.070%	0.6092	-0.0132	0.1517	0.0748	0.0383		0.0054	66.87%
	(1.002)	(145.163)*	(-0.789)	(2.734)*	(39.403)*	(6.75)*		(6.355)*	
Ethical	0.000%	0.7010	0.0154	0.1534	-0.0484	0.0088		0.0052	84.26%
	(0.016)	(110.945)*	(0.958)	(2.17)**	(-16.168)*	(1.904)**		(6.265)*	

Panel E: Carhart									
$\overline{TNA}$	$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	CSK	R^2
Small	-0.180%	0.5465	-0.1096	-0.0330	0.0873	0.0171	0.0183		61.33%
	(-2.99)*	(51.374)*	(-6.131)*	(-0.5)	(20.932)*	(2.759)*	(5.93)*		
Medium	-0.180%	0.5158	-0.0475	0.0849	0.0607	0.0335	0.0033		61.30%
	(-3.73)*	(75.595)*	(-2.88)*	(1.774)***	(23.252)*	(5.195)*	(1.365)		
Large	-0.180%	0.6063	-0.0253	0.1804	0.0770	0.0286	0.0049		67.36%
	(-3.83)*	(139.519)*	(-1.812)**	(4.119)*	(44.826)*	(4.315)*	(2.04)**		
Ethical	-0.250%	0.6967	0.0018	0.1134	-0.0304	0.0115	0.0007		85.19%
	(-5.63)*	(114.462)*	(0.12)	(1.859)**	(-9.399)*	(2.28)**	(0.148)		

Panel E: Carhart + CSK									
$\overline{TNA}$	$\hat{\alpha}$	$R_m - R_f$	$TERM$	$Default$	SMB	HML	MOM	CSK	R^2
Small	0.300%	0.5449	-0.1314	-0.3321	0.0857	0.0209	0.0192	0.0025	63.13%
	(2.897)*	(52.254)*	(-5.829)*	(-4.105)*	(20.386)*	(3.426)*	(6.276)*	(2.969)*	
Medium	0.050%	0.5139	-0.0230	-0.0836	0.0578	0.0354	0.0054	0.0027	63.05%
	(0.751)	(77.882)*	(-1.178)	(-1.394)	(21.647)*	(5.715)*	(2.207)**	(3.51)*	
Large	0.060%	0.6036	-0.0089	0.1014	0.0737	0.0303	0.0065	0.0043	68.93%
	(0.876)	(147.268)*	(-0.52)	(2.019)**	(39.983)*	(4.754)*	(2.738)*	(5.706)*	
Ethical	-0.180%	0.6918	0.0235	0.2107	-0.0334	0.0090	0.0017	0.0033	85.68%
	(-2.743)*	(116.077)*	(1.372)	(3.188)*	(-10.547)*	(1.881)**	(0.372)	(4.412)*	

*** **Significant at the 10% 1.65;** ** **Significant at the 5% level 1.96;** * **Significant at the 1% level 2.57**

Across models, I find evidence of a positive coskewness effect, consistent with the definition of the factor. Overall, the impact of the third moment seems to decrease when other factors are taken into consideration, which is expected given a mild correlation between the coskewness factor and all other factors[22]. For ethical funds, an increase in coskewness risk will increase returns by 66 basis points under

[22] For simplicity, the correlations are not reported.

CAPM, but the same increase will only increase returns by 33 basis points under Carhart's four factor model.

Regarding performance, negative alphas will suggest overvaluation (underperformance) and positive alphas will suggest undervaluation (over performance). In financial terms, negative (positive) alphas suggest that the stock received a lower (higher) return for its level of risk. Looking at the results, adding a coskewness measurement changes stock valuation from under to over pricing. That is, when coskewness is used as a risk factor, assets seem to be mainly underpriced instead of overpriced. If coskewness is indeed a risk factor, this shows that investors are systematically outperforming the market, as the realized risk-adjusted returns are larger than expected.

Rather than looking at the effect of the coskewness measurement, I focus on looking at the relative performance of socially responsible funds. At first impression, regardless of the asset pricing specification, ethical funds seem to have the lowest level of average mispricing error. That is, the difference between investors required rate of return and expected theoretical return seem to be lower for ethical funds, and not different from zero under CAPM and Fama and French with the coskewness measure. In this regard, this shows ethical funds to be accurately priced.

From an investment standpoint, however, undervaluation is preferred to accurately valuated assets. In this sense, it is better to buy an undervalued asset than an accurately priced one. Looking at the alphas in Table IX, across panels, it can be seen that traditional investment always outperforms ethical investment, except under CAPM. Though the results do not provide a model consistent performance ranking, the lowest size portfolio of traditional investments seems to usually outperform all other funds, except under CAPM. The second and third places are rather tied depending on the model. And ethical investment is last in 4/6 specifications. It is worth noting that all three orthodox portfolios are equally ranked under Carhart's model; i.e. all alphas outperformed the market by exactly 18 basis points resulting in no apparent difference across size.

It should be emphasized that many alphas are of no statistical significance, especially with CSK as a factor. This comes as no surprise, since CSK explains most of the variation in excess returns that other simpler models cannot. Yet, on the matter of performance, non-significant alphas could bias the interpretation of the results.

For example, neither alpha is significant under CAPM plus the coskewness factor, and the numerical difference from top (traditional funds of small size) to bottom (ethical investment) is only 5 basis points. While the difference makes ethical investment the worst performing portfolio, the actual difference in ranking is no different than zero. Going forward, under Fama and French and CSK, only the alpha for the small portfolio is significant. But in this case, at least, one can conclude that ethical investment is, at the very best, tied to second with the remaining funds.

All and all, it is expected that the most important results will come from the last model: the four factor model plus coskewness. Taking prior literature as a given, and accepting as a given that this is the best model to describe asset pricing, ethical funds still seem to underperform the market. And, according to this model, socially responsible investment underperforms assets in their same category for 48 basis points, with a statistically significant difference.

While section 4 shows weak evidence of the underperformance of ethical investment, this section provides further, stronger evidence, supporting this claim. It is expected that no investor will be compensated for holding extra levels of systematical risk, which is the case with ethical investments (Markowitz, 1959).

1.6. Summary of Findings

Socially Responsible mutual funds are not expected to perform as well as traditional investment assets due to a restricted asset universe; it is expected that they will not be able to achieve the same level of diversification, and thus performance, as an unconstrained investment asset. Overall, my results are in line with the fact that no investor will be compensated for holding extra levels of systematical risk which is the case of ethical investments. In lieu of this argument, I provide two types of evidence that show underperformance of ethical mutual funds: (1) I estimate a DEA based efficiency score that allows for direct comparison between funds ex-post and test the validity of said score into asset pricing methods and (2) I check if these results are consistent when comparing the performance of said funds based on the alphas of traditional asset pricing models as well as the introduction of the new coskewness factor.

Contrary to prior studies, the results suggest that, based on the efficiency score alone, ethical funds seem to underperform traditional unconstrained investment assets. Based on cross-tabulations, I find that there are more ethical funds within the low efficiency quintiles compared to more traditional mutual funds on the efficiency quintiles. Moreover, including an ethical dummy in cross-section regressions at $t+1$ shows that ethical funds can expect to receive a discount in next period returns. Thought the parameter estimates are only significant at the 10% level.

Though the use of an efficiency score might be enough for classification purposes, from an investment perspective, it does not bring any new opportunity to the field. I, thus, check if knowing the asset's performance score can either help accurately price returns and if it can help to define a feasible investment strategy. While the former goal is achieved, the second is somehow inconclusive.

Knowing the fund efficiency score, and creating a subsequent measurement of risk based on said score, can help explain the time-series returns. When efficiency is included to an asset pricing model, the absolute value of the average mispricing error is decreased, which is taken as evidence of the explanatory power of efficiency scores. That is, investors do consider the fund's performance when making investment decisions. It can be estimated that funds in the high efficiency scores (BCC=0.90) outperform those in the low efficiency scores (BCC=0.10) by 1.10%, approximately, under the Modified CAPM specification, and by 0.85%, approximately, under the modified four factor model.

However, knowing past performance scores does not seem to have high predictive power. I find inconclusive evidence, time inconsistent at most, that knowing prior efficiency scores can help predict future cross-section returns. In fact, the estimation of the risk premia is highly statistically insignificant.

