DOES A SOCIALLY RESPONSIBLE PORTFOLIO OUTPERFORM A CONVENTIONAL PORTFOLIO? (THE CASE OF THE JANTZI SOCIAL INDEX)

by

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This thesis is dedicated to

My father,

My mother,

My brother

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Abstract

Socially responsible investment (SRI) takes financial return as well as environmental, social, and governance issues into consideration. Although SRI is becoming popular, a controversy exists among investors regarding its performance compared to conventional investments. In this thesis, we compare a socially responsible (SR) portfolio composed of members of Jantzi Social Index (JSI) with two conventional portfolios between March 2003 to December 2015. The members of the conventional portfolios match the industry and size of the companies in our SR portfolio. The SR and matched portfolios are compared on several dimensions, including risk-adjusted return measures. We find that our SR portfolio outperforms the matched portfolios based on all commonly used risk-adjusted return measures. In addition, by performing an event study, we find that while market response is insignificant for companies that enter JSI, those that exit this index experience a significantly negative effect on their returns.

List of Abbreviations and Symbols Used

SRI	Socially Responsible Investment
ESG	Environmental, Social, and Governance
SR	Socially Responsible
CSR	Corporate Social Responsibility
JSI	Jantzi Social Index
TSX	Toronto Stock Exchange
MPT	Modern Portfolio Theory
NAICS	North American Industry Classification System
C1	Best Matched Portfolio
C2	Average Matched Portfolio
R	Total Return
P	Equity Price
D	Dividends
w	Weight of an Equity in a Portfolio
σ	Total Risk
S	Sharp Ratio
R_f	Risk-free Rate of Return

M^2	M-squared Measure
R_m	Return of the Market
ST	Sortino Ratio
σ_d	Downside Deviation
β	Market Risk
T	Treynor Ratio
T^2	T-squared Measure
CAPM	Capital Asset Pricing Model
α	Abnormal Return
ε	Residual Return
SMB	Small Minus Big
HML	High Minus Low
WML	Winners Minus Losers
RMW	Robust Minus Weak
CMA	Conservative Minus Aggressive
I	Information Ratio
T	Tobin's Q
MC	Market Capitalization

TL	Total Liabilities
TA	Total Assets
L	Leverage Ratio
TD	Total Debt
AR	Abnormal Return
CAR	Cumulative Abnormal Return
AAR	Average Abnormal Return
CAAR	Cumulative Average Abnormal Return
FF3	Fama-French Three-Factor Model
FF4	Fama-French Four-Factor Model
FF5	Fama-French Five-Factor Model
DF	Degrees of Freedom
MATCH	Matched Portfolio

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Chapter 1 – Introduction

1.1 Socially Responsible Investment

Socially responsible investment (SRI) not only considers the financial return, but also takes into consideration the non-financial concerns of investors such as environmental, social, and governance issues known as ESG factors (Scholtens, 2014). *ESG factors* are activities companies engage in to reduce or eliminate the adverse effects of their operations on environment, society, and stakeholders.[1] The term "socially responsible" (SR) can be used with a company, a portfolio, a fund, an index, or an investor. A SR company is one that engages in corporate social responsibility (CSR) activities, of which the most important are the ESG factors (Scholtens, 2014). A SR portfolio, fund, or index consists of SR companies. A *portfolio* is a collection of investments held by an individual investor or an institution (Bodie, Kane, and Marcus, 2014). A *fund* is a pool of investments owned by a group of investors and managed by a fund manager who trades securities on behalf of the investors (Bodie et al., 2014).[2] An *index* is another type of a portfolio that is mainly used as a benchmark by investors and portfolio managers (Bodie et al., 2014). Investors do not directly invest in indices; however, they can form their

[1] A *stakeholder* is a party that has an interest in a corporation. A stakeholder can be an investor, an employee, a customer, a community, or a government (Bodie et al., 2014).

[2] A *security* is a financial instrument. It can be a stock, a bond, or an option (Bodie et al., 2014).

portfolios based on the members and weights of an index. Investors in SR companies, portfolios, or funds are referred to as SR investors.

Although SRI has a long history, its modern era began in the 1960s when the main areas of concern for SR investors were civil rights and equality for women (Schueth, 2003). During the 1970s, management and labor issues became the main concerns of SR investors. In the 1980s it was the environment and, subsequently, issues such as global warming and ozone depletion were brought to the attention of the public. In the 1990s, SR investors significantly reduced their investments in companies associated with tobacco, gambling, and firearms (Schueth, 2003).

SRI is growing fast in terms of the amount of investments. As an example of this rapid growth, we can look at the European and United States (US) SRI market, which, according to Revelli (2017), represents approximately 95% of the global SRI market. For Europe, we see an increase in the capitalization of the SRI market from $336 billion in 2003 to $13,608 billion in 2014—a growth of 3950%. For the US, this growth is 204%, from $2164 billion in 2003 to $6572 billion in 2014 (Revelli, 2017). According to Schueth (2003), there are three main reasons for the rapid growth of SRI. The first reason is information. All around the world, investors are better educated and informed today compared to any other time in history. Moreover, the quality, accuracy, and depth of information provided by social research organizations is continuously improving. The second reason lies in the growing role of women in the society (Schueth, 2003). As women become more active in society and assume many important roles in the workforce, they bring a natural attraction to the concept of SRI. The third reason is the good performance of SR companies, portfolios, funds, and indices, which shows that investors do not necessarily sacrifice financial return to protect their ethical concerns (Schueth, 2003).

As SRI is growing in financial markets, more SR indices and funds are introduced to the financial world. An example of such indices is the Domini 400 Social Index. It consists of 400 SR companies in US. This index is designed to help SR investors incorporate ESG factors in their investment choices (Bloomberg, 2017). An example of SR funds is the Domini Impact Equity Fund, a diversified portfolio of SR companies designed to have expected long-term total return, while protecting social and environmental concerns of investors (Bloomberg, 2017).

In this study, our focus is on the performance of a SR portfolio constructed from members of the Jantzi Social Index (JSI). JSI is managed by Sustainalytics, a global investment research firm specializing in ESG research and analysis (Sustainalytics, 2017). Sustainalytics defines JSI as “a socially screened, market capitalization-weighted common stock index modeled on the S&P/TSX 60 which consists of 50 Canadian companies that pass a set of broadly based ESG criteria”, and are listed on the Toronto Stock Exchange (TSX). *S&P/TSX 60* is an index constituting 60 large companies listed on the TSX. The underlying pool of companies used by Sustainalytics to choose the constituents of JSI is S&P/TSX Composite Index (Sustainalytics, 2017). *S&P/TSX Composite* is an index constituting the largest companies listed on the TSX. This index is mainly considered to be the proxy for the market of Canada.

Sustainalytics uses two exclusionary criteria to form JSI, “product involvement” and “major negative ESG impact.” For the “product involvement” criterion, those companies considered controversial due to their negative impact on environment and society are not eligible to be members of JSI. These negative impacts are the effects of being associated with environmental pollution, military contracting, nuclear power, and tobacco (Sustainalytics, 2017). For “major negative ESG impact”, companies will be excluded from the list of eligible companies for adverse effect on the health of employees and customers, inability to pay the wages of employees on time, and lack of a positive relationship with communities and government (Sustainalytics, 2017). Sustainalytics ranks corporate controversies on a scale of 1 to 5 with 1 being least controversial and 5 being most controversial. Companies with Category 4 or Category 5 controversies cannot be members of JSI (Sustainalytics, 2017).

Sustainalytics reviews JSI each year in March to update its constituents and to ensure that the goals of JSI are maintained. The first goal is to include the top SR companies. To achieve this and ensure that JSI always has the best sustainability performance, Sustainalytics adds and removes companies based on their ESG performance (Sustainalytics, 2017). The second goal is to ensure “investability”. To accomplish this, Sustainalytics maintains the market capitalization of JSI equal to at least 50% of the market capitalization of S&P/TSX 60. Market capitalization is the market value of the shares of a company, and is calculated as the number of outstanding shares of a company multiplied by its share price. The third goal is to maintain sector weights close to those of S&P/TSX 60. Sector weight refers to the percentage of investment in a specific sector or industry. To reach this goal, Sustainalytics keeps the weights of JSI industry sectors close to those of S&P/TSX 60 in a way such that the difference is not more than 5% (Sustainalytics, 2017).

The constituents of JSI may also change between the annual reviews due to other reasons such as deletion from S&P/TSX Composite index, bankruptcy, insolvency, liquidation, acquisition, or splitting (Sustainalytics, 2017). In the case where one JSI member is acquired by another JSI member, or one JSI member acquires a non-member, the new company will be eligible to be included in JSI. If a member of JSI is split, only one of the two securities resulting from this split will remain a member. In the case that both companies are eligible to remain in JSI, the one with higher market capitalization will stay in (Sustainalytics, 2017).

1.2 Comparing SR and Conventional Portfolios

As SRI grows in financial markets, the number of studies comparing its performance with that of conventional investments is increasing. There are two main views on this relative performance: that of supporters and that of opponents. Supporters of SRI argue that the performance of SR portfolios is either superior or similar to the performance of conventional portfolios, while opponents of SRI believe that SR portfolios underperform conventional portfolios. The discussion between supports and opponents of SRI is mainly based on portfolio selection models. Although various investors and academics use different portfolio selection models, modern portfolio theory is the foundation of many of these models.

In 1952, Harry Markowitz, an American economist, introduced a series of arguments referred to as modern portfolio theory (MPT). Based on this theory, a risk-averse investor can minimize the risk of a portfolio for any specified level of return or, alternatively, can maximize the return for any specified level of risk (Bodie et al., 2014).[3] Based on MPT, a more diversified portfolio has a better risk-adjusted performance compared to a less diversified portfolio.[4] *Diversification* is the process of including a wide range of companies in a portfolio, which reduces the risk associated with individual companies. This kind of risk is called *unsystematic* or *firm-specific* risk. The other part of the risk of a portfolio comes from the sensitivity of returns to the return of the market, which is called *systematic* or *market* risk. This type of risk cannot be reduced through diversification (Bodie et al., 2014).

The optimization model based on MPT consists of an objective function and a few constraints. The objective function minimizes the risk of a portfolio or, alternatively, maximizes the return of the portfolio. The constraints of this model can change depending on the objectives of the investor (Bodie et al., 2014). To create a SR portfolio, we must add a SR constraint to this model, which forces the portfolio to choose only SR companies. Since a conventional portfolio can invest in both SR and non-SR companies, it does not require this constraint. Adding a constraint decreases the size of the investment pool and results in a less diversified portfolio. Based on the premise of MPT, this portfolio is expected to underperform a more diversified portfolio on a risk-adjusted

[3] A risk-averse investor accepts more risk only if it is rewarded with a higher level of return (Bodie et al., 2014)

[4] A *risk-adjusted return* is a measure that takes into consideration the amount of risk taken to create that return (Bodie et al., 2014).

basis (Bodie et al., 2014). This is the main argument of the opponents of SRI. They believe that SR portfolios underperform conventional ones since their pool of investment is limited to SR companies. On the other hand, supporters of SRI believe that the performance of SR portfolios is similar to that of conventional ones, or can even be better thanks to the superior financial performance of the constituents of a SR portfolio. They believe this superiority is the result of characteristics of SR companies, which include attraction of better and more productive employees, lower environmental costs, superior reputation, better risk management, and better relations with government and communities (Schueth, 2003).