Furthermore, I find consistent results under Jensen's alphas as a performance measurement. By incorporating a coskewness risk factor, the results suggest that, contrary with prior research, ethical investments seems to underperform orthodox funds. When comparing ethical investment to a size-adjusted portfolio of traditional mutual funds, the latter outperforms the former in 4/6 models; three of which include a coskewness factor. Quite remarkably, under the four factor model plus a factor of coskewness, socially responsible investment underperforms assets in the same category for 48 basis points, where the difference is highly statistically significant.

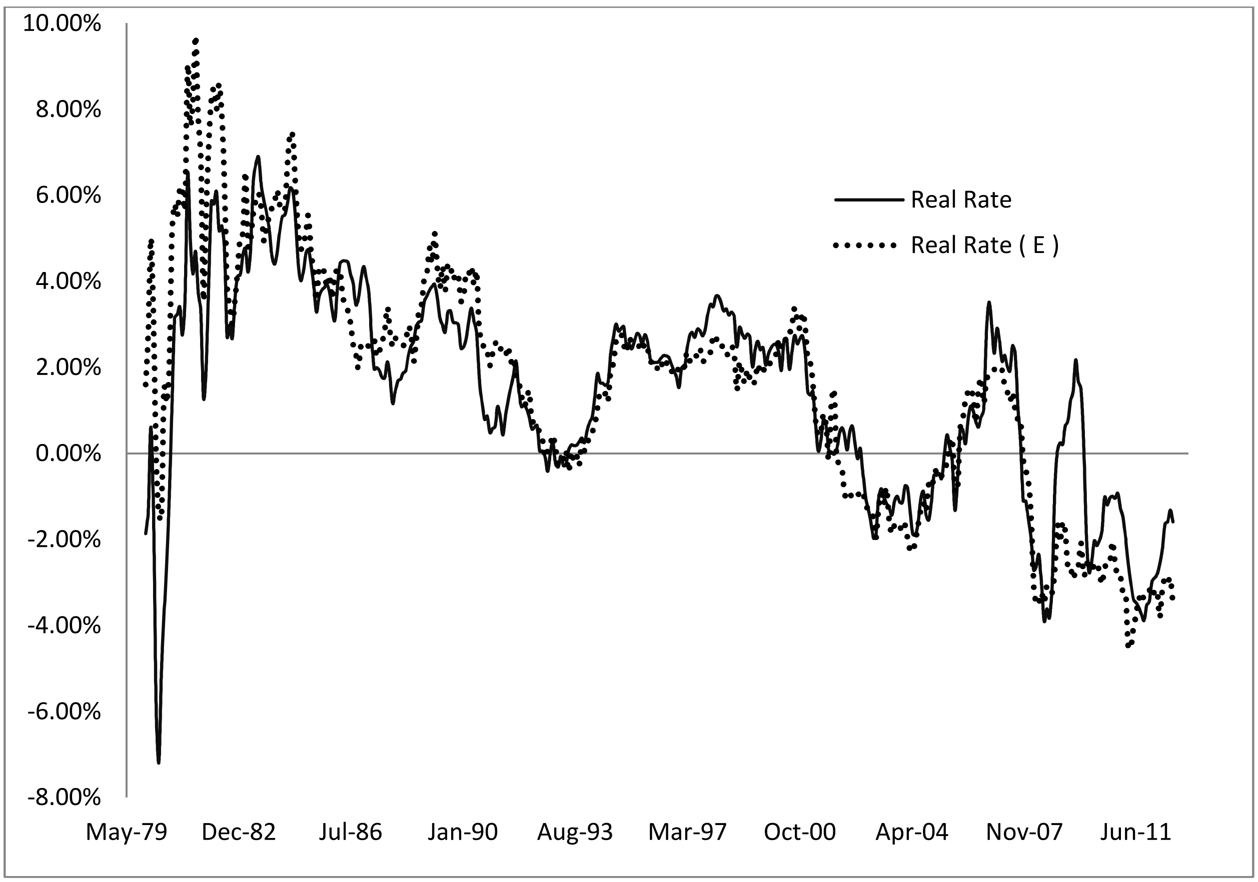
Though I find the traditional investment outperforms ethical funds, the reason for such is not quite obvious. On one hand, it can be driven due to pricing the social characteristic of funds, as explained by Hamilton's second hypothesis that the risk-adjusted expected returns of socially responsible portfolios are lower than the expected returns of conventional portfolios because the market increasing the value of socially responsible companies. But in the other in can be due to a loss on opportunity cost. I tilt towards the latter since the underperformance results from lower relative efficiency scores for ethical mutual funds compared to higher efficiency scores of unconstrained investment assets.

2. Chapter 2: Do Near Zero Nominal Rates Imply Negative Real Rates?

2.1. Introduction

Real interest rates since 2000, as traditionally defined by Fisher's relation, have been near zero or negative for long periods of time. Negative real rates, while expected to be characteristic of the "Great Recession", now characterize long periods of economic expansion which concerns investors, trouble policy makers and puzzles academics. Figure 1 plots real returns since 1980 (i.e., the Post-Volcker Period). The nominal rate is proxied by the 3-month T-bill and inflation is proxied by a CPI measure, and an expected inflation index. Nominal interests fall precipitously throughout the Post-Volcker period causing the real rate to dip below zero for long periods of time. Further, TIPs, or inflation protected securities with maturities from 5 to 30 years, available since 1997, are the purest indicators of real rates. TIPs yields while low have dipped below zero only briefly.[23]

Figure 2.1: Ex-ante and ex-post measures of the short term real T-bill rates since 1980.



The nominal rate is the 3-month T-bill yield converted to monthly yields. The solid line is nominal rate minus actual inflation as measured by monthly changes in the CPI-U. The dotted line real (E) is the nominal rate minus expected inflation as measured by the University of Michigan Excepted inflation index. All data retrieved from the St. Louis FRED database.

[23] http://www.stlouisfed.org/publications/pub_assets/pdf/re/2013/a/investments.pdf

Although TIPS may contain a significant interest rate risk premium over longer horizons the difference between real rates from TIPS yields and those calculated with Fischer's equation applied to short term T-bills may imply an inflation discount is present in short term nominally denominated assets. This paper examines the possibly that a time-varying inflation risk explains the recent real interest rate behavior in the US.

Calculating real rates with the Fisher equation may either over or underestimate real rates depending on expected inflation measure and risk premia estimates. From any asset pricing model T-bills are not truly risk free as they do not guarantee purchasing power as TIPS do. That is the interest rates on T-bills should include a inflation risk premium, $r = R + \pi^e + \lambda$. If an inflation risk premia/discount is present then the difference between the behavior of TIPs and T-bills may be reconciled and real rates may not be as low as the fisher equation would suggest. This paper employs the asset pricing model of Campbell and Cochrane (2000) whereby inflation covariance results in a time varying risk premium and has the potential of explaining the last decade's near zero nominal T-Bill rates.

The behavior of short term rates in the last decade has perplexed Federal Reserve Chairpersons and academics alike. Alan Greenspan, before leaving the Fed, documented that the rates of return of treasury securities did not react accordingly to a series of positive shocks on the federal funds rate. In fact, the rates remained surprisingly low. For lack a suitable explanation, he referred to such low rates as a conundrum. Ben Bernanke then argued that a possible explanation could be what he called "a global savings glut":

> "After the stock-market decline that began in March 2000, new capital investment and thus the demand for financing waned around the world. Yet desired global saving remained strong. The textbook analysis suggests that, with desired saving outstripping desired investment, the real rate of interest should fall to equilibrate the market for global saving. Indeed, real interest rates have been relatively low in recent years..." [24]

Although Bernanke's and further explanations (like Nakamura, et al, 2013) explain the decrease in real rates, it does not account for the fact that real rates, even by 2005, were mostly negative and persistently so. A partial explanation may be that real rates have remained negative after 2008 due to the latest world financial crisis. However, the US economy experienced negative real well before the start of the financial crisis.

Caballero, Farhi, and Gourinchas (2008) develop a model that supports Bernanke's view. They show that in a world with three economies, a large economy, a middle economy, and everyone else, growth slowdown in the middle economy and a collapse in asset markets in the rest of the world, will increase capital flows towards the large economy, the US, causing a decline in real interest rates and an increase in the importance of US financial assets. However, they do not consider the possibility of negative real rates.

Even more puzzling than why the interest rates are so low, is why investors accept negative real yields, because this should decrease their desired level of savings (Hamilton and Clemens, 1999).

[24] Taken from the Remarks by Governor Ben S. Bernanke at the Sandridge Lecture, Virginia Association of Economists, Richmond, Virginia (April, 2005): www.federalreserve.gov/boarddocs/speeches/2005/200503102/

However, despite the negative real returns, the market for short term treasury securities continues to be highly liquid (Krishnamurthy and Vissing-Jorgensen, 2012).