Many studies have been conducted to analyze the debate between supporters and opponents of SRI. As an example, we can refer to the monthly reports of Sustainalytics on the performance of the Jantzi Social Index (JSI) (see Figure 1 and Table 1). Figure 1 compares JSI with two conventional indices—S&P/TSX Composite and S&P/TSX 60. 'Inception annualized' and 'Inception cumulative' are the annualized and cumulative returns, respectively, of JSI since its inception in January 2000. As we can see, JSI almost moves in line with these two indices. Moreover, Table 1 shows that JSI achieved an annualized and cumulative return of 6.53% and 193.14%, respectively, from inception to December 2016. In the same period, S&P/TSX Composite and S&P/TSX 60 achieved annualized returns of 6.14% and 6.09%, and cumulative returns of 175.34% and 173.39%, respectively.

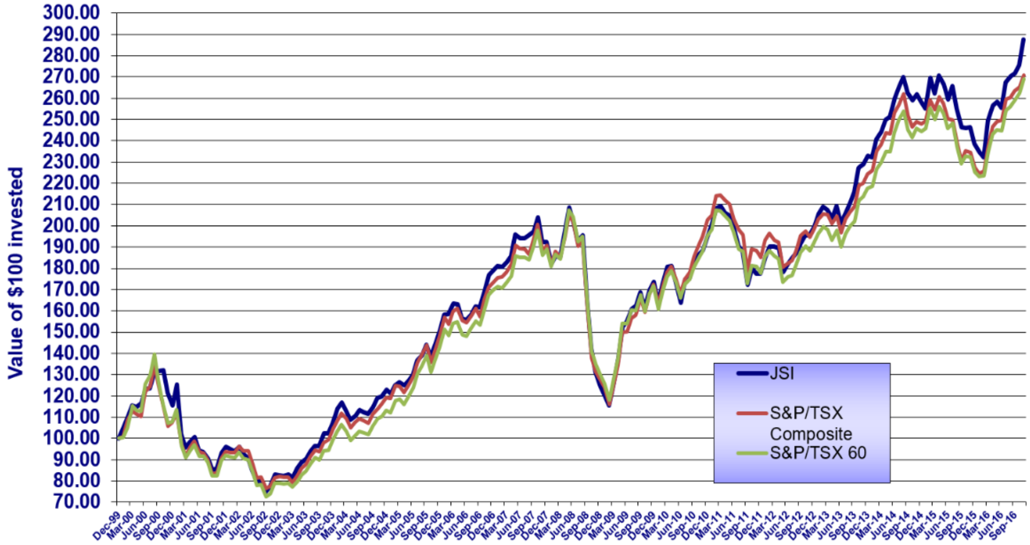

Figure 1: Relative performance of JSI, S&P/TSX Composite, and S&P/TSX 60 (Sustainalytics, 2017)

Table 1: Total return of JSI, S&P/TSX Composite, and S&P/TSX 60 (Sustainalytics, 2017)

Period	**JSI**	**S&P/TSX Composite**	**S&P/TSX 60**
December 2016	1.77%	1.66%	1.63%
3 months	7.77%	4.54%	5.59%
1 year	22.68%	21.08%	21.36%
3 years	7.98%	7.06%	7.92%
5 years	10.55%	8.25%	8.99%
10 years	5.06%	4.72%	4.86%
Inception annualized	6.53%	6.14%	6.09%
Inception cumulative	193.14%	175.34%	173.39%

From Figure 1 and Table 1, a naïve conclusion may be drawn that JSI either moves in line with or outperforms these two indices. Apart from the fact that the numbers in Table 1 are not adjusted for risk, there are flaws in such conclusions since, in general, SR and conventional portfolios may not be comparable. First, the industries to which the members of SR and conventional portfolios belong may be different and, as a result, the overall weights in any specific industry may vary. As the financial performance of companies is affected by their industries, a comparison between the performance of a SR portfolio and a conventional one can produce misleading results if the industry weights vary. Second, SR and conventional portfolios might be of different sizes; their total market capitalization and that of their members can differ significantly. As size can have a huge effect on the return and risk of a portfolio, any result of a comparison between the performance of a SR portfolio and a conventional one, without considering their sizes, cannot be attributed to the superiority or inferiority of SRI. Third, SR and conventional portfolios may have different risk profiles. *Risk profile* refers to the threats that a company could face (Bodie et al., 2014). One such threat comes from the risk associated with the amount of debt in the capital structure of a company compared to its total assets. Leverage ratio is the measure mainly used as the proxy for this type of risk. *Leverage* is a ratio calculated by dividing the total debt of a company by its total assets (Bodie et al., 2014). A company that is highly leveraged is much riskier than one with a low level of debt in its capital structure. As a result, in comparing SR and conventional portfolios, special attention must be given to their leverage ratios. Finally, the SR and conventional portfolios may have different styles of management. Managerial style can be active, passive, or a combination of both. An active portfolio manager trades mispriced securities to outperform the market while a passive portfolio manager invests in line with a major index (Bodie et al., 2014).[5] The investment style of a portfolio manager can have significant effect on the return of the portfolio. Thus, the difference in performance

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[5] The price of a mispriced security does not reflect its true worth; it is either overvalued or undervalued. Active portfolio managers sell overvalued, and buy undervalued securities with the expectation of beating the market (Bodie et al., 2014).

between an SR portfolio and a conventional one may be due to this factor, and not the superiority or inferiority of SRI.

Chapter 2 – Literature Review

The debate over the relationship between CSR activities and the value of a company goes back many decades. At first, these studies were mostly ideological. As an example, Friedman (1970) believes that managers of a company are only responsible for maximizing wealth of shareholders. Contrary to this belief, Freeman (1984) argues that companies are responsible for all the people and entities associated with them. Although early studies on this subject hold contradicting ideologies, they conclude that CSR activities come at an expense to shareholders. In other words, from the point of view of these early studies, there is no benefit to shareholders from using companies resources in CSR activities.

Gradually, these studies started to focus on the economic aspects of CSR activities. We can identify three main views in such studies. The first view states that CSR comes at an expense to shareholders. Based on the second view, CSR activities create value for companies. Finally, the third view argues that the relationship between the costs associated with CSR activities and the value of a company has a U shape, which means that up to a certain level it benefits shareholders.

Holding the first view, Izzo and Magnanelli (2012), by studying 332 companies over five years from 2005 to 2009, report that CSR activities result in a higher cost of debt for companies. Thus, they conclude that involvement in these activities leads to waste of resources. In other words, they argue that, the market does not recognize any financial premium for CSR activities and banks, which are the major lenders of money, do not believe that these activities enhance the value of companies or reduce their level of risk. In another study, Servaes and Tamayo (2013) study the relationship between CSR activities and the value of companies for different levels of customer awareness. To measure customer awareness, they use the amount of advertising expenditure. Researchers report that for those companies with low customer awareness, CSR activities are a waste of resources and create no additional value.

Regarding the second view, Verwijmeren and Derwall (2010) report that bankruptcy risk is lower in companies with high levels of employee satisfaction. They state that these companies reduce the probability of bankruptcy by operating with a lower leverage ratio. Moreover, these companies have better credit ratings. After reviewing the performance of a large number of companies in the US between July 1992 and June 2008, Manescu (2011) reports that companies with better community relations experience a positive effect on their risk-adjusted performance. Dimson, Karakas, and Li (2015) study a group of US companies between 1999 and 2009 and report that companies that engage in CSR activities create an average abnormal return of 1.8%. They state that engaging in these activities improves the profitability and efficiency of companies.

As an example of researchers that hold the third view, Barnea and Rubin (2010) argue that there is a positive relationship between the value of a firm and its CSR expenditure up to a level. If CSR expenditure goes beyond that level, no additional value is created for the company, and the resources will be wasted. They also argue that managers of companies may overinvest in CSR activities for their own reputation at the expense of the shareholders. In another study, Goss and Roberts (2011) investigate the relationship between the level of CSR activities and the cost of debt. By analyzing a sample of 3996 loans to US companies, they find that there is a U-shaped relationship between the amount of investment in CSR activities and the cost of debt. Up to a level, CSR activities create value for companies by reducing the cost of debt (between 7 and 18 basis points), but beyond that level no additional value is created for companies and the cost of debt starts to increase.[6]

To this point, we have reviewed research that studies the relationship between CSR activities and the value of companies. Another major part of studies on the subject of social responsibility is the comparison of performance between SR portfolios, funds, or indices and conventional ones. These studies can be categorized into three main groups. First, some demonstrate underperformance of SR portfolios, funds, or indices compared to conventional ones. Second, some researchers show similar performance or outperformance of SR portfolios, funds, or indices compared to conventional ones. Third, others show that the difference between the financial performance of SR portfolios, funds or indices, and conventional ones is dependent on the market cycle, or is the result of other factors and not the superiority or inferiority of SRI.[7]

Beginning with the first group, in a study by Geczy, Stambaugh, and Levin (2005) the cost of SR constraint is studied by comparing the performance of a group of SR funds

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[6] One basis point is equal to 0.01%.

[7] Two terms describe the cycle in the stock market, "bull" and "bear." Bull (bear) market is the period of increase (decrease) in market prices (Bodie et al., 2014).

with a group of funds constructed from a broader universe of companies. They argue that the estimate of this cost on one hand depends on the asset pricing model used to make the estimate, and on the other hand, depends on the type of fund manager (active, passive, or mixed style). An asset pricing model describes the relationship between the expected return of an asset and its risk factors. For example, if Capital Asset Pricing Model is used, the cost is usually low. As the asset pricing model includes more factors, such as size and value, the estimate of the cost increases. Moreover, when the SR fund is managed actively, the cost of SR constraint becomes higher. All in all, Geczy et al. argue that there is a cost associated with SR constraint. In another study, Adler and Kritzman (2008) argue that since SR portfolios exclude some attractive companies from their pool of investments, there must be a cost associated with SRI. They report that on average, the annual return of SR funds is 0.17% to 2.4% lower than the conventional ones, and conclude that SR funds underperform conventional funds. Cortez, Silva, and Areal (2012) compare 39 European SR funds in Austria, Belgium, France, Germany, Italy, Netherlands, and United Kingdom (UK), and 7 US SR funds to the MSCI AC World Index.[8] In this study, researchers use two different asset pricing models, Market model and Fama-French model, to calculate abnormal return. The results show that although the performance of most of the European SR funds is not significantly different from MSCI, US and Austrian SR funds show evidence of underperformance.

[8] MSCI AC World is a conventional index managed by Morgan Stanley, a financial services institution, and is composed of both developed and developing markets companies (Cortez et al., 2012).

Regarding the second group, by comparing a sample of SR funds with a group of conventional ones that match the SR funds based on net assets, Bello (2005) reports that when the number of companies in a portfolio is large enough, adding extra companies to that portfolio does not significantly affect its performance. As a result, he concludes that there is no significant difference in the performance of SR and conventional portfolios because the number of available SR companies is large enough. Milevsky et al. (2006) study the effects of SR constraint on the performance of a portfolio. They replaced the constituents of S&P/TSX 60 with SR companies in the same industry, and conclude that the difference in performance is not statistically significant. In another study by Schroder (2007), 29 SR indices from different parts of the world are compared to conventional benchmark indices in a period with different start dates (depending on the index) and a specific end date, December 2003. Schroder concludes that although many SR indices show higher market risk compared to their benchmarks, based on abnormal return as a risk-adjusted return measure, performance of the two groups are not different. In a study by Fatemi, Fooladi, and Wheeler (2009) the performance of the Domini 400 is compared to a group of conventional companies that match each constituent of Domini 400 based on their industries and market capitalizations. These two groups are compared based on measures such as total return, total risk, market risk, unsystematic risk, and leverage ratio. The authors report that, although the difference between the total return and market risk of the two groups is not statistically significant, Domini 400 dominates the control group based on total risk and unsystematic risk. They also state that, on average, the constituents of Domini 400 have lower levels of debt in their capital structures. Moreover, they study the impact on the performance of the companies that enter or exit the Domini 400 index and report positive abnormal returns for included companies, and negative abnormal returns for excluded ones. In another study by Gil-Bazo, Ruiz-Verdu, and Santos (2010), a group of SR funds in the US is compared to a group of hypothetical conventional funds that match the SR funds mainly based on their sizes. The period of this study is from 1997 to 2005. Based on abnormal return as a risk-adjusted return measure, the researchers conclude that SR funds outperform conventional ones. Managi, Okimoto, and Matsuda (2012) compare the performance of a group of SR funds in the US, UK, and Japan to conventional indices including S&P 500 Index, FTSE 100 Index, and TOPIX Index.[9] Researchers conclude that there is no significant difference in the total return and total risk of the two groups and, as a result, the SR funds and conventional indices show no sign of underperformance or outperformance.

In a study within the third group, Statman (2005) compares the performance of four SR indices with the S&P 500. He reports that the SR indices outperform S&P 500 during the boom of the late 1990s, while in the bear market of the early 2000s, S&P 500 outperforms these indices. In another study by Areal, Cortez, and Silva (2010), 38 SR funds are compared to the Vice fund between October 1993 and September 2009. The Vice fund, now known as the Barrier fund, invests in companies significantly involved in gambling, tobacco, alcohol, and weapons. The result of this research indicates that the Vice fund outperforms during periods of low volatility and underperforms in high volatility periods. Areal et al. (2010) argue that since SR funds do not adjust their risk

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[9] FTSE 100 is an index of 100 companies on the London Stock Exchange with the largest market capitalizations, and TOPIX represents the largest companies listed on the Tokyo Stock Exchange.

according to market condition, SR funds perform better during periods of crisis. In another study by Kurtz and diBartolomeo (2011) the performance of the Domini 400 Social Index is compared to S&P 500 between January 1992 and June 2010. The results show that Domini 400 outperforms S&P 500 between January 1992 and November 1999, but for the rest of the period, Domini 400 underperforms S&P 500. They conclude that the outperformance of Domini 400 is factor driven. This factor is guessed to be the overweight investment in the IT industry, which was growing very fast during that period. On the other hand, the Domini 400 underperformed because of the dependence on investment in the IT sector, which lost its dramatic growth potential after the market crisis. In another study by Nofsinger and Varma (2014), the performance of a group of SR funds is compared to the performance of a matched group of conventional funds. For each SR fund, three conventional funds that have the same "Lipper objective", close "inception date", and close "total net assets" are found.[10] Although not the main focus of this study, they report that SR funds outperform the matched sample during market crisis/stress, while during non-crisis periods, the SR funds underperform the sample group.

In this thesis, we add to the existing SRI literature by performing a study on the Canadian market. We compare a SR portfolio constructed from the members of JSI with two hypothetical conventional portfolios, matched based on industry and size. To match for industry we use the NAICS codes, and for size we use the "total assets" of companies. By

[10] "Lipper objective" is a code that describes how a fund intends to invest, "inception date" refers to the date on which a fund starts its operations, and "total net assets", which is mainly used for funds, is equal to total assets minus total liabilities.

comparing our SR portfolio with these matched portfolios, we investigate how SRI can affect the performance of a portfolio. The measures we use are total return, risk measures including total risk, downside risk, and market risk, and their associated risk-adjusted return measures. We also compare the performance of the portfolio manager of our SR and matched portfolios by comparing the unsystematic risk, information ratio, and market timing of these portfolios. Moreover, by comparing the Tobin's Q of our SR and matched portfolios, we investigate whether CSR activities can create value for companies, and affect their performances in a positive way. We also compare the leverage ratio of our SR and matched portfolios since leverage is one of the measures that affect the valuation. Finally, to eliminate any possible effect of the study period, models, or the data set on our conclusion regarding the relative performance of our SR and matched portfolios, we perform an event study on the companies that enter or exit JSI to investigate the response of the market to SRI.

CHAPTER 3 – Methodology

In this chapter, we introduce the methodology used in this thesis. There are four main sections. In the first, we describe the data used in this study. In the second, we explain how two matched portfolios are created for our SR portfolio. In the third, we introduce the measures used for comparing our SR and matched portfolios and in the fourth, we describe the details of our approach to examining impacts of including companies in JSI or excluding them from the index on their stock returns.

3.1 Data

Data used in this research are from two sources: Bloomberg and Kenneth French's website. Bloomberg is a database used by investors and academics to obtain real-time data about markets, news, and research (Bloomberg, 2017). Table 2 displays a sample of data from Bloomberg used in this study. In this table, we see five members of JSI, their industries, and their sizes (represented by total assets).

Kenneth French's website is owned by Professor Kenneth French, one of the founders of the Fama-French asset pricing model. Every month this website publishes the Fama-French factors for different markets, including North America (French, 2017). A sample of North American Fama-French factors used in this study is shown in Table 3. In this table, we see Fama-French factors for August 2015 to December 2015. These factors are described in detail later in this chapter.

Table 2: Sample of data about JSI taken from Bloomberg

JSI member	NAICS	Industry	Total assets (in Million CAD)
Canadian Pacific	482111	Line-Haul Railroads	9956.70
Canfor Corp.	113310	Logging	2447.30
Magna Intl.	336211	Motor Vehicle Body Manufacturing	12788.68
Manitoba Telecom	517110	Wired Telecommunications Carriers	1683.00
Precision Drill	213111	Drilling Oil and Gas Wells	2908.39

Table 3: Sample of North American Fama-French factors

Month	SMB	HML	WML	RMW	CMA
August 2015	0.56%	2.92%	-2.15%	0.05%	0.83%
September 2015	-2.87%	0.63%	3.34%	0.81%	-0.34%
October 2015	-2.03%	0.63%	-2.95%	0.13%	0.12%
November 2015	2.12%	-0.95%	2.39%	-1.82%	-0.65%
December 2015	-3.02%	-2.17%	3.02%	-0.63%	0.47%

3.2 Creating Matched Portfolios

As discussed earlier, comparing JSI with conventional indices like S&P/TSX Composite may not produce valid results due to the differences in characteristics such as risk profile, industry, composition, and size. As a result, we create a SR portfolio consisting of companies included in JSI, using the same weights they carry in JSI. To have a better benchmark for this portfolio, we create two hypothetical conventional portfolios from conventional companies that match the industry and size of companies in our SR portfolio with exactly the same weights. To match for industry, we use the North American Industry Classification System (NAICS) codes. These 6-digit codes categorize businesses based on their type of economic activity (Bloomberg, 2017). To match for size, we use the total assets of companies. *Total assets*, which is the sum of a company's liabilities and its shareholder's equity, is commonly used as the proxy for size (Bodie et al., 2014).

For each company in our SR portfolio, we identify all conventional companies that are in the same industry, based on their 6-digit NAICS codes, from companies listed in TSX. In cases when we could not find a conventional company with the same 6-digit code, we define "the same industry" by matching 5-digit (or, in some cases, 4-digit, 3-digit, or 2-digit) codes. We then rank these conventional companies by comparing their sizes to the sizes of our SR companies, from closest to furthest, and select the three top-ranked companies. Our best-matched portfolio (labeled as C1) consists of all companies that rank first. Our second matched portfolio (labeled as C2) consists of 60 hypothetical members. Each of these members is assumed to have total return equal to the average total return of the three top matches.

To begin the matching process, we construct the matched portfolios for March 2003, the first month of our study. For the following months, we update these portfolios to match the updates by Sustainalytics. As mentioned, Sustainalytics reviews JSI yearly in March. There is also a possibility that JSI members change during other months of the year. Between March 2003 and December 2015, the last month of our study period, there are a total of 38 months in which JSI members have been updated. These months are shown in Table 4.

Table 4: Months with change/changes in the constituents of JSI

Year	Month (Number of changes)
2003	July (1)
2004	March (1), October (1), November (1)
2005	May (1), June (1), July (1), October (1), November (1)
2006	February (1), March (2), June (1), August (1)
2007	March (2), May (1), October (1), November (1), December (1)
2008	February (1), April (1)
2009	January (1), July (1), August (1)
2010	May (1)
2011	October (1)
2012	February (1), March (1), September (1), October (5)
2013	February (1), March (5), April (1), November (1)
2014	March (1), April (1), December (1)
2015	March (4), May (1)

To clarify our matching process, let us begin with the first month of our study period, March 2003. To find the matches for this month, we find three companies closest to JSI members in terms of NAICS code and total assets. As mentioned, these companies are picked from TSX. We use these companies to form C1 and C2 for March 2003.

For the months of April 2003, May 2003, and June 2003, there is no need to update the matched portfolios since no change in the members of JSI occurred during these months.

The first change occurred in July 2003 when "Shoppers Drug Mart Corporation" replaced "Dupont Canada Incorporation" in the index. In this month, we make the same replacement in our SR portfolio and change our matched portfolios, accordingly, by finding three new companies for the newly added member. We then substitute the new member of JSI and matches for the previous member and matches. The matched companies for other members of JSI in this month remain untouched. We continue this process until the last month of the study period, December 2015. The results of this process are two matched portfolios, C1 and C2, each including 60 members that are updated over time.[11] As a sample, the members of our SR portfolio and the members of C1 in March 2003 can be seen in the Appendix A. The process of finding the matched portfolios is programmed in Python programming language. This program can be seen in the Appendix B. Here is the pseudocode for this program:

- Read the data of JSI and TSX members including tickers, NAICS codes, and total assets.[12]
- For each member of JSI, find those members of TSX that have the same NAICS code as the JSI member. Save them in a list and denote it Group 1.
- For each member of JSI, find those members of TSX that have the same first five-digits NAICS code as the JSI member. Save them in a list and denote it Group 2.
- For each member of JSI, find those members of TSX that have the same first four-digits

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[11] The number of constituents of JSI was 60 prior to March 2016. In this month, Sustainalytics changed the number of JSI members from 60 to 50. Since our study period ends in December 2015, our SR portfolio which is based on the members of JSI, has 60 members.
[12] *Ticker* is a combination of letters and numbers that represents a specific security listed on a stock exchange.

NAICS code as the JSI member. Save them in a list and denote it Group 3.

- For each member of JSI, find those members of TSX that have the same first three-digits NAICS code as the JSI member. Save them in a list and denote it Group 4.

- For each member of JSI, find those members of TSX that have the same first two-digits NAICS code as the JSI member. Save them in a list and denote it Group 5.

- For each member of JSI, in each of these five groups, find those members that are also a member of JSI and remove them from that group.[13]

- For each member of JSI, sort the members of each group based on the closeness of their total assets to that of the JSI member ('closeness' means the absolute value of the difference).

- For each member of JSI, combine the five groups into one list. The members of Group 1 are the first, and the members of Group 5 are the last in this list.

- For each member of JSI, pick the first three members from this list. These companies are the three matches for the JSI member.

- Construct C1 and C2 based on these matched companies.

3.3 Comparing the Performance of our SR and Matched Portfolios

After finding the matched portfolios, we compare them with our SR portfolio based on several measures. We begin with total return.

[13] Because we do not want any member of JSI to be a member of the matched portfolios.