A few additional explanations arise: (1) the U.S. dollar is a safe haven currency (Kaul and Sapp, 2006) and thus foreign investors will rather hold U.S. treasury securities with a low yield rather than their own; (2) investor consider the “flight to quality” aspect of treasury securities (Caballero and Krishnamurthy, 2008; McCauley and McGuire, 2009), or (3) individuals remained in a state of distress after the financial crisis and thus their desire for precautionary savings increased (see Modigliani and Brumberg, 1954; Ando and Friedman (1957); Carroll, 2001b; Carroll and Kimball, 2001 among others for a discussion on precautionary savings).

From an asset pricing perspective, however, these explanations do not address the pricing of inflation risk. A rational explanation of asset prices has to include how risk affects the return of the underlying asset. It is well known that the slope of the conditional mean-variance frontier changes through time according to the business cycle (Harvey, 1989; Chou, Engle, and Kane, 1992) and investors thereby update their required rates accordingly. Campbell and Cochrane (2000) incorporate time-varying risk premia into a consumption based asset pricing model through deviations from slow moving habit. Investors in their desire to maintain habit become more risk averse when consumption moves closer to habit. The increase in risk aversion in recession states increases prices and lowers expected returns and vice-versa in periods of economic expansion.

I extend the habit formation model, adapted for inflation, with a time varying discount factor that accounts for variation in the intertemporal marginal rates of substitution (IMRSs) over the business cycle and their covariance with inflation that contributes to the pricing of short term nominal otherwise risk free securities. In this way, the model allows for a for a time-varying risk free rate, which is more consistent with the literature (see for example: Hamilton, 1985; Hamilton, 1988; Gray, 1996; Bekaert, Hodrick, and Marshall, 2001; Bansal and Zhou, 2002; Bansal, Tauchen, and Zhou, 2004).

Such inflation risk premium is due to the covariance between the IMRSs of the economy and inflation innovations, assumed to be zero in the standard model. I show that the risk free rate is comprised of a constant real rate, a constant expected inflation rate, and a time varying premium that is a function of the covariance between real consumption growth innovations and inflation innovations.

Pricing with the Campbell and Cochrane model, and its application to T-bill rates, hinges crucially on the covariance of the consumption growth and inflation innovations. A nominal asset where consumption/inflation innovations are negatively correlated is less desirable than a nominal asset in an economy where such innovations are positively correlated. When unanticipated high inflation is associated with unanticipated low consumption growth the nominal asset will pay less, in real terms, in bad states of the world than if the correlation is reversed. Assets that pay more in bad states are more valuable. Thus, investors will pay more for the nominal asset, and accept lower returns, in an economy where the consumption/inflation correlation is positive. So an inflation premium arises in nominally denominated assets in economics with negative correlation, and an inflation discount arises in economies with positive correlation.

Unlike Ang et al. (2008), Lee (1992) and Ehling, et al (2012), who show that all movements in the risk free rate come from unexpected inflation shocks, or Kurmann and Otrok (2012), who show that movements in the rate result only from monetary shocks, I show that volatility of the risk free rate results from said time varying inflation premia.

I find that the modified version of the habit formation model can replicate the level of the average risk free rate, but it does not account neither for the level nor the volatility of the real rate in the post Volker period. While including a time-varying inflation premium is appealing, such premium will have to be empirically at least thirty times larger in magnitude and opposite sign to avoid negative real rates. Unconditional consumption-inflation innovations are negatively correlated resulting in an inflation risk premium; not a discount. Further estimations of the conditional covariance after the millennium result in an inflation discount, consistent with a decreasing nominal risk free rate. Yet the magnitude is even smaller than the unconditional covariance. The persistence of a negative real rate of return is therefore even more puzzling as the use of the Fischer equation to adjust rates results in an over estimate of the real rate due to the existence of a modest inflation risk premium. And even after the presence of a discount, its magnitude makes negligible.

The remainder of this paper is developed as follows. Section 2 develops the habit formation model with a time-varying risk-free rate. Section 3 then summarizes an initial calibration of the model with data following the post Volker period. Section 4 then estimates the necessary parameters for the model. Finally, section 5 provides concluding remarks.

2.2. The Habit Formation Model

Campbell and Cochrane (1995, 2000) describe a consumption based asset pricing model that differentiates from the literature as it describes consumption as a slow moving habit. The model explains that as consumption declines towards the habit, the price of risky assets fall and expected returns rise. This feature of the model allows explaining various features of assets returns, such as moments, equity premium, and Sharpe ratio. But it fails to acknowledge any direct variations on the risk free rate, as it assumes the rate is constant.

Campbell and Cochrane derive an *sdf* m_t from a Habit formation utility and log normality where model agents maximize the utility of the form

$$E\sum_{t=0}^{\infty}\delta^t\frac{(C_t - X_t)^{1-\gamma} - 1}{1-\gamma} \tag{5}$$

where X_t is a level of habit that responds slowly to past consumption, δ is the time preference, and γ is an utility curvature parameter. This framework offers much richer dynamics than the standard utility model such as time varying risk premia and uses local curvature of the utility function to increase the volatility of the discount factor which is key to success in pricing assets for which conventional models fall woefully short. For convenience, since habits cannot be directly observed, utility is recast in terms of the surplus consumption ratio

$$S_t = \frac{C_t - X_t}{C_t}, S = \{0,1\} \tag{6}$$

It is easy to see that in bad states, meaning that consumption becomes equal to the habit, the surplus consumption goes to zero. By the same token, extremely bullish periods will put the surplus consumption ratio at its largest, meaning that individuals are enjoying abundance in consumption. It is easier to model the log of this ratio instead of modeling X_t itself. The surplus consumption ratio is also called the "recession" state variable as "good" and "bad" states are defined by how far consumption strays from habit.

The asset pricing literature shows that with log normality of the discount factor, or *sdf*, M_t, and gross returns, R_t, the law of one price will state that,

$$E_{t-1}(M_t R_t) = e^{E_{t-1}(m_t)+E_{t-1}(r_t)+\frac{1}{2}[\sigma^2_{t-1}(m_t)+\sigma^2_{t-1}(r_t)+2cov_{t-1}(m_t,r_t)]} = \alpha_t \tag{1}$$

where $\alpha_t = 1$ will rule out any under or over pricing. Taking logs we find

$$\begin{aligned} &ln\big(E_{t-1}(M_t R_t)\big) \\ &\quad = E_{t-1}(m_t) + E_{t-1}(r_t) + .5[\sigma^2_{t-1}(m_t) + \sigma^2_{t-1}(r_t) + 2cov_{t-1}(m_t, r_t)] \\ &\quad = ln(\alpha_t) \end{aligned} \tag{2}$$

where small letters denote logs. Noting the log of the risk free rate is,

$$r_{f,t} = ln\big(R_{f,t}\big) = ln\left(\frac{1}{E_{t-1}(M_t)}\right) = -ln\big(E_{t-1}(M_t)\big) \tag{3}$$

and defining $\alpha_t^* = \; ln(\alpha_t)$, expected returns are,

$$E_{t-1}(r_t) - r_{f,t} = \alpha_t^* - .5\sigma^2_{t-1}(r_t) - cov_{t-1}(m_t, r_t) \tag{4}$$

The variance term is from Jensen's Inequality. The form of *sdf* m_t in the covariance term either is derived from projection on returns data or the intertemporal marginal rate of substitution (*IMRS*) of a specific utility framework. In this case, the *sdf* m_t is derived from the habit formation utility framework.

Let consumption growth follow an i.i.d. process such that,

$$\Delta c_t = g + v_t, \;\; v_t \sim i.i.d.\, N(0, \sigma^2) \tag{7}$$

Then the surplus consumption ratio, $Log(S_t)$, is defined as an $AR(1)$ square root process, such that,

$$s_t = (1-\phi)\bar{s} + \phi s_{t-1} + \lambda(s_{t-1})v_t \tag{8a}$$

$$\Delta s_t = (1-\phi)(\bar{s} - s_{t-1}) + \lambda(s_{t-1})v_t \tag{8b}$$

where $\bar{S} = \sigma\sqrt{\frac{\gamma}{1-\phi}}$ is the steady state value of the surplus consumption ratio. Taken from Campbell and Cochrane, I define the sensitivity function for the surplus consumption as,

$$\lambda(s_{t-1}) = \frac{1}{\bar{S}}\sqrt{1 - 2(s_{t-1} - \bar{s})} - 1, \text{for } s_{t-1} \le \mathrm{s}_{\max}, \text{and 0 otherwise} \tag{9}$$

Where $\mathrm{s}_{\max} = \bar{s} + \frac{1}{2}(1 - \bar{S}^2)$

The features of this process ensure that consumption remains above habit, habit moves positivity with consumption, a countercyclical price of risk, habit has no influence on steady state consumption growth, and a constant risk free rate.