3.3.1 Total Return

To assess performance of our SR and matched portfolios, we first compare their total returns. *Total return* is the amount of gain or loss on an investment over a period of time. Total return is mainly calculated on a daily, weekly, monthly, quarterly, or yearly basis (Bodie et al., 2014). In this study, our calculations are monthly. Total return of equity i in month t ($R_{i,t}$) can be calculated by Equation 3.1.

$$R_{i,t} = \frac{P_{i,t} - P_{i,(t-1)} + D_{i,t}}{P_{i,(t-1)}} \qquad 3.1$$

In this equation, $P_{i,t}$ is the price of equity i at the end of month t, $P_{i,(t-1)}$ is the price of equity i at the start of month t, and $D_{i,t}$ stands for the dividends paid for equity i in month t. *Dividends* is a part of the earnings of an equity commonly paid to the shareholders on a quarterly basis (Bodie et al., 2014). The total return of a portfolio is equal to the weighted average of the returns of its constituents as shown in Equation 3.2.

$$R_{p,t} = w_{1,t}R_{1,t} + w_{2,t}R_{2,t} + \cdots + w_{n,t}R_{n,t} \qquad 3.2$$

In this equation, $R_{p,t}$ is the return of the portfolio in month t, $R_{i,t}$ is the return of the i^{th} member of the portfolio in month t, $w_{i,t}$ is the weight of the i^{th} member in the portfolio in month t, and n is the number of the members in the portfolio. Weights of JSI constituents in each month are used for our SR and matched portfolios in these calculations. By using Equation 3.2, we can find the total return of our SR and matched portfolios for each month between March 2003 and December 2015.

3.3.2 Total Risk, Sharpe Ratio, and M^2 Measure

In comparing two portfolios, it can be concluded that the one with higher total return outperforms the one with lower total return only if they have the same level of risk. As a result, by merely looking at the total return of our SR and matched portfolios we are not able to draw a conclusion regarding their relative performances. One very common measure of risk used in financial markets is the total risk, measured by the standard deviation of returns.

We can compare the performance of two portfolios by simultaneously looking at their total returns and total risks. However, there are some cases in which we cannot draw a valid conclusion simply based on these two measures. For example, assume that portfolio A has both higher total return and higher total risk compared to portfolio B. In this case, although portfolio A has higher total return, since its total risk is also higher, we cannot claim that portfolio A outperforms portfolio B. To compare the performance of these two portfolios, we must adjust their total returns for their total risks. Sharpe ratio and M^2 measure are two risk-adjusted return measures used for this purpose (Bodie et al., 2014).

Sharpe ratio shows the excess return that an investor can gain per each unit of total risk. Between two portfolios, the one with higher Sharpe ratio outperforms the portfolio with lower Sharpe ratio. Sharpe ratio is calculated by Equation 3.3.

$$S_p = \frac{R_p - R_f}{\sigma_p} \tag{3.3}$$

In this equation, S_p is the Sharpe ratio of a portfolio for a period, R_p is the return of the portfolio in that period, R_f is the risk-free rate of return in that period, and σ_p is the total risk of the portfolio in that period. The *risk-free rate of return* is the return on an investment that has no risk. Treasury bills are commonly used as risk-free investments (Bodie et al., 2014).

We can compare the Sharpe ratio of our SR and matched portfolios for the period of March 2003 to December 2015. To do that, we measure the average return and standard deviation of the portfolios, as well as the average risk-free rate for the period of study. Alternatively, we can measure the Sharpe ratio of each portfolio in each month using monthly portfolio returns, risk-free rate, and standard deviation. The monthly standard deviation can be calculated by Equation 3.4.

$$\sigma_{p,t}^2 = \sum_{i=1}^{n} w_{i,t}\left(R_{i,t} - R_{p,t}\right)^2 \qquad 3.4$$

In this equation, $\sigma_{p,t}$ is the volatility of the return distribution of a portfolio in month t, $w_{i,t}$ is the weight of the i^{th} member of the portfolio in month t, $R_{i,t}$ is the return of the i^{th} member of the portfolio in month t, $R_{p,t}$ is the return of the portfolio in month t, and n is the number of constituents of the portfolio.

M^2 measure is another risk-adjusted return measure that adjusts the return of a portfolio for its total risk. To calculate this measure for a portfolio, we must combine the portfolio with a risk-free investment in a way that makes the total risk of the portfolio equal to the total risk of the market (Bodie et al., 2014). For instance, assume that the total risk of a portfolio is m% and the total risk of the market is n%. By investing "(n ÷ m) %" in that

portfolio, and the rest in a risk-free investment, a new portfolio that has the same total risk as the market is created.[14] In case market has higher total risk compared to the portfolio (n>m), we borrow in risk-free rate and invest in the portfolio. After this combination, we can calculate the M^2 measure with Equation 3.5 (Bodie et al., 2014).

$$M_p^2 = R_{p_*} - R_m \qquad 3.5$$

In this equation, R_{p*} is the return of the combined portfolio, and R_m is the average return of the market in our study period. The return of a major index is commonly used as the proxy for the return of the market. For example, for Canada the return of the S&P/TSX Composite index is considered the return of the market. The return of the combined portfolio (R_{p*}) is the weighted average of the average return of the original portfolio and the average return of the risk-free investment in our study period (Bodie et al., 2014). Between two portfolios, the one with higher M^2 measure outperforms the other. Both Sharpe ratio and M^2 measure adjust the return of a portfolio for its total risk; the difference is that they use different approaches. As a result, comparing two portfolios based on these two measures leads to the same outcome (Bodie et al., 2014). For example, if portfolio A has higher Sharpe ratio compared to portfolio B, it will also have higher M^2 measure.

[14] If equity 1 has a total risk of σ_1, and equity 2 has a total risk of σ_2, the total risk of the combination of these two equities is equal to the square root of "$w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2\sigma_1\sigma_2 cov(R_1, R_2)$", in which "w" refers to weight, and "R" refers to return.

3.3.3 Downside Risk and Sortino Ratio

Although total risk is a very common measure of risk in financial markets, some investors and academics argue that it is not the best representative of the risk to a company or a portfolio (Ang, Chen, and Xing, 2006). Standard deviation treats both upside volatility and downside volatility equally. However, while deviation of returns towards negative amounts is unfavorable for investors, any deviation on the positive side is advantageous to investors. As a result, some investors and academics use downside risk as the proxy for risk. One very common measure for downside risk is the downside deviation. This measure is calculated as the standard deviation of those returns below a specific level. This level can be the mean, the risk-free rate of return, or zero (Ang et al., 2006).

Two portfolios can be compared based on their total return and downside risk. However, as mentioned, in some cases, we cannot make a valid decision unless we adjust the total return for the level of risk. *Sortino ratio* is a risk-adjusted measure of return used for this purpose and can be calculated for a portfolio using Equation 3.6 (Ang et al., 2006).

$$ST_p = \frac{R_p - R_f}{\sigma_d} \qquad 3.6$$

In this equation, R_p is the mean return of the portfolio, R_f is the mean return of the risk-free investment, and σ_d is the downside deviation of the portfolio. Between two portfolios, the one with higher Sortino ratio outperforms the portfolio with lower Sortino ratio.

3.3.4 Market Risk, Treynor Ratio, and T^2 Measure

Both total risk and downside deviation are volatility-based measures of risk. The volatility of returns is the result of the exposure to two different types of risk, unsystematic and systematic (Bodie et al., 2014). Unsystematic risk can be significantly reduced through diversification, while diversification cannot eliminate the systematic risk. As a result, the major part of the risk of a diversified portfolio is due to systematic risk, which is commonly referred to as market risk. *Market risk*, surrogated by beta, measures the sensitivity of the return of a company or a portfolio to the return of the market (Bodie et al., 2014). Examples of this type of risk include recessions, changes in interest rates, and natural disasters. Beta is the slope of a regression line, where the dependent variable is the return (or the excess return) of a company or a portfolio, and the independent variable is the return (or the excess return) of the market (Bodie et al., 2014).

We can compare the beta of our SR and matched portfolios for the period of March 2003 to December 2015. To do that, we regress the monthly excess return of the portfolios on the monthly excess returns of the market. Alternatively, we can compare the portfolios based on their monthly betas. The portfolio beta is measured as the weighted average of the betas of its members as shown in Equation 3.7.

$$\beta_{p,t} = w_{1,t}\beta_{1,t} + w_{2,t}\beta_{2,t} + \cdots + w_{n,t}\beta_{n,t} \qquad 3.7$$

In this equation $\beta_{p,t}$ is the beta of a portfolio in month t, $\beta_{i,t}$ is the beta of the i^{th} member of the portfolio in month t, $w_{i,t}$ is the weight of the i^{th} member of the portfolio in month t, and n is the number of constituents of the portfolio. The regression that is used to measure each company's beta in each month utilizes prior 60 month of return data up to each month.

The higher the beta, the more sensitive the return of the portfolio to fluctuations of the market. As a result, higher beta indicates higher level of risk (Bodie et al., 2014). The beta of the market is equal to 1. If a portfolio has a beta of 1, its return moves in line with the return of the market. A beta less than 1 shows that the return of the portfolio is less volatile compared to the return of the market, and a beta more than 1 indicates that the return of the portfolio is more volatile in comparison to the return of the market. In case beta is equal to 0, the return of the portfolio does not have any sensitivity to the return of the market. If beta is negative, the return of the portfolio has negative correlation with the return of the market (Bodie et al., 2014).

The performance of two portfolios can be compared based on their total returns and betas. However, as mentioned, we might need to adjust the total returns for their associated betas. Treynor ratio and T^2 measure are used for this purpose.

Treynor ratio is a risk-adjusted return measure that shows the excess return an investor can gain per unit of market risk (Bodie et al., 2014). Between two portfolios, the one with the higher Treynor ratio outperforms the other. Treynor ratio for a portfolio can be calculated by Equation 3.8.

$$T_p = \frac{R_p - R_f}{\beta_p} \quad 3.8$$

In this equation, R_p is the average return of the portfolio in the study period, R_f is the average risk-free rate of return in the study period, and β_p is the beta of the portfolio in the study period (Bodie et al., 2014). Alternatively, we can compare the Treynor ratio of our SR and matched portfolios on a monthly basis. In this case, the variables in Equation 3.8 must be monthly.

T^2 measure is another risk-adjusted return measure that adjusts the return of a portfolio for its market risk (Bodie et al., 2014). The process of calculating T^2 is similar to that of M^2 with only one difference. To calculate T^2, instead of total risk, we make the beta of the portfolio equal to the beta of the market, which is equal to 1. T^2 measure can be calculated using Equation 3.9 (Bodie et al., 2014).

$$T_p^2 = R_{p_*} - R_m \qquad 3.9$$

In this equation, R_m is the mean return of the market in our study period, and R_{p*} is the return of the combined portfolio, which is equal to the weighted average of the mean return of the original portfolio and the mean return of the risk-free investment in our study period. Between two portfolios, the one with higher T^2 measure outperforms the other. Since both Treynor ratio and T^2 measure adjust the return of a portfolio for the market risk, comparing two portfolios based on these two measures leads to the same outcome (Bodie et al., 2014). For example, if portfolio A has higher Treynor ratio compared to portfolio B, it will also have higher T^2 measure.

3.3.5 Abnormal Return

Another way to compare the performance of our SR portfolio with matched portfolios is to compare them against a benchmark and calculate their abnormal returns. *Abnormal return* is any return in excess of the benchmark and is calculated as the intercept of a regression based on an asset pricing model (Bodie et al., 2014). CAPM and Fama-French are two models we use to calculate the abnormal return. Between two portfolios, the one with higher abnormal return outperforms the other.

CAPM is one of the major asset pricing models used in financial markets. Based on CAPM, the expected return of an equity has a linear relationship with the excess return of the market (Bodie et al., 2014). CAPM equation can be seen in Equation 3.10.

$$R_i - R_f = \beta_i \left(R_m - R_f\right) \tag{3.10}$$

In this equation, R_i is the expected return of equity i, R_f is the risk-free rate of return, R_m is the expected return of the market, and β_i is the beta of equity i. The intercept of a regression based on CAPM is the abnormal return of a company or a portfolio. The CAPM regression can be seen in Equation 3.11 (Bodie et al., 2014).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - R_{f,t}\right) + \varepsilon_{i,t} \tag{3.11}$$

In this equation, $R_{i,t}$ is the return of equity i in month t, $R_{m,t}$ is the return of the market in month t, $R_{f,t}$ is the risk-free rate of return in month t, $\varepsilon_{i,t}$ is the residual return of equity i in month t, β_i is the beta of equity i, and α_i is the abnormal return of equity i, also referred to as CAPM alpha. In running these regressions for both our SR and matched portfolios we assume S&P/TSX Composite Index to be the market. Moreover, we use the rate of return on Canadian Treasury bills as the risk-free return.

Fama-French is another asset-pricing model. As mentioned, based on CAPM, market premium is the only risk factor that affects the return of equities. However, based on Fama-French, other factors also affect the returns. Fama-French has three variations: the three-factor, the four-factor, and the five-factor version (French, 2017).

The factors included in the three-factor version are market premium, size factor, and value factor (French, 2017). In this model, the size factor is represented by SMB, and the value factor is represented by HML. SMB stands for "Small Minus Big" also called the size premium. Prices of companies tend to appreciate faster in smaller companies compared to larger ones. By implication, an investor can beat the market by investing heavily in companies with small market capitalization. By including a measure that captures the difference in returns on companies with small market capitalization and those with large market capitalization, the Fama-French model attempts to control for this effect. SMB is the average return on three portfolios of small companies minus the average return on three portfolios of large companies (French, 2017). The other factor, HML stands for "High Minus Low." High and low refer to the ratio of stock price to book value. Book value is the difference between the company's assets and liabilities. A low price-to-book ratio suggests that the stock is undervalued and that its price might increase in the future. By including a measure that captures the difference in returns on companies with high price-to-book ratio and those with low price-to-book ratio, the

Fama-French model attempts to control for this effect. HML is the average return on two value portfolios minus the average return on two growth portfolios (French, 2017).[15] The Fama-French three-factor model can be seen in Equation 3.12.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i(SMB_t) + h_i(HML_t) + \varepsilon_{i,t} \qquad 3.12$$

In this equation, $R_{i,t}$ is the return of equity i in month t, $R_{f,t}$ is the risk-free rate of return in month t, $R_{m,t}$ is the return of the market in month t, SMB_t is the SMB in month t, HML_t is the HML in month t, $\varepsilon_{i,t}$ is the residual return of equity i in month t, β_i is the beta of equity i, s_i is the sensitivity of the return of equity i to SMB, h_i is the sensitivity of the return of equity i to HML, and α_i is the abnormal return of equity i which is also referred to as Fama-French three-factor alpha (French, 2017).

The Fama-French four-factor model, also known as the Carhart model, adds an additional factor to the three-factor model, namely momentum shown by WML (Winners Minus Losers) (French, 2017). Momentum is the tendency for a stock to continue moving in the direction it moved last period. The momentum factor is calculated by subtracting the return of an equally weighted average of highest performing companies from the return of an equally weighted average of the lowest performing ones, lagged by one month (French, 2017). This model can be seen in Equation 3.13.

[15] A value portfolio consists of value stocks, and a growth portfolio consists of growth stocks. A *value stock* is a stock that tends to trade at a lower price compared to what its fundamentals indicate. A *growth stock* is a stock whose earnings are expected to grow at an above-average rate (Bodie et al., 2014).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i(SMB_t) + h_i(HML_t) + w_i(WML_t) + \varepsilon_{i,t} \quad 3.13$$

In this equation WML_t refers to the momentum in month t, w_i is the sensitivity of the return of equity i to WML, and α_i is the abnormal return of equity i which is also referred to as Fama-French four-factor (Carhart) alpha (French, 2017).

The Fama-French five-factor model adds two factors to the three-factor version, the "operating profitability" and the "investment" factors (French, 2017). In this model, operating profitability is represented by RMW (Robust Minus Weak) and investment factor by CMA (Conservative Minus Aggressive). By implication, higher expected earnings imply higher expected return, which is the idea behind adding the RMW factor. Moreover, higher expected growth in shareholder's equity implies a lower expected return, which is the idea behind adding the CMA factor (French, 2017). RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios.[16] CMA is the average return on two conservative investment portfolios minus the average return on two aggressive investment portfolios (French, 2017).[17] The Fama-French five-factor model can be seen in Equation 3.14.

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[16] A robust operating profitability portfolio consists of stocks that create profit irrespective of the market condition, and a weak operating profitability portfolio consists of stocks with weak ability in creating profit (French, 2017).

[17] A conservative portfolio mainly consists of lower risk securities such as bonds and cash, while an aggressive portfolio consists of higher risk securities such as stocks (French, 2017).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i(SMB_t) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + \varepsilon_{i,t} \qquad 3.14$$

In this equation, RMW_t is the RMW in month t, CMA_t is the CMA in month t, r_i is the sensitivity of the return of equity i to RMW, c_i is the sensitivity of the return of equity i to CMA, and α_i is the abnormal return of equity i which is also referred to as Fama-French five-factor alpha (French, 2017).

3.3.6 Unsystematic Risk, Information Ratio, and Market Timing

As mentioned, a portfolio faces two major types of risk, systematic and unsystematic. Systematic or market risk cannot be eliminated through diversification. However, unsystematic or firm-specific risk can be eliminated through diversification. Unsystematic risk is associated with individual companies in a portfolio (Bodie et al., 2014). For example, the risk associated with the change in the management of a company is an unsystematic risk because it is related to a specific company and not to the swings of the market. The more diversified a portfolio is, the less unsystematic risk it has. Although, logically, it is better to have less unsystematic risk, active portfolio managers are willing to bear some unsystematic risk with the expectation of beating the market (Bodie et al., 2014). For example, depending on the condition of the market, an active portfolio manager may overinvest in a specific industry. This overinvestment can make the portfolio less diversified, which, in turn, increases its level of unsystematic risk. However, the expectation of the active portfolio manager is that the return which can be gained from this overinvestment is worth increasing the firm-specific risk (Bodie et al., 2014). Unsystematic risk can be calculated as the variance of residual returns.

To compare the ability of active portfolio managers, investors and academics calculate a risk-adjusted return measure called information ratio. *Information ratio* shows the return of a portfolio in excess of the return of the market per each unit of the standard deviation of residual returns (Bodie et al., 2014). Information ratio for a portfolio can be calculated by Equation 3.15.

$$I_p = \frac{\alpha_p}{\sigma(\varepsilon_p)} \qquad 3.15$$

In this equation, α_p is the abnormal return of the portfolio, and $\sigma(\varepsilon_p)$ is the standard deviation of residual returns. Between two portfolios, the one with higher information ratio has a superior portfolio manager (Bodie et al., 2014).

We can also compare the market timing ability of the hypothetical portfolio managers of our SR and matched portfolios. *Market timing* is the act of moving in and out of the market, or switching between asset classes by predicting the future direction of the market (Bodie et al., 2014). To find the market timing ability, one method is to add the square of the excess return of the market to the CAPM regression. If the coefficient of this factor is significantly positive, we can conclude that the portfolio manager has market timing ability (Bodie et al., 2014). This regression can be seen in Equation 3.16.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - R_{f,t}\right) + k_i \left(R_{m,t} - R_{f,t}\right)^2 + \varepsilon_{i,t} \qquad 3.16$$

In this equation, k_i is the coefficient that we need to check its sign and statistical significance. The rest of the variables are similar to the ones in the CAPM regression.

3.3.7 Tobin's Q and Leverage

In the previous sections, we described how to compare the performance of our SR and matched portfolios based on several measures. In other words, we showed how to investigate whether SRI creates a superior risk/return performance compared to conventional investments. We can also check whether SRI has a superior ability in creating value. Creating value refers to the increase in the stock prices of the members of a portfolio. To analyze the value creation ability of SRI, we compare the Tobin's Q of our SR and matched portfolios.

Tobin's Q or *Q ratio* is the ratio of the market value of a company to the replacement cost of that company. It is based on the hypothesis that in the long run, the market value of a company should roughly be equal to the cost of replacing the company's assets (Bloomberg, 2017). The market value of a company is estimated by its market capitalization plus the market value of debt. The *replacement cost* of a company is the cost of replacing all the assets of that company. Replacement cost is commonly estimated using total assets (Bloomberg, 2017). Tobin's Q of company i in month t ($T_{i,t}$) can be calculated by Equation 3.17.

$$T_{i,t} = \frac{MC_{i,t} + TL_{i,t}}{TA_{i,t}} \qquad 3.17$$

In this equation, $MC_{i,t}$ is the market capitalization of company i in month t, $TL_{i,t}$ is the total liabilities of company i in month t, and $TA_{i,t}$ is the total assets of company i in month t (Bloomberg, 2017). One way to find the monthly Tobin's Q for our SR and matched portfolios is to calculate the equally weighted average of the Tobin's Q of their constituents in each month.

A portfolio that has a higher Tobin's Q has a higher valuation compared to a portfolio with a lower Q ratio. By comparing the Tobin's Q of our SR and matched portfolios, we can determine whether SRI creates value in a portfolio. We must also be aware that other factors such as leverage ratio can affect the value of companies. As a result, we also compare the leverage ratio of our SR and matched portfolios.

Leverage ratio is a measure that compares the amount of debt of a company to its equity or assets. The leverage ratio of company i in month t ($L_{i,t}$) is calculated by Equation 3.18 (Bloomberg, 2017).

$$L_{i,t} = \frac{TD_{i,t}}{TA_{i,t}} * 100 \qquad 3.18$$

In this equation, $TD_{i,t}$ is the total debt of equity i in month t, and $TA_{i,t}$ is the total assets of equity i in month t. One way to find the monthly leverage for our SR and matched portfolios is to calculate the equally weighted average of the monthly leverage of their constituents.

There are several theories on the effects of leverage on the value of a company. In their initial study on capital structure, Modigliani and Miller argue that leverage increases the expected return, and at the same time increases the risk, leaving the value of the company unchanged. As a result, they state that the percentage of debt in the capital structure of a company does not have any effect on its value (Brealey et al., 1992). This theory is very simplistic and does not include other factors such as corporate income tax. Under the corporate income tax system in most countries, at the corporate level, the interest paid to debtholders is tax exempt. As a result, corporations transfer part of their interest expenses to the government. By including corporate income tax to their initial theory, Modigliani and Miller illustrated that an increase in the leverage ratio creates value. Their model implies that there is no limit to this value creation. This, in turn, implies that companies are best to operate with 100% debt level. Again, this modified theory is not completely realistic due to the fact that there is a positive correlation between leverage ratio and bankruptcy cost. As a result, although up to a level, the increase in leverage ratio increases the value of a company, beyond that level, it has negative effects on the valuation since the bankruptcy cost becomes significant. This level differs for different industries (Brealey et al., 1992).

3.4 Event Study

Any result we achieve from comparing the performance of our SR and matched portfolios could potentially be an artifact of the time period, the models used, or the data set. To test for this possibility, we perform an event study on the companies that enter or exit JSI to investigate the response of the market to SRI.

Event study is a statistical method used to investigate the effects of an event on the return of a company (Bodie et al., 2014). We perform an event study to find out how the inclusion in or exclusion from JSI can affect the return of companies. Based on the efficient market hypothesis, the price of a company share at any point in time represents all the information related to that company. This price can only change if new information about that company becomes available to the market. New information can be the result of an event (Bodie et al., 2014). In this research, the events that may affect the return of JSI members are the inclusion in or exclusion from JSI. We deal with these two events separately.