Campbell and Cochrane develop the *sdf* from a real-variables perspective. But in order to explain the relationship between interest rates and inflation, it is the necessary to differentiate between real and nominal rates. Thus, including a price level, the specific *sdf* is placed into the generic present value relation as:

$$\frac{P_{t-1}}{\Pi_{t-1}} = E_{t-1}\left(M_t^* \frac{X_t}{\Pi_t}\right) => E_{t-1}\left(M_t^* \frac{\Pi_{t-1}}{\Pi_t} R_t\right) = E_{t-1}(M_t R_t) = 1 \tag{10a}$$

where P_{t-1} is the nominal price of the payoff X_t divided by the price levels at each date and R_t is the nominal gross return. The nominal[25] discount factor for of the habit formation is

$$M_t = \delta\left(\frac{S_t}{S_{t-1}}\frac{C_t}{C_{t-1}}\right)^{-\gamma}\frac{\Pi_{t-1}}{\Pi_t} = \delta e^{-\gamma[\Delta s_t + \Delta c_t] - \pi_t} = \delta e^{-\gamma[\Delta s_t + \Delta c_t]} e^{-inf} \tag{10b}$$

[25] Small letters denote logs rather than nominal variables

This definition of the discount factor differs from Campbell and Cochrane by the inflation adjustment $\frac{\Pi_{t-1}}{\Pi_t}$. Thus a process that describes such inflation is required. Following Boudoukh (1993); Cox, Ingersoll, and Ross (1985); and Wachter (2004), inflation is also defined as an *i.i.d*. process such that,

$$\pi_t = \tau + \eta_t,\ \ \eta_t \sim i.i.d.N\left(0, \sigma_\eta^2\right) \tag{11}$$

Then the nominal log discount factor becomes:

$$\begin{gathered} m_t = ln(\delta) - \gamma[\Delta s_t + \Delta c_t] - \pi_t \\ m_t = ln(\delta) - \gamma[(1-\phi)(\bar{s} - s_{t-1}) + \lambda(s_{t-1})v_t + g + v_t] - \tau - \eta_t \end{gathered} \tag{12}$$

with expectation and deviation

$$\begin{gathered} E_{t-1}(m_t) = ln(\delta) - \gamma[(1-\phi)(\bar{s} - s_{t-1}) + g] - \tau \\ m_t - E_{t-1}(m_t) = -\gamma[\lambda(s_{t-1}) + 1]v_t - \eta_t \end{gathered} \tag{13}$$

and variance

$$\begin{gathered} \sigma_{t-1}^2(m_t) = E_{t-1}[m_t - E_{t-1}(m_t)]^2 = E_{t-1}[-\gamma[\lambda(s_{t-1}) + 1]v_t - \eta_t]^2 \\ = \gamma^2[\lambda(s_{t-1}) + 1]^2\sigma_c^2 + \sigma_\eta^2 + \ 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t) \\ = \gamma(1-\phi)\big(1 - 2(s_{t-1} - \bar{s})\big) + \sigma_\eta^2 + \ 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t) \end{gathered} \tag{14}$$

Taking log of the expected value,

$$\begin{aligned} ln\big(E_{t-1}(M_t)\big) = E_{t-1}(m_t) + \frac{1}{2}\sigma_{t-1}^2(m_t) \\ &= ln(\delta) - \gamma(1-\phi)(\bar{s} - s_{t-1}) - \gamma g - \tau \\ &+ \frac{1}{2}\Big(\gamma(1-\phi)\big(1 - 2(s_{t-1} - \bar{s})\big) + \sigma_\eta^2 + \ 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t)\Big) \\ &= ln(\delta) - \gamma g - \tau + \frac{1}{2}\gamma(1-\phi) + \frac{1}{2}\sigma_\eta^2 + \ \gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t) \end{aligned} \tag{15}$$

the (nominal) risk free rate results

$$r_{f,t} = -ln\big(E_{t-1}(M_t)\big) = -ln(\delta) + \gamma g - \frac{1}{2}\gamma(1-\phi) + \left(\tau - \frac{1}{2}\sigma_\eta^2\right) - \ \gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t) \tag{16}$$

Note that if real consumption growth and inflation are uncorrelated the risk free rates becomes constant as previously proposed, that is,

$$r_{f,t} = -ln\big(E_{t-1}(M_t)\big) = -ln(\delta) + \gamma g + \tau - \frac{1}{2}\gamma(1-\phi) - \frac{1}{2}\sigma_\eta^2 \tag{16b}$$

It can be seen that the nominal risk free rate is equal to the real rate plus inflation and a time-varying adjusting factor. The real rate is captured by $-ln(\delta) + \gamma g - \frac{1}{2}\gamma(1-\phi)$, where the expression is always positive given that the log discount factor is always negative, the second term is expected to be positive, and the last term is extremely small since the coefficient of persistence is close to 1. Then inflation is given by $\left(\tau - \frac{1}{2}\sigma_\eta^2\right)$ which is the log-normal mean inflation rate. Finally, the term $-\ \gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t)$ will induce volatility to the risk free rate.

The last term allows for a positive premium in times of negative covariance between inflation and consumptions growth, and a discount otherwise. Given that individuals prefer low inflation in bad consumption states, $E(v_t, \eta_t) > 0$, the risk free rate will be lower in such periods. This suggests that investors are willing to pay more[26] for cash holdings because the returns are better in bad states.

The covariance term is then,

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[26] The cost of money is express as a loss to inflation.

$$\begin{aligned} cov_{t-1}(m_t, r_t) &= E_{t-1}\big[\big(-\gamma[\lambda(s_{t-1}) + 1]v_t - \eta_t\big)\big(r_t - E_{t-1}(r_t)\big)\big] \\ &= -\gamma[\lambda(s_{t-1}) + 1]E_{t-1}(v_t, r_t) - E_{t-1}(\eta_t, r_t) \\ &= -\gamma[\lambda(s_{t-1}) + 1]E(v_t, r_t) - E(\eta_t, r_t) \end{aligned} \tag{17}$$

$$E_{t-1}(r_t) - r_{f,t} = \alpha_t^* - .5\sigma_{t-1}^2(r_t) + \gamma[\lambda(s_{t-1}) + 1]E(v_t, r_t) + E(\eta_t, r_t) \tag{18}$$

$$E_{t-1}(r_t) = 1 - \sqrt{1 - 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, r_t) - 2E(\eta_t, r_t) + E(r_t)^2 - 2r_{f,t}}. \tag{19}$$

Because the expectation involve the conditional variance we pick the root that yields expected returns under 100%. The ex-post formulation used in estimation is:

$$r_t - r_{f,t} = -.5[r_t - E_{t-1}(r_t)]^2 + \gamma[\lambda(s_{t-1}) + 1]v_t r_t + \eta_t r_t. + \varepsilon_t \tag{20}$$

with risk free given by:

$$r_{f,t} = -ln(\delta) + \gamma g + \tau - .5\gamma(1 - \phi) - .5\eta_t^2 - \gamma[\lambda(s_{t-1}) + 1]v_t\eta_t + \xi_t \tag{21}$$

Note that the standard CRRA model results if the sensitivity function of surplus consumption, which allows for time varying risk premia, is equal to zero and the coefficient of persistence is equal to one, $\lambda(s_{t-1}) = 0$ and $\phi = 1$.

2.3. Empirical Calibration of the Habit Formation Model

I proceed to check if the new specification of the habit formation model can explain the persistence of negative real rates. I start by taking prior parameter estimates as a given and move on from there. The initial approach is to try to calibrate the model, manually adjusting the parameters, in order to find a set of values that replicate the first two moments of the short term riskless rate. In this regard, I also look for a match to the minimums and maximums.

Time series data comes from the Federal Reserve Bank of St. Louis. I analyzed the time period that the FED changed their monetary policy to target interest rates instead of money supply, i.e. after 1980. I use monthly PCE growth to measure consumption, the monthly 3-month T-bill rate[27] as the nominal interest rate, and the monthly CPI growth to measure inflation. This could be further extended to use different proxies of a nominal interest rate such as the CRSP value/equally weighted returns, other types of commercial bonds, or ETF's. However, this paper aims to provide a rational explanation on why investors accept a negative real rate, thus it is expected that using the T-bill rate will suffice, at least as an initial approach.