The main step in an event study is to find the difference between the actual return of a company and the return predicted by an asset pricing model. The asset pricing model that we use here is the Market model, which states that the return of an equity has a linear relationship with the return of the market. The Market model can be seen in Equation 3.19 (Bodie et al., 2014).

$$R_{i,t} = a_i + b_i R_{m,t} + \varepsilon_{i,t} \tag{3.19}$$

In this equation, $R_{i,t}$ is the return of equity i in month t, $R_{m,t}$ is the return of the market in month t, b_i is the sensitivity of the return of equity i to the return of the market, a_i is the intercept, and $\varepsilon_{i,t}$ is the residual return of equity i in month t.

In every event study, we are faced with three periods: event window, estimation window, and post-event window (Bodie et al., 2014). *Event window* is a period that includes the event day and some days before and after it. In this research, we assume 20 days before and 20 days after the event day to form the event window. *Estimation window* is the period based on which we find 'a_i' and 'b_i' in Equation 3.19. We assume a period of 36 months prior to the start of the event window to be the estimation window. Estimation window and event window should remain separate from each other to ensure that the estimations of 'a_i' and 'b_i' are not influenced by the data in the event period. *Post-event window* is the period after the last day of the event window used to investigate the post-event effects of an event on the return of a company (Bodie et al., 2014).

To perform the event study, first we find the coefficients of the Market model, 'a_i' and 'b_i' for each included and excluded member of JSI (Bodie et al., 2014). To find these coefficients, we form the estimation window and event window based on the event dates. These event dates denote when new members of JSI were included or past members of JSI excluded. Next, we run a regression for each included and excluded member based on the Market model. Since JSI members are Canadian companies, we assume the S&P/TSX Composite Index to be the market. After finding the coefficients, we calculate the abnormal return of the included and excluded members of JSI for each day of their event windows based on Equation 3.20 (Bodie et al., 2014).

$$AR_{i,t} = R_{i,t} - (a_i + b_i R_{m,t}) \qquad t = -20, -19, \dots, 0, \dots, 19, 20 \qquad 3.20$$

In this equation, $AR_{i,t}$ is the abnormal return of company i in day t, $R_{i,t}$ is the actual return of company i in day t, $R_{m,t}$ is the return of the Market in day t, and a_i and b_i are the coefficients of the Market model for company i. If the event affects the company in a positive way, the abnormal returns should be positive and significant. If it doesn't have any effect on the company, the abnormal returns should not differ from zero. If the event affects the company in a negative way, the abnormal returns should be negative and significant (Bodie et al., 2014).

Event studies have two main difficulties. One is to determine if the changes in the stock returns are just the result of the particular event we are studying or if other factors have also affected the returns. In any period of time, there may be several news and events that affect the return of a company. Separating and categorizing these to capture the effects of a specific event we are analyzing is almost impossible (Bodie at al., 2014). To simplify our event study, we assume that the only event that affects the return of companies in the event period is the inclusion in or exclusion from JSI. Another difficulty in event studies is due to information leakage, which happens when new information becomes available to some investors prior to the event day. Information leakage causes stock prices to change before the whole market becomes aware of the information. As a result, an abnormal return on the event day may not reflect the whole effect of the event on the return of the company. One way to capture effects of information leakage is to calculate abnormal returns not only for the event day, but also for some days prior to that (Bodie et al., 2014). In this event study, we capture the effects of information leakage by calculating abnormal returns up to 20 days prior to the event day.

In order to draw overall inferences, abnormal returns must be aggregated over time. In other words, we must calculate the cumulative abnormal return (CAR). CAR is equal to sum of the abnormal returns from the first day of the event window to the day that we want to find the CAR. CAR of company i in day T in the event window can be calculated by Equation 3.21 (Bodie et al., 2014).

$$CAR_{i,T} = \sum_{t=-20}^{T} AR_{i,t} \tag{3.21}$$

In this equation, $AR_{i,t}$ is the abnormal return of company i in day t, and T is the day in the event window for which we want to calculate the CAR. In order to eliminate idiosyncrasies in measurement, AR and CAR are averaged across companies. The results are average abnormal return (AAR) and cumulative average abnormal return (CAAR). By analyzing the movements and statistical significance of AAR and CAAR in the event window, we can investigate how the returns of a group of companies are affected by a particular event (Mackinlay, 1997).

CHAPTER 4 – Conclusion

4.1 Results

In Chapter 3 we explained the process of creating two portfolios matched to our SR portfolio. We also described how to compare our SR and matched portfolios based on different measures. Moreover, we showed how to perform an event study for the companies included in or excluded from JSI. Results are summarized in Tables 5, 6, and 7.

Table 5 shows the summary of results for the measures we use in comparing our SR and matched portfolios. In each row, we see a different measure. The magnitude of each measure is shown for our SR and matched portfolios. In rows 1, 3, 5, 12, 14, 23, and 24, the results of a paired t-test (t-statistic) are shown in parenthesis, and in rows 2, 7, 8, 9, and 20, the results of a F-test (F-statistic) are shown in parenthesis. In rows 16, 17, 18, and 19, the results of a pooled regression with a dummy variable are shown in parenthesis, the first number being the coefficient of the dummy variable, and the second being its t-statistic.[18] In row 10, the results of the Sortino ratio can be seen for different types of downside deviation (first number: mean as the level, second number: risk-free rate as the level, third number: zero as the level). In row 22, the numbers in parentheses are the p-values used to test the significance of market timing ability of portfolio

[18] Information regarding pooled regression with dummy variable is available in Section 4.2.5.

managers. In rows 1, 3, 5, 23, and 24, the degrees of freedom are equal to 153. In rows 12 and 14, the degrees of freedom are equal to 141. In rows 2, 7, 8, 9, and 20, the degrees of freedom for numerator are equal to 153, and the degrees of freedom for denominator are equal to 153. In rows 16, 17, 18, and 19, the degrees of freedom are equal to 304, 300, 298, and 296 respectively. In Table 6, the summary of results for our event study can be seen. In this table, "I" stands for inclusions, and "E" stands for exclusions. In each cell, the first row belongs to AAR and the second row belongs to CAAR. Numbers in parentheses show the t-statistics used to judge whether or not the AAR or CAAR is significantly different from zero. In this table, the degrees of freedom are equal to 50. In both Table 5 and Table 6, those t-statistics, F-statistics, and p-values that are significant are shown with ***, **, and * for 1%, 5%, and 10% level of significance, respectively. In Table 7, those critical t-values and F-values that we need for our statistical tests are shown.

Table 5: Summary of results for the measures of performance[19]

	Portfolio	SR	C1	C2
1	Total return (monthly)	1.272%	0.711% (2.62) ***	0.781% (2.92) ***
2	Total risk	3.753%	3.781% (0.99)	3.368% (1.24) *
3	Total risk (monthly)	6.689%	8.552% (-6.20) ***	5.376% (5.94) ***
4	Sharpe ratio	0.300	0.149	0.188
5	Sharpe ratio (monthly)	0.178	0.059 (3.97) ***	0.101 (2.52) ***
6	M^2 measure	0.537%	-0.028%	0.118%
7	Downside deviation (level=mean)	2.077%	2.206% (0.89)	1.986% (1.09)
8	Downside deviation (level=risk free)	2.031%	2.190% (0.86)	1.960% (1.07)
9	Downside deviation (level=zero)	2.030%	2.190% (0.86)	1.959% (1.07)
10	Sortino ratio	0.542 0.554 0.554	0.256 0.258 0.258	0.319 0.323 0.324
11	Beta	0.948	0.789	0.784
12	Beta (monthly)	0.840	0.910 (-0.47)	0.800 (0.54)
13	Treynor ratio	1.187	0.715	0.808
14	Treynor ratio (monthly)	1.249	0.604 (2.87) ***	0.674 (1.97) **

[19] In this table, ***, **, and * show statistical significance at 1%, 5%, and 10% levels, respectively. AR stands for abnormal return, FF3 stands for Fama-French three-factor model, FF4 stands for Fama-French four-factor model, and FF5 stands for Fama-French five-factor model. If the term "monthly" is seen under a measure, it is calculated on a monthly basis, and is represented by its mean value. Otherwise, the measure is calculated as one number for the whole period of study.

	Portfolio	SR	C1	C2
15	T^2 measure	0.598%	0.126%	0.220%
16	AR CAPM	0.567%	0.100% (0.561, 2.61) ***	0.172% (0.492, 2.96) ***
17	AR FF3	0.572%	0.101% (0.561, 2.61) ***	0.163% (0.492, 2.96) ***
18	AR FF4	0.581%	0.088% (0.561, 2.61) ***	0.161% (0.492, 2.96) ***
19	AR FF5	0.597%	0.051% (0.561, 2.61) ***	0.143% (0.492, 2.96) ***
20	Unsystematic risk	1.425	5.556 (0.26) ***	2.657 (0.54) ***
21	Information ratio	0.478	0.043	0.106
22	Market timing	0.010 (0.003) ***	0.008 (0.220)	0.003 (0.516)
23	Tobin’s Q (monthly)	1.519	1.363 (26.01) ***	1.384 (20.51) ***
24	Leverage (monthly)	22.516%	21.530% (11.57) ***	19.684% (32.06) ***

Table 6: Summary of results for our event study

Day	AAR & CAAR (I)	AAR & CAAR (E)	Day	AAR & CAAR (I)	AAR & CAAR (E)
-20	0.027 (0.15) 0.027 (0.15)	-0.700 (-1.48) -0.576 (-1.34)	+1	-0.639 (-1.60) -1.705 (-1.37)	-0.220 (-0.49) -3.512 (-2.04) **
-19	0.165 (0.71) 0.193 (0.57)	0.120 (0.32) -0.459 (-0.71)	+2	0.096 (0.28) -1.609 (-1.16)	0.353 (1.17) -3.263 (-1.96) *
-18	0.212 (0.88) 0.396 (0.94)	0.751 (0.85) 0.292 (0.55)	+3	0.566 (1.84) * -1.043 (-0.75)	-0.146 (-0.59) -3.357 (-1.89) *
-17	0.249 (0.96) 0.645 (1.36)	-0.599 (-0.74) -0.272 (-0.25)	+4	0.562 (2.27) ** -0.526 (-0.37)	0.297 (0.65) -3.183 (-2.04) **
-16	-0.066 (-0.27) 0.582 (1.01)	-1.028 (-1.02) -1.300 (-0.65)	+5	-0.104 (-0.30) -0.628 (-0.44)	-0.155 (-0.35) -3.262 (-1.98) *
-15	0.304 (1.48) 0.880 (1.58)	-0.697 (-2.47) ** -1.955 (-0.97)	+6	-0.116 (-0.40) -0.739 (-0.51)	0.013 (0.04) -3.255 (-1.90) *
-14	-0.203 (-0.83) 0.677 (1.19)	1.156 (1.13) -0.845 (-0.75)	+7	-0.306 (-1.07) -1.045 (-0.70)	0.619 (2.64) ** -2.927 (-1.70) *
-13	-0.191 (-0.61) 0.487 (0.72)	-0.199 (-0.79) -1.040 (-0.90)	+8	0.474 (1.85) * -0.590 (-0.40)	0.362 (1.74) * -2.736 (-1.64)
-12	0.047 (0.16) 0.533 (0.75)	-0.148 (-0.80) -1.188 (-1.00)	+9	-0.120 (-0.49) -0.695 (-0.48)	1.025 (1.42) -2.394 (-1.64)
-11	-0.376 (-1.64) 0.164 (0.21)	0.331 (0.86) -0.864 (-0.68)	+10	0.088 (0.44) -0.610 (-0.43)	-0.319 (-1.06) -2.550 (-1.66)
-10	-0.210 (-0.88) -0.046 (-0.05)	0.321 (1.12) -0.548 (-0.41)	+11	0.018 (0.09) -0.593 (-0.42)	0.455 (1.61) -2.327 (-1.58)
-9	-0.052 (-0.21) -0.097 (-0.11)	0.103 (0.14) -0.445 (-0.47)	+12	-0.026 (-0.10) -0.619 (-0.43)	-0.048 (-0.23) -2.350 (-1.59)
-8	-0.127 (-0.49) -0.221 (-0.23)	-0.613 (-1.14) -1.034 (-0.93)	+13	0.493 (2.03) ** -0.145 (-0.10)	-0.052 (-0.28) -2.376 (-1.60)
-7	-0.130 (-0.55) -0.351 (-0.37)	-0.553 (-2.23) ** -1.565 (-1.41)	+14	-0.549 (-2.07) ** -0.695 (-0.52)	-0.312 (-1.23) -2.522 (-1.67)
-6	-0.214 (-0.95) -0.560 (-0.55)	-0.533 (-2.13) ** -2.077 (-1.74) *	+15	-0.104 (-0.46) -0.799 (-0.58)	-0.151 (-0.62) -2.597 (-1.68) *
-5	-0.383 (-1.26) -0.928 (-0.92)	-0.140 (-0.45) -2.209 (-1.71) *	+16	0.277 (1.01) -0.522 (-0.38)	-0.154 (-0.69) -2.672 (-1.68) *
-4	0.040 (0.16) -0.887 (-0.84)	0.505 (0.58) -1.724 (-1.27)	+17	-0.366 (-1.89) * -0.887 (-0.63)	0.231 (0.95) -2.559 (-1.57)
-3	0.512 (2.12) ** -0.386 (-0.37)	-0.035 (-0.09) -1.758 (-1.11)	+18	0.011 (0.05) -0.877 (-0.61)	0.310 (0.89) -2.407 (-1.50)
-2	-0.066 (-0.22) -0.451 (-0.44)	-0.268 (-0.42) -2.010 (-1.64)	+19	-0.051 (-0.25) -0.926 (-0.68)	-0.495 (-2.20) ** -2.640 (-1.64)
-1	-0.165 (-0.71) -0.613 (-0.61)	-1.257 (-0.97) -3.193 (-2.16) **	+20	-0.177 (-0.80) -1.103 (-0.79)	-0.112 (-0.39) -2.694 (-1.60)
0	-0.453 (-2.01) ** -1.066 (-1.02)	-0.166 (-0.58) -3.343 (-2.13) **	***, **, and * show statistical significance at 1%, 5%, and 10% levels, respectively.		