The purpose of the calibration is to check if the risk free rate can be described by the model. Thus I only focus on the estimation of the risk free rate and not on the assets in general. That is, I manipulate *δ*, *γ, and*, φ in equation 16 in order to replicate the risk free rate based on the time series data. This describes the relationship between consumption and inflation and its effect on the nominal risk free rate. I start calibration anchored on Campbell and Cochrane suggested discount factor, *δ=0.9893*; utility curvature, *γ=2.37*[28]; and persistence coefficient, *φ=0.9884*. With such parameters, I try to replicate the first two moments of the risk free rate as given by the data. Table X summarizes the descriptive statistics of the data and parameters.

I find that average consumption is higher and more volatile than reported in Campbell and Cochrane (2000). This, in time, has implications in the remaining parameters. I expect that this difference is given

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[27] Based on the Annual Percentage Rate

[28] Campbell and Cochrane (2000) report γ=2.00, but this does not fit their results; γ=2.37 does.

by one of two reasons: (1) ex-post revisions to the data set that were not available in their time of estimation, or (2) the extension of the data set. I expect the late financial crisis to have induced some extra level of uncertainty and thus creating a structural break on the time series; this could be a sufficient reason for the excessive volatility of consumption growth.

Table X: Habit Formation Model Parameters

Descriptive statistics of the parameters for the habit formation model given by equation 16

From the Data	
Mean of consumption growth, $12g$, %	2.456%
Standard deviation of consumption growth, $\sqrt{12}\sigma$, %	1.861%
Mean of inflation rate, 12τ, %	3.355%
Standard deviation of consumption growth, $\sqrt{12}\sigma_{\eta}$, %	1.051%
Campbell and Cochrane Parameters	
Subjective discount factor, δ^{12}	0.88
Utility curvature, γ	2.37
Persistence coefficient, ϕ^{12}	0.87
Estimated Parameters	
Steady-state surplus consumption ratio, $\bar{S}$	0.065
Maximum surplus consumption ratio, $S_{\max}$	0.11
Covariance between real consumption growth and inflation, $E(v_t, \eta_t)$	-0.015%

The steady state of surplus consumption is estimated at 6.5%, which is 2% larger than previous estimations. Perhaps though we faced two strong recessions in the last twenty years, total consumption is still larger than prior decades, putting it well above habit levels. Further estimation of the maximum surplus consumption ratio also confirms this intuition. I estimate $S_{\max} = 11\%$ compare to prior estimations of 7.5%, which is consistent with higher than habit consumption.

Based on the parameters from Table X, I proceed to calibrate the expected risk free rate. At first trial, the risk free rate is very difficult to replicate; that is, to match the expected risk free rate with the ex-post rate. The expected risk free rate does not seem to move according to the realized rate. Yet, more importantly is that I cannot seem to be able to replicate any of the significantly low risk free rates post 2008. Table XI, Panel A, shows the replication of the first two moments based on the T-bill rate and the expected risk free rate and Table X parameters.

Though the estimation appears to be extremely sensitive to small changes in all parameters, the second moment can never be replicated. For example, holding everything else constant, setting *δ=0.98999* can help exactly replicate the expected risk free return. It is worthwhile noting that while the model can help replicate expected risk free returns, it cannot describe the individual monthly returns.

Table XI: Calibration of the Habit Formation Model

Table XI shows the results of the calibration of Equation 16 based on the parameters shown in Table X. Panel A is the estimation of the suggested risk free rate by the habit formation model explained in Equation 16; Panel B extends the same estimation to include a Covariance Adjustment (multiplier) of 30 to the estimation of Panel A.

Panel A: Moments Replication Based on Parameters		
	Realized Risk Free Rate	Expected Risk Free Rate
Average	0.416%	0.485%
Standard Deviation	0.286%	0.007%

Panel B: Moments Replication Based on Parameters and a Covariance Adjustment		
	Realized Risk Free Rate	Expected Risk Free Rate
Average	0.416%	0.416%
Standard Deviation	0.286%	0.286%

The variance of the risk free rate is $Var(r_{f,t}) = [\gamma E(v_t, \eta_t)]^2 Var(\lambda(s_{t-1}))$. This is the relationship between the utility curvature, and the covariance between inflation and consumption growth, as well as the variance of changes in surplus consumption over time. Note that the variance of the surplus consumption sensitivity function in time depends on γ and ϕ.

It is clear that the problem with the model is the expected second moment. This makes it almost impossible to accurately describe positive real rates during the 1980's and subsequent negative real rates for the majority of the 2000 decade. While monthly risk-free rates vary from 1.43 to 0.01[29] percent, the model predicts rates from 0.441 to 0.413 percent. The only solution is to induce extra volatility to the estimation of the risk free rate, in order to make real rates positive during the 1980's and negative during the 2000's. Or, put it another way, a systematically decreasing risk free rate.

Since the covariance $E(v_t, \eta_t)$ cannot be directly modified, I expect that only changes in utility preferences or the persistence coefficient can help replicate real rates. The problem with changing such parameters is that they also have a direct impact on the risk free rate. In fact, holding everything else constant, merely increasing gamma by 0.5 will make risk free rates negative, and an even smaller decrease of phi of 0.005 will make the average return almost zero, in my simulation. Moreover, the $Var(r_{f,t})$ does not seem to be sensitive to changes on either parameters. It appears that the effect are only seen in the risk free rate but not on volatility it itself.

Thus, a feasible solution will be to induce extra volatility by including a covariance adjustment term, say θ such that:

[29] The data actually has months with a 0.00% return.

$$r_{f,t} = -ln(\delta) + \gamma g - \frac{1}{2}\gamma(1-\phi) + \left(\tau - \frac{1}{2}\sigma_\eta^2\right) - \gamma[\lambda(s_{t-1}) + 1][\theta E(v_t, \eta_t)] \qquad (16^*)$$

I hope that by increasing volatility of expected risk free rate, I can calibrate parameters that yield the latest negative real rates. Note that large changes in θ will have little net effect on average risk free rates, but it will provide the ability to increase time changes. Arbitrarily setting $\theta > 30$ will provide closer estimates to expected moments. Using values less than 30 makes the calibration of the parameters extremely difficult because the model is extremely sensitive to changes on all parameters. For example, using $\theta = 10$ will drive the discount factor and the persistence coefficient to be closer to 0.5 which is inconsistent with prior estimates. Instead, values of more than 30 will allow such parameters to remain closer to prior estimations.

Figure 2.2: Real Rate Comparisons

Real interest rate from 1980 to 2012 in comparison to the theoretical risk free rate given by the habit formation model and a negative covariance adjustment

* Looking from the left, the real rate is the first curve, followed by HF, and HF+ θ at lat.

Setting $\theta = 30$ and adjusting the subjective discount factor, *δ=0.98735*; utility curvature, *γ=2.37198*; and persistence coefficient, *⍰=0.98215* will replicate the two moments identically. Furthermore, the maximum expected risk free rate will sit now at 1.08%, still lower than the realized value but larger than previously estimated; by the same token, the minimum will be also closer to the data by achieving values of 0%.[30]

Following the original specification of the model, given an inflation rate of 0.60% and a consumption growth of -0.09% for August 2012, the expected risk free rate should be 0.427%, compared to the realized rate of 0.01%. It is worth noting, however, that this specification does reproduce a negative real rate but it is not time consistent. After including the covariance adjustment, the moments are a closer match to the data but the expected risk free rate increases to 0.886% which is even further deviated from the realized rate.

Though including the parameter θ helps replicate the first two moments, this is not a full solution to the problem. First, the habit formation model does not call for such a parameter which reduces the likelihood that this model can fully explain investors' behavior towards their acceptance of a negative rate of return. Second, even after replicating the moments, the model inaccurately predicts the level of the monthly risk free rate. In fact, the best possible outcome comes when the covariance adjustment has a negative sign.

Figure 2 plots the realized risk free rate from 1980 to 2012. Also, it shows the theoretical risk free rate estimation based on the habit formation model according to equation 16. Except for small deviation, the expected risk free rate produces a rate that mimics the real rate rather well before 2000. After 2000, however, it can be seen that the model fails to replicate the negative rates after the dot-com bubble but catches up when the real rate becomes positive briefly only to deviate again after a few observations.

Proceeding with the covariance adjustment, it allows the expected risk free rate to further adapt to the fluctuations of the realized rate. Setting $\theta = 30$ produces negative real rates at the beginning of the 2000 decade but not after 2007. In fact, this definition will set real risk free rates even higher than without the covariance adjustment, as previously stated. Yet making $\theta = -30$ does accurately replicate the after 2007 period.

Table XI also shows a plot of the expected risk free rate based on the habit formation model with a negative covariance adjustment. Though this version of the adjustment fails to capture the negative rates following the dot-com bubble, it can accurately predict negative real rates following 2007. The fit of the model with the latter period is in fact quite impressive. However, this still does not imply a rational explanation of current rates. Instead, it shows that not only the covariance term will have to be higher, but also in opposite direction. Typically, as expected future inflation increases, individuals plan to decrease consumption (Deaton, 1977); this will not be true with a negative covariance adjustment.

It is worth noting that leaving the utility curvature close to Campbell and Cochrane estimate is nor arbitrary. Gamma shifts the model upwards (downwards) depending on the magnitude of the change. Keeping it at such level provides the closest fit to the negative real rates following 2007. It is almost impossible to accurately explain the whole time series of real rates, but in this context at least the latest period if almost perfectly replicated.

Granted, manual calibration is not an appropriate way of conducting research. However, it does provide a good stepping stone to future research. It shows the difficulty of explaining current

[30] Constrained upon $Rf > 0$. If let free, the minimum risk free rate value is -0.04%.

interest rates, as well as providing some insight on the direction of consumption and inflation. In the following section I estimate try to estimate the parameters.

2.4. Empirical Estimation of the Habit Formation Model

There are certainly many ways to parameterize the *sdf* M_t to match the average market rate of return and risk premium over the last 50 years. For convenience, I impose the following two moment conditions onto equations 21 and 22:

$$E\begin{bmatrix}\varepsilon_t\\ \xi_t\end{bmatrix} = \begin{bmatrix}0\\ 0\end{bmatrix}, \tag{22}$$

The first moment condition guarantees the discount factor reproduces the average rate on the market, but does not fix the premium. The second moment is the definition of the risk free rate which then fixes the premium. In the spirit of minimum variance, the persistence parameter ϕ is chosen to minimize the Sharpe ratio $\frac{\sigma_m}{E_m}$ or the variance of the discount factor needed to price the market and still fit the risk premium.[31]

The starting value for surplus consumption is held at its steady state value ($s_0 = \bar{s}$) and updated with changes in γ with the consumption growth mean and its standard deviation coming from time series data. The moment conditions are then iterated until parameters and the process for surplus consumption converges.

Table XII: Estimation of the Real Risk-Free Rate

Descriptive statistics of the estimated risk free rate, according to equation 21, as well as its exogenous parts.

	Mean	Standard Deviation
Estimated Risk Free Rate	0.4268%	0.2204%
Estimated Real Rate	0.0957%	0.0213%
Inflation	0.3378%	0.0314%
Covariance Premium	0.0429%	0.0079%
Actual Risk Free Rate	0.4160%	0.2860%

Following equations 20 and 21, as well as the moment conditions for the errors, I estimate the parameters that fit the data. There are two moment conditions, and three parameters, which allows for multiple solutions. Still, I can estimate a GMM model to fit 2/3 parameters, and check how changes in the third affect the estimation.

The risk free rate is estimated based on two steps. The first step estimates a rolling discount factor. I set the starting value for surplus consumption at its steady state value ($s_0 = \bar{s}$), which will be

[31] Estimations of the system with a third moment condition to fix the Sharpe ratio and estimate $\boldsymbol{\phi}$ from $\frac{\sigma_m}{E_m} = \boldsymbol{c}$ gave two solutions because the steady state value of surplus consumption is a function of both $\boldsymbol{\gamma}$ and $\boldsymbol{\phi}$ and variance of the discount factor is affected by both. Higher value of $\boldsymbol{\phi}$ dampens variance resulting in failure to converge if the value is too high for the system to fit both conditions.

subsequently changed based on changes in γ. Given the multiple solutions of the model, I iterate between different values of ▯. I start with values of phi close to 1 and decrease it in 0.001 intervals. This provides different combinations of a feasible solution for γ and δ for different values of ▯. This initial step generates time varying parameters to be later used to estimate equation 21.

In the same way as before, equation 21 can be broken down into three components: the first component, $-ln(\delta)+\gamma g-.5\gamma(1-\phi)$, accounts for the real rate; the second, $\tau-.5\eta_t^2$, accounts for the inflation rate; and finally the third, $-\gamma[\lambda(s_{t-1})+1]v_t\eta_t$, accounts for the covariance between inflation and consumption growth. It is expected that most of the variation of the risk free rate will come from the latter. Table XII summarizes de descriptive statistics of the estimation of equation 21.

Against expectations, the covariance seems to be the least volatile factor of all risk free variation. It seems that the moments are almost fully replicated except for some small differences. The mean risk free rate differs for about 0.01% and the standard deviation differs for about 0.06%. Unlike the prior section, estimation of the model does not require a covariance adjustment term. However, the estimation does not seem to solve all problems.

Figure 3 plots the resulting risk free rate and real rate resulting from equation 21. Panel A shows the difference between the theoretical and the actual rate. Even though the model can replicate the first two moments almost perfectly, the model does seem to be unable to replicate extreme risk free rate movements. That is, looking at the difference in the rates, there are several picks on which the realized risk free rate is up to 2 percentage points higher than the theorized rate (see December 2007).

The below zero difference in rate after the year 2000 suggests that the actual risk free rate should be almost 0.5% higher. Furthermore, a real rate comparison shows that the model never generates a negative real risk free; that is expected due to the inflation premium due to the unconditional covariance being negative; perhaps suggesting the need to look at the conditional covariance during a smaller time period. Indeed, the conditional covariance after year 2000 becomes positive, $E(v_t,\eta_t)=0.000049376\%$, but it is still extremely small to suggest a significant discount. But in the very least this provides evidence of a discount on the risk free rate after the millennium.

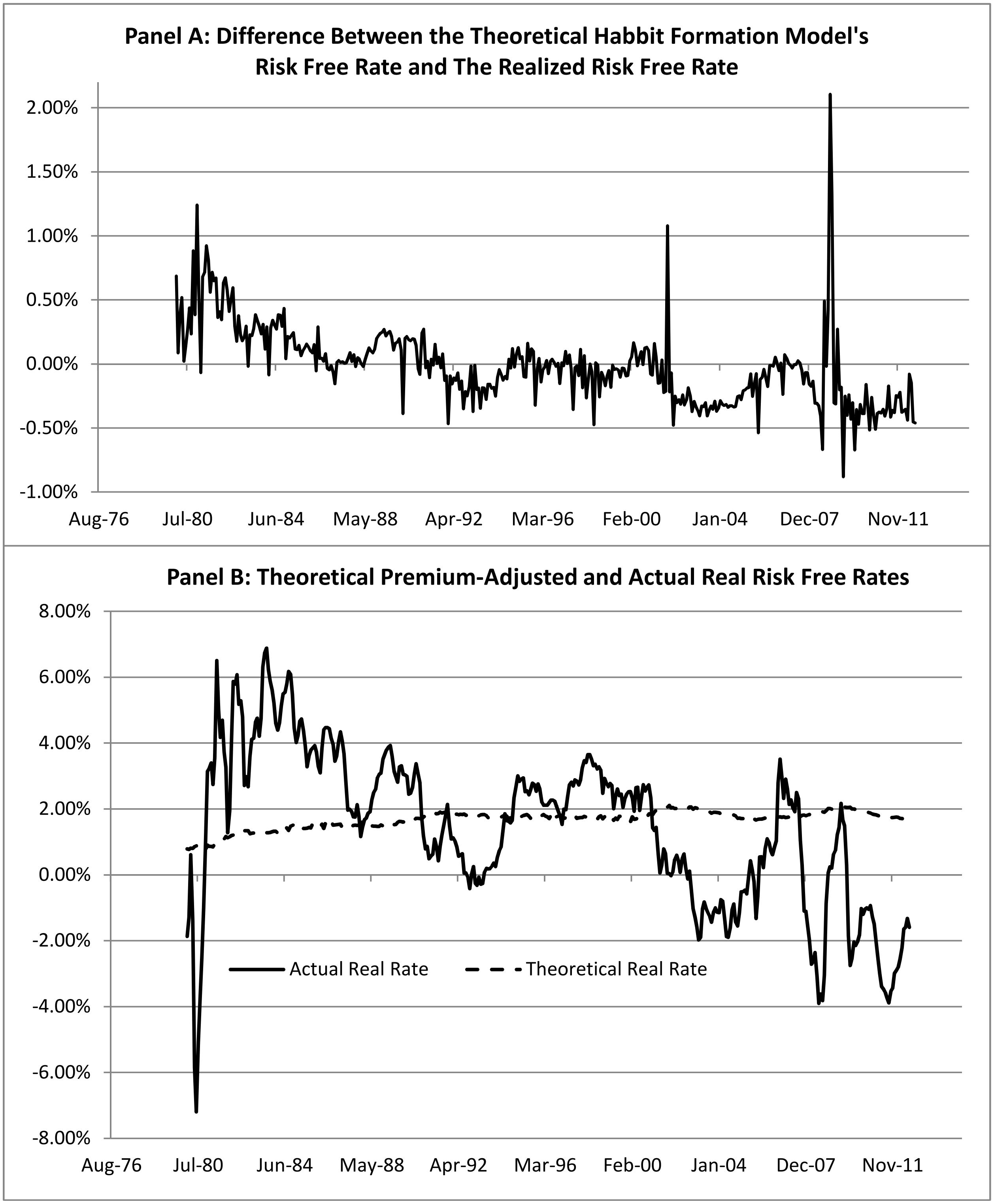
As shown in Figure 3 Panel B, the inflation-risk-adjusted real risk free rate is always smooth and positive. If anything, it suggests an ever increasing theoretical real risk free rate. Even after estimating the model parameters, there is a significant lack of volatility when compared to the realized real risk free rate. All and all, the habit formation model does not seem to fully explain the periods on which the real risk free rate is negative.