Table 7: Critical t-values and F-values

	DF	α = 1%	α = 5%	α = 10%
t-value (two-tail)	50	2.68	2.01	1.68
t-value (one-tail)	141	2.35	1.66	1.29
t-value (one-tail)	153	2.35	1.65	1.29
t-value (one-tail)	296	2.34	1.65	1.28
t-value (one-tail)	298	2.34	1.65	1.28
t-value (one-tail)	300	2.34	1.65	1.28
t-value (one-tail)	304	2.34	1.65	1.28
F-value (one-tail)	153, 153	1.46	1.31	1.23

4.2 Analyzing the Results

4.2.1 Total Return

As we can see in Table 5, while on average our SR portfolio creates a monthly return of 1.272%, C1 and C2 create monthly returns of 0.711% and 0.781%, respectively. Clearly, our SR portfolio is producing higher total return. To test if the difference between the mean total return of our SR portfolio and that of the matched portfolios is statistically significant, we perform a t-test. We have three choices: paired t-test, two sample t-test with equal variances, and two sample t-test with unequal variances. A paired t-test is preferred to the other two methods when analyzing a paired sample, which is the case in our study (Hines et al., 2003).

The null hypothesis, the alternative hypothesis, the t statistic, and the degrees of freedom can be seen in Equations 4.1 to 4.4, respectively.

$$H_0: R_{SR} = R_{MATCH} \tag{4.1}$$

$$H_1: R_{SR} > R_{MATCH} \tag{4.2}$$

$$t = \frac{d}{S_d/\sqrt{N}} \tag{4.3}$$

$$DF = N - 1 \tag{4.4}$$

In these equations, R_{SR} and R_{MATCH} are the mean total return of our SR and matched portfolios respectively, d is the average difference in monthly returns of our SR and matched portfolios, S_d is the standard deviation of the difference in monthly returns of our SR and matched portfolios, and N is the number of data points for our SR and matched portfolios which is equal to 154.[20] The null hypothesis in Equation 4.1 states that the mean total returns are not different from each other, while the alternative hypothesis in Equation 4.2 states that our SR portfolio has significantly higher mean total return compared to matched portfolios.

As shown in Table 5, the null hypothesis regarding the difference between the mean total return of our SR portfolio and that of C1 and C2 is rejected at 1% level of significance. As a result, our SR portfolio has statistically higher total return compared to both matched portfolios. Moreover, in 62% of the months in our study period, our SR portfolio

[20] There is a total of 154 months between March 2003 and December 2015.

has higher total return compared to C1, and in 61% of the months, our SR portfolio has higher total return compared to C2. By performing a Sign test, we investigate if these percentages indicate that the total return of our SR portfolio is statistically higher than that of matched portfolios. In other words, we perform a non-parametric test in addition to the parametric test. We get a p-value of 0.002 for comparing the total return of our SR portfolio and C1, and a p-value of 0.004 for comparing the total return of our SR portfolio and C2, both p-values indicate statistical significance.[21] As we can see, the results of the parametric test (paired t-test) and the non-parametric test (Sign test) are consistent. As a result, we can conclude that in terms of total return, our SR portfolio dominates both matched portfolios.

4.2.2 Total Risk, Sharpe Ratio, and M^2 Measure

As mentioned in the previous section, our SR portfolio dominates the matched portfolios based on total return. However, we cannot argue that our SR portfolio is superior since we must also take into consideration the level of risk associated with this return. As we discussed in Chapter 3, total risk is the most common measure of risk. Since our SR portfolio has higher total return, we need to check whether our SR portfolio has higher total risk as well. To test if the difference in total risk of our SR and matched portfolios is

[21] We consider any p-value less than 0.1 to be statistically significant.

statistically significant, we perform a F-test in case one total risk is calculated for the whole study period, and a paired t-test in case total risk is calculated monthly.

The null hypothesis, the alternative hypothesis, the F statistic, and the degrees of freedom can be seen in Equations 4.5 to 4.8, respectively. The t statistic and its associated degrees of freedom are similar to the ones in Section 4.2.1

$$H_0: \sigma_{SR} = \sigma_{MATCH} \tag{4.5}$$

$$H_1: \sigma_{SR} > \sigma_{MATCH} \tag{4.6}$$

$$F = \frac{\sigma_{SR}^2}{\sigma_{MATCH}^2} \tag{4.7}$$

$$DF_{NUMERATOR} = N_{SR} - 1 \;\&\; DF_{DENOMINATOR} = N_{MATCH} - 1 \tag{4.8}$$

In these equations, σ_{SR} and σ_{MATCH} are the total risk for our SR and matched portfolios, respectively, N_{SR} is the number of data points for our SR portfolio, and N_{MATCH} is the number of data points for our matched portfolios. The null hypothesis in Equation 4.5 states that the total risk of our SR portfolio and that of the matched portfolios is equal, while the alternative hypothesis in Equation 4.6 states that the total risk of our SR portfolio is higher than the total risk of the matched portfolios.

First, we look at the results regarding the total risk calculated for the whole study period (not monthly). As we can see in Table 5, while there is not a statistically significant difference in the total risk of our SR portfolio and that of C1, C2 has statistically lower total risk compared to our SR portfolio, the difference being significant at 10% level.

However, when we adjust the total returns for total risk (calculating Sharpe ratio), our SR portfolio outperforms both matched portfolios. As we can see in Table 5, the Sharpe ratio of our SR portfolio is 0.300, while C1 and C2 have Sharpe ratios of 0.149 and 0.188 respectively for the period of study.

Second, we look at the results regarding the monthly total risk in Table 5. We can see that while our SR portfolio has a mean total risk of 6.689%, C1 and C2 have mean total risks of 8.552% and 5.376%, respectively, the differences being significant at the 1% level. Moreover, in only 26% of the months in our study period, our SR portfolio has higher total risk compared to C1, while in 73% of the months our SR portfolio has higher total risk compared to C2. By performing a Sign test, we can determine if these percentages indicate statistical significance. We get a p-value of 0.000 for comparing the total risk of our SR portfolio and C1, and a p-value of 0.000 for comparing the total risk of our SR portfolio and C2; both p-values indicate statistical significance. As we can see, the results of the parametric test (paired t-test) and the non-parametric test (Sign test) are consistent. As a result, we can conclude that in terms of total risk, our SR portfolio outperforms C1, while C2 outperforms our SR portfolio. By looking at the results of the monthly Sharpe ratio in Table 5, we can conclude that our SR portfolio dominates both C1 and C2 based on this risk-adjusted return measure. As we can see, our SR portfolio has an average Sharpe ratio of 0.178, while C1 and C2 have average Sharpe ratios of 0.059 and 0.101, respectively, the differences being significant at the 1% level. Moreover, in 64% of the months in our study period, our SR portfolio has a higher Sharpe ratio compared to C1, and in 58% of the months, our SR portfolio has a higher Sharpe ratio compared to C2. By performing a Sign test, we can determine if these percentages indicate statistical significance. We get a p-value of 0.000 for comparing the Sharpe ratio of our SR portfolio and C1, and a p-value of 0.032 for comparing the Sharpe ratio of our SR portfolio and C2; both p-values indicate statistical significance. As we can see, the results of the parametric test (paired t-test) and the non-parametric test (Sign test) are consistent.

In addition to Sharpe ratio, our SR portfolio has a M^2 measure of 0.537%, while this risk-adjusted return measure is -0.028% and 0.118% for C1 and C2, respectively.[22] As a result, we can conclude that if total risk is considered as the proxy for risk, our SR portfolio outperforms both matched portfolios.

4.2.3 Downside Risk and Sortino Ratio

As mentioned, comparing two portfolios merely on total return is not enough to draw a conclusion regarding their relative performance; we need to also consider the amount of risk associated with those returns. As mentioned, some investors and academics may consider downside risk (represented by downside deviation in this study) to be a better proxy for the risk of a company or a portfolio than total risk. Since the total return of our SR portfolio is higher than that of C1 and C2, a logical act is to investigate whether or not our SR portfolio also has higher downside deviation. To test this supposition, we perform a F-test.

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[22] C1 has a negative M-squared measure, which means that it underperforms the market.

The null hypothesis, and the alternative hypothesis can be seen in Equations 4.9 and 4.10, respectively. The F-statistic, and the degrees of freedom are similar to the ones in Section 4.2.2.

$$H_0: \sigma_{d,SR} = \sigma_{d,MATCH} \quad 4.9$$

$$H_1: \sigma_{d,SR} > \sigma_{d,MATCH} \quad 4.10$$

In these equations, $\sigma_{d,SR}$ and $\sigma_{d,MATCH}$ are the downside deviation for our SR and matched portfolios respectively. The null hypothesis in Equation 4.9 states that the downside deviation of our SR portfolio and that of the matched portfolios is equal, while the alternative hypothesis in Equation 4.10 states that the downside deviation of our SR portfolio is higher than the downside deviation of the matched portfolios.

Based on the results in Table 5, we can conclude that irrespective of the target level (being mean, risk-free rate, or zero), the difference between the downside deviation of our SR and matched portfolios is not statistically significant. However, when we adjust the total returns for downside deviation (calculating Sortino ratio), irrespective of the target level, our SR portfolio outperforms the matched portfolios. For example, assuming the target level being zero, our SR portfolio has a Sortino ratio of 0.554, while C1 and C2 have Sortino ratios of 0.258 and 0.324 respectively. As a result, if downside deviation is considered to be the proxy for risk, our SR portfolio outperforms the matched portfolios on a risk-adjusted basis.