2.5. Summary of Findings

Traditional consumption based asset pricing models, though helpful to explain pricing, fail to incorporate time variable risk premium, and thus predict a constant risk free rate. In reality, the risk free rate is not only highly variable, but also quite small during the last decade. In fact, after the dot-com bubble, real rates have remain, on average, below zero; thus the need for a time varying asset pricing model that can adjust risk free rates to such periods of time. I, therefore, adjusted the habit formation model to include an inflationary process.

Figure 2.3: Estimation of the Habit Formation Model

Differences between the proposed habit formation model and realized risk-free return and real rate of return.



The resulting model suggest that perhaps the real rate is not in fact negative due to a misspecification in Fisher's equation, which assumes that the real rate will be negative as long as $r < \pi$. I show that the nominal risk free rate is equal to not only the real rate plus an inflation adjustment, but also a time-varying inflation risk premium/discount that accounts for the covariance between consumption growth and inflation; that is, $r = R + \pi - \lambda$. If such premium/discount exists, then it could also reconcile differences in the yields between indexed and unprotected treasury securities. But the effect of such factor remains negligible.

All and all, the habit formation model does not seem to have the power to explain the near zero nominal risk free rate. Current economic circumstances suggest a negative covariance between inflation and consumption growth, which then results on a premium rather than a discount. That is, if anything, rates should be larger than currently realized. Moreover, although looking at the post-millennium covariance provides a discount, it is even smaller in magnitude than for the whole sample. In order to explain current risk free rates, the covariance between consumption growth and inflation would have to be significantly larger in magnitude. That is, we should see investors changing consumption behavior for every small change in inflation rate.

It is worth noting that the objective of this paper is not to challenge the current macroeconomic targets in place by the Federal Reserve, such as a low but positive inflation rate and low risk free rates; in this sense, a normal explanation for the existence of negative real rates of return will be that it is the result of current monetary policy. Instead, I seek for a rational explanation that describes the behavior or the risk-free rate. The answer to this question, however, remains a puzzle.

REFERENCES

Chapter 1

Ang, J. S., & Chua, J. H. (1979). Composite measures for the evaluation of investment performance. Journal of Financial and Quantitative Analysis, 14(02), 361-384.

Barnett, M. L., & Salomon, R. M. (2006). Beyond dichotomy: The curvilinear relationship between social responsibility and financial performance. Strategic Management Journal, 27(11), 1101-1122.

Ball, C. A., & Torous, W. N. (1983). A simplified jump process for common stock returns. Journal of Financial and Quantitative analysis, 18(1), 53-65.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis.Management science, 30(9), 1078-1092.

Basso, A., & Funari, S. (2001). A data envelopment analysis approach to measure the mutual fund performance. *European Journal of Operational Research*, *135*(3), 477-492.

Basso, A., & Funari, S. (2003). Measuring the performance of ethical mutual funds: a DEA approach. *Journal of the Operational Research Society*, *54*(5), 521-531.

Basso, A., & Funari, S. (2005). A generalized performance attribution technique for mutual funds. *Central European Journal of Operations Research*, *13*(1), 65.

Basso, A., & Funari, S. (2008). DEA models for ethical and non ethical mutual funds. *Mathematical Methods in Economics and Finance*, *2*(1), 21-40.

Bauer, R., Koedijk, K., & Otten, R. (2005). International evidence on ethical mutual fund performance and investment style. *Journal of Banking & Finance*,*29*(7), 1751-1767.

Blattberg, R. C., & Gonedes, N. J. (1974). A comparison of the stable and student distributions as statistical models for stock prices. *The Journal of Business*, *47*(2), 244-280.

Bollen, N. P. (2007). Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, *42*(3), 683.Renneboog et al., 2005)

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57-82.

Chang, K. P. (2004). Evaluating mutual fund performance: an application of minimum convex input requirement set approach. *Computers & Operations Research*, *31*(6), 929-940.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978, 1979). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429-444.

Choi, Y. K., & Murthi, B. P. S. (2001). Relative Performance Evaluation of Mutual Funds: A Non-Parametric Approach. *Journal of Business Finance & Accounting*, *28*(7-8), 853-876.

Darling, G., Mukherjee, K., & Wilkens, K. (2004). CTA performance evaluation with data envelopment analysis. *Commodity Trading Advisors: Risk, Performance Analysisand Selection, John Wiley, Hoboken, NJ*.

Diltz, D. J. (1995). The private cost of socially responsible investing. *Applied Financial Economics*, *5*(2), 69-77.

Eling, M. (2006). Performance measurement of hedge funds using data envelopment analysis. *Financial Markets and Portfolio Management*, *20*(4), 442-471.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, *38*(1), 34-105.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607-636.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3-56.

Galagedera, D. U., & Silvapulle, P. (2002). Australian mutual fund performance appraisal using data envelopment analysis. *Managerial Finance*, *28*(9), 60-73.

Geczy, C., Stambaugh, R., & Levin, D. (2005). Investing in socially responsible mutual funds. *Available at SSRN 416380*.

Gil-Bazo, J., Ruiz-Verdú, P., & Santos, A. A. (2010). The performance of socially responsible mutual funds: the role of fees and management companies.*Journal of Business Ethics*, *94*(2), 243-263.

Glawischnig, M., & Sommersguter-Reichmann, M. (2010). Assessing the performance of alternative investments using non-parametric efficiency measurement approaches: Is it convincing?. *Journal of Banking & Finance*,*34*(2), 295-303.

Goldreyer, E. F., & Diltz, J. D. (1999). The performance of socially responsible mutual funds: incorporating sociopolitical information in portfolio selection.*Managerial Finance*, *25*(1), 23-36.

Gray, J. B., & French, D. W. (1990). Empirical comparisons of distributional models for stock index returns. *Journal of Business Finance & Accounting*,*17*(3), 451-459.

Gregoriou, G. N. (2003). Performance appraisal of funds of hedge funds using data envelopment analysis. *Journal of Wealth Management*, *5*(4), 88-95.

Gregoriou, G. N., & McCarthy, K. (2005). Efficiency of funds of hedge funds: A data envelopment analysis approach. *Hedge Funds: Insights in Performance Measurement, Risk Analysis, and Portfolio Allocation. John Wiley & Sons: New Jersey*, 365-380.

Gregoriou, G. N., Rouah, F., Satchell, S., & Diz, F. (2005). Simple and cross efficiency of CTAs using data envelopment analysis. *The European Journal of Finance*, *11*(5), 393-409.

Gregoriou, G. N. (2006). Trading efficiency of commodity trading advisors using Data Envelopment Analysis. *Derivatives Use, Trading Regulation*, *12*(1), 102-114.

Gregoriou, G. N., & Chen, Y. (2006). Evaluation of commodity trading advisors using fixed and variable and benchmark models. *Annals of Operations Research*, *145*(1), 183-200.

Guerard Jr, J. B. (1997). Additional evidence on the cost of being socially responsible in investing. *The Journal of Investing*, *6*(4), 31-36.

Hamilton, S., Jo, H., & Statman, M. (1993). Doing well while doing good? The investment performance of socially responsible mutual funds. *Financial Analysts Journal*, 62-66.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, *55*(3), 1263-1295.

Haslem, J., & Scheraga, C. (2003). Data envelopment analysis of Morningstar's large-cap mutual funds. *Journal of Investing*, *12*(4), 41-48.

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255-259.

Bera, A. K., & Jarque, C. M. (1981). Efficient tests for normality, homoscedasticity and serial independence of regression residuals: Monte Carlo evidence. *Economics Letters*, *7*(4), 313-318.

Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review/Revue Internationale de Statistique*, 163-172.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, *23*(2), 389-416.

Klemkosky, R. C. (1973). The bias in composite performance measures.*Journal of Financial and Quantitative Analysis*, *8*(3), 505-514.

Kon, S. J. (1984). Models of stock returns—a comparison. *The Journal of Finance*, *39*(1), 147-165.

Kraus, A., & Litzenberger, R. H. (1976). Skewness Preference and The Valuation Of Risk Assets*. *The Journal of Finance*, *31*(4), 1085-1100.

Kurtz, L., & DiBartolomeo, D. (1996). Socially screened portfolios: an attribution analysis of relative performance. *The Journal of Investing*, *5*(3), 35-41.

Kurtz, L. (1997). No effect, or no net effect? Studies on socially responsible investing. *The Journal of Investing*, *6*(4), 37-49.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics*, *47*(1), 13-37.

Mandelbrot, B. (1963). The stable Paretian income distribution when the apparent exponent is near two. *International Economic Review*, *4*(1), 111-115.

Markowitz, H. (1952). Portfolio selection*. *The journal of finance*, *7*(1), 77-91.

Markowitz, H. (1959). *Portfolio selection: efficient diversification of investments*(No. 16). Yale university press.

McMullen, P. R., & Strong, R. A. (1998). Selection of mutual funds using data envelopment analysis. *Journal of Business and Economic Studies*, *4*(1), 1-12.

Moreno, D., & Rodríguez, R. (2009). The value of coskewness in mutual fund performance evaluation. *Journal of Banking & Finance*, *33*(9), 1664-1676.

Morey, M. R., & Morey, R. C. (1999). Mutual fund performance appraisals: a multi-horizon perspective with endogenous benchmarking. *Omega*, *27*(2), 241-258.

Moskowitz, M. (1972). Choosing socially responsible stocks. *Business and Society Review*, *1*(1), 71-75.

Murthi, B. P. S., Choi, Y. K., & Desai, P. (1997). Efficiency of mutual funds and portfolio performance measurement: A non-parametric approach. *European Journal of Operational Research*, *98*(2), 408-418.

Praetz, P. D. (1972). The distribution of share price changes. *Journal of business*, 49-55.

Press, S. J. (1967). A compound events model for security prices. *Journal of business*, 317-335.

Sauer, D. A. (1997). The impact of social-responsibility screens on investment performance: Evidence from the Domini 400 Social Index and Domini Equity Mutual Fund. *Review of Financial Economics*, *6*(2), 137-149.

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). The price of ethics and stakeholder governance: The performance of socially responsible mutual funds.*Journal of Corporate Finance*, *14*(3), 302-322.

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*,*39*(1), 119-138.

Simkowitz, M. A., & Beedles, W. L. (1980). Asymmetric stable distributed security returns. *Journal of the American Statistical Association*, *75*(370), 306-312.

Smith, J. B. (1981). *The probability distribution of market returns: a logistic hypothesis* (Doctoral dissertation, Graduate School of Business, University of Utah.).

So, J. C. (1987). The distribution of foreign exchange price changes: Trading day effects and risk measurement—A comment. *The Journal of Finance*, *42*(1), 181-188.

Statman, M. (2000). Socially responsible mutual funds. *Financial Analysts Journal*, 30-39.

Treynor, J. L. (1965). How to rate management of investment funds. *Harvard Business Review*, V. 43: pp 63-75.

Chapter 2

Anderson, R. & Liu, Y. (2013). How Low Can You Go? Negative Interest Rates and Investors' Flight to Safety. *The Regional Economist.* Federal Reserve Bank of St. Louis Quarter Publications. January.

Ando, A., & Modigliani, F. (1963). The "life cycle" hypothesis of saving: Aggregate implications and tests. *The American Economic Review*, 53(1), 55-84.

Ang, A., Bekaert, G., & Wei, M. (2008). The term structure of real rates and expected inflation. *The Journal of Finance*, 63(2), 797-849.

Bansal, R., & Zhou, H. (2002). Term structure of interest rates with regime shifts. *The Journal of Finance,* 57(5), 1997-2043.

Bansal, R., Tauchen, G., & Zhou, H. (2004). Regime shifts, risk premiums in the term structure, and the business cycle. *Journal of Business & Economic Statistics*, 22(4), 396-409.

Bekaert, G., Hodrick, R. J., & Marshall, D. A. (2001). Peso problem explanations for term structure anomalies. *Journal of Monetary Economics*,48(2), 241-270.

Bernanke, B. Lecture at the Virginia Association of Economists, Richmond, Virginia (April, 2005)

Caballero, R. J., Farhi, E., & Gourinchas, P. O. (2006). An equilibrium model of" global imbalances" and low interest rates (No. w11996). *National Bureau of Economic Research.*

Caballero, R. J., & Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *The Journal of Finance*, 63(5), 2195-2230.

Campbell, J. Y., & Cochrane, J. H. (1995). By force of habit: A consumption-based explanation of aggregate stock market behavior (No. w4995). *National Bureau of Economic Research.*

Campbell, J. Y., & Cochrane, J. H. (2000). Explaining the Poor Performance of Consumption-based Asset Pricing Models. *The Journal of Finance,* 55(6), 2863-2878.

Carroll, C. D., & Kimball, M. S. (2001). Liquidity constraints and precautionary saving (No. w8496). *National Bureau of Economic Research.*

Carroll, C. D. (2001b). A theory of the consumption function, with and without liquidity constraints. *The Journal of Economic Perspectives*, 15(3), 23-45.

Chou, R., Engle, R. F., & Kane, A. (1992). Measuring risk aversion from excess returns on a stock index. *Journal of Econometrics*, 52(1), 201-224.

Ehling, P., Gallmeyer, M., Heyerdahl-Larsen, C., & Illeditsch, P. (2012). Beliefs about inflation and the term structure of interest rates. *Available at SSRN 2028391.*

Fisher, I. (1930). The theory of interest. New York, 43.

Friedman, M. 1957. “A Theory of the Consumption Function.” *Princeton University Press*

Gray, S. F. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, 42(1), 27-62.

Hamilton, J. D. (1985). Historical causes of postwar oil shocks and recessions.*The Energy Journal*, 6(1), 97-116.

Hamilton, J. D. (1988). A neoclassical model of unemployment and the business cycle. *The Journal of Political Economy*, 593-617.

Hamilton, K., & Clemens, M. (1999). Genuine savings rates in developing countries. *The World Bank Economic Review*, 13(2), 333-356.

Harvey, C. R. (1989). Forecasts of economic growth from the bond and stock markets. *Financial Analysts Journal*, 38-45.

Kaul, A., & Sapp, S. (2006). Y2K fears and safe haven trading of the US dollar. *Journal of international money and finance*, 25(5), 760-779.

Krishnamurthy, A., & Vissing-Jorgensen, A. (2012). The aggregate demand for treasury debt. *Journal of Political Economy*, 120(2), 233-267.

Kurmann, A., & Otrok, C. (2012). News shocks and the slope of the term structure of interest rates. *Federal Reserve Bank of St. Louis* Working Paper No.

Lee, C. (1992). Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics*, 15(2), 265-302.

McCauley, R., & McGuire, P. (2009). Dollar appreciation in 2008: safe haven, carry trades, dollar shortage and overhedging. *BIS Quarterly Review*.

Mishkin, F. S. (1992). Is the Fisher effect for real?: A reexamination of the relationship between inflation and interest rates. *Journal of Monetary Economics*, 30(2), 195-215.

Modigliani, F., & Brumberg, R. (1954). Utility analysis and the consumption function: An interpretation of cross-section data. FRANCO MODIGLIANI, 1.

Nakamura, E., Steinsson, J., Barro, R., & Ursua, J. (2013). Crises and Recoveries in an Empirical Model of Consumption Disasters. *American Economic Journal: Macroeconomics* 2013, 5(3): 35–74

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