4.2.4 Market Risk, Treynor Ratio, and T^2 Measure

As mentioned in previous sections, market risk (beta) is another common measure of risk that shows the sensitivity of the return of a company or a portfolio to the return of the market. Since our SR portfolio has higher total return, it makes sense to test whether or not our SR portfolio has higher beta as well. To test if the beta of our SR portfolio is higher than that of C1 and C2 (in case beta is calculated on a monthly basis), we perform a paired t-test. The null and alternative hypothesis can be seen in Equations 4.11 and 4.12, respectively. The t-statistic and degrees of freedom are similar to the ones in Section 4.2.1.

$$H_0: \beta_{SR} = \beta_{MATCH} \tag{4.11}$$

$$H_1: \beta_{SR} > \beta_{MATCH} \tag{4.12}$$

In these equations, β_{SR} and β_{MATCH} are the beta for our SR and matched portfolios respectively.

First, we look at the results regarding the beta calculated for the whole study period (not monthly). As we can see in Table 5, our SR portfolio has higher beta compared to both matched portfolios; our SR portfolio has a beta of 0.948, while C1 and C2 have beta of 0.789 and 0.784 respectively for the whole study period. However, when we adjust the total returns for beta (calculating Treynor ratio), our SR portfolio outperforms the matched portfolios. As we can see in Table 5, the Treynor ratio of our SR portfolio is

1.187, while C1 and C2, have Treynor ratios of 0.715 and 0.808 respectively for the whole study period.

Second, we look at the results regarding the monthly beta in Table 5. We can see that our SR portfolio has an average beta of 0.840, while C1 and C2 have average beta of 0.910 and 0.800, respectively. Based on the results in Table 5, the null hypothesis in Equation 4.11 cannot be rejected. In other words, the difference between the average monthly beta of our SR and matched portfolios is not statistically significant. Moreover, in 58% of the months in our study period, our SR portfolio has higher beta compared to C1, and in 54% of the months, our SR portfolio has higher beta compared to C2. By performing a Sign test, we can determine if these percentages indicate statistical significance. We get a p-value of 0.039 for comparing the beta of our SR portfolio and C1, and a p-value of 0.225 for comparing the beta of our SR portfolio and C2, only the first p-value indicates statistical significance. For C2, the results of the paired t-test and the Sign test are consistent, but as we can see, this is not the case for C1. While based on the results of the paired t-test, there is no statistically significant difference between the beta of our SR portfolio and C1, the results of the Sign test suggest that our SR portfolio has statistically higher beta. However, generally, parametric tests have stronger power compared to non-parametric tests unless the sample size is too small, which is not the case in our study (Hines et al., 2003). The main reason a paired t-test is stronger than a Sign test lies in the fact that a Sign test does not consider the magnitude of differences, and only takes signs of differences into consideration (Hines et al., 2003). As a result, for the comparison between the beta of our SR portfolio and C1, we trust the results of the paired t-test, which indicates the lack of any statistically significant difference in their betas. Thus, we can conclude that the sensitivity of the return of our SR and matched portfolios to the return of the market is similar. Moreover, since the average beta of our SR and matched portfolios is less than 1, on average, they are basically defensive portfolios. By adjusting the total returns for beta (calculating Treynor ratio), we can compare the relative risk/return performance of our SR and matched portfolios. As we can see in Table 5, our SR portfolio has an average Treynor ratio of 1.249, while the Treynor ratios of C1 and C2 are 0.604 and 0.674, the differences being significant at 5% and 10% level, respectively. Moreover, in 58% of the months in our study period, our SR portfolio has higher Treynor ratio compared to C1, and in 57% of the months, our SR portfolio has higher Treynor ratio compared to C2. By performing a Sign test, we can determine if these percentages indicate statistical significance. We get a p-value of 0.027 for comparing the Treynor ratio of our SR portfolio and C1, and a p-value of 0.055 for comparing the Treynor ratio of our SR portfolio and C2; both p-values show statistical significance. As we can see, the results of the paired t-test and the Sign test are consistent.

In addition to Treynor ratio, our SR portfolio has a T^2 measure of 0.598% while C1 and C2 have T^2 measures of 0.126% and 0.220%, respectively. As a result, we can conclude that if market risk is the proxy for the risk of portfolios, our SR portfolio outperforms the matched portfolios.

4.2.5 Abnormal Return

As mentioned, another approach that we can take to compare our SR and matched portfolios is to compare them against a benchmark and calculate their abnormal returns. As we can see in Table 5, based on CAPM, our SR portfolio has an abnormal return of 0.567%, while the matched portfolios have abnormal returns of 0.100% and 0.172%, respectively. The adjusted R^2 measures are 89.93%, 61.24%, and 76.60% for our SR portfolio, C1, and C2 respectively. These adjusted R^2 measures are relatively high, which shows that market premium is explaining a great deal of variability of the return of portfolios. By changing our model, from CAPM to Fama-French three-factor, we get abnormal returns of 0.572%, 0.101%, and 0.163% for our SR portfolio, C1, and C2 respectively. In this case, the adjusted R^2 measures are 89.86%, 61.36%, and 77.03%, respectively, which indicates that the addition of SMB and HML has not resulted in a better fit. Based on Fama-French four-factor model, the abnormal returns are 0.581%, 0.088%, and 0.161%, respectively. For this model, the adjusted R^2 measures are 90.19%, 61.79%, and 76.89%, respectively. As we can see, adding the momentum factor does not add any significant power to our model. By using the Fama-French five-factor model, we get abnormal returns of 0.597%, 0.051%, and 0.143%, respectively, with the adjusted R^2 measures being 89.95%, 61.21%, and 76.84%, respectively. Again, there doesn't seem to be any significant difference in the power of CAPM and Fama-French five-factor model in explaining the variability of the returns of portfolios.

To test whether the difference between the abnormal return of our SR and matched portfolios is statistically significant, we add an intercept dummy to the CAPM and Fama-

French regressions. This intercept dummy shows the difference between the intercepts of two regressions and takes the value of 1 if the data belong to our SR portfolio, and 0 if the data belong to the matched portfolios. In other words, the addition of the intercept dummy enables us to run a pooled regression—a regression with a pooled data set—which is the combination of the individual data sets of our SR and matched portfolios. If the intercept dummy in this pooled regression is significant, we can conclude that the difference between the abnormal return of our SR and matched portfolios is significant. In Equations 4.13 to 4.16, we can see the regression equation based on CAPM and Fama-French three-factor model, Carhart model, and Fama-French five-factor model, respectively, with the intercept dummy.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \left(R_{m,t} - R_{f,t}\right) + \varepsilon_{i,t} + \gamma D_{i,t} \tag{4.13}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + s_i(SMB_t) + h_i(HML_t) + \varepsilon_{i,t} + \gamma D_{i,t} \tag{4.14}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + s_i(SMB_t) + h_i(HML_t) + w_i(WML_t) + \varepsilon_{i,t} + \gamma D_{i,t} \tag{4.15}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + s_i(SMB_t) + h_i(HML_t) + r_i(RMW_t) + c_i(CMA_t) + \varepsilon_{i,t} + \gamma D_{i,t} \tag{4.16}$$

In these equations, $D_{i,t}$ is the intercept dummy for equity i in month t, and γ is the coefficient of the intercept dummy. The rest of the variables were explained in Chapter 3.

The null hypothesis, the alternative hypothesis, and the degrees of freedom for testing the statistical significance of the intercept dummy can be seen in Equations 4.17 to 4.19.

$$H_0: \gamma = 0 \tag{4.17}$$

$$H_1: \gamma > 0 \tag{4.18}$$

$$DF = N_{SR} + N_{MATCH} - n \tag{4.19}$$

In Equation 4.19, N_{SR} and N_{MATCH} are the number of data points for our SR and matched portfolios, respectively, which is equal to 154. "n" in Equation 4.19 is equal to 4 for CAPM, 8 for Fama-French three-factor model, 10 for Carhart model, and 12 for Fama-French five-factor model.[23] The null hypothesis in Equation 4.17 states that the coefficient of the dummy variable is equal to zero, while the alternative hypothesis in Equation 4.18 states that the coefficient of the dummy variable is greater than zero. In other words, the null hypothesis states that the abnormal return of our SR and matched portfolios are not different from each other, while the alternative hypothesis states that our SR portfolio has significantly higher abnormal return compared to matched portfolios.

As we can see in Table 5, for our SR portfolio and C1, the coefficient of the dummy variable is 0.561 with the t-value of 2.61. For our SR portfolio and C2, the coefficient of the dummy variable is 0.492 with the t-value of 2.96. As we see in Table 5, the dummy variables and their t-values are similar for CAPM and different versions of Fama-French model. Based on the t-values (2.61 and 2.96), we can argue that our SR portfolio has significantly higher abnormal return compared to matched portfolios at 1% level of

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[23] The magnitude of "n" depends on the number of variables predicted by each model.

significance. Thus, we can conclude that based on abnormal return, our SR portfolio outperforms the matched portfolios. As we can see, the results achieved from this section are consistent with the other risk-adjusted return measures in previous sections. Another point worth mentioning here is that the addition of Fama-French factors to the CAPM model does not result in any significant additional power. As a result, we can conclude that market premium ($R_m - R_f$) is the most important risk factor in explaining the return of our SR and matched portfolios.

As mentioned, our study period is March 2003 to December 2015 during which, in 2008, one of the greatest financial crises in the history of the US occurred. This crisis affected the markets of other countries including Canada. To test if the abnormal returns of our SR and matched portfolios in this year are significantly different from the rest of the period, we add a dummy variable to our CAPM and Fama-French regressions. This dummy variable takes the value of 0 if the data belong to the non-crisis period, and 1 if the data belong to the crisis period (2008). The regressions with this dummy variable are similar to the ones in Equations 4.13 to 4.16; however, they are regular regressions, and not pooled regressions. The results regarding the coefficient of the dummy variable and its associated p-value for different models can be seen in Table 8, which shows that none of the dummy variables is significant due to high p-values. Therefore, we can conclude that the financial crisis of 2008 did not have any significant effect on the abnormal returns of our SR and matched portfolios.

Table 8: Coefficient of the dummy variable and its associated p-value for the financial crisis of 2008

Model	Coefficient	p-value
CAPM	0.164	0.67
FF three-factor	0.189	0.62
FF four-factor	0.242	0.52
FF five-factor	0.362	0.36

4.2.6 Unsystematic Risk, Information Ratio, and Market Timing

Assuming that our SR and matched portfolios are managed by active portfolio managers, we compare the unsystematic risk, information ratio, and market timing of these portfolios. As we can see in Table 5, while our SR portfolio has an unsystematic risk of 1.425, C1 and C2 have unsystematic risks of 5.556 and 2.657, respectively. By performing a F-test, we conclude that the differences in unsystematic risk of our SR and matched portfolios are statistically significant at 1% level. As we see, our SR portfolio has lower unsystematic risk. This is consistent with the characteristics of the constituents of SR portfolios. Generally, these companies are less exposed to negative events such as scandals and lawsuits. Companies that show ESG responsibility are less likely to suffer from negative events during different conditions of market. For example, negative events associated with pollution are less likely in companies with strong environmental concern. Companies with strong social concern are less likely to face employee-related lawsuits. These SR companies suffer less from legal prosecutions and fines, and they benefit from their superior relations with communities and governments.

Looking at the information ratios of our SR and matched portfolios, we can see that while our SR portfolio has an information ratio of 0.478, C1 and C2 have information ratios of 0.043 and 0.106, respectively. As a result, the performance of the portfolio manager of our SR portfolio is better than the portfolio manager of the matched portfolios. In other words, the portfolio manager of our SR portfolio has a superior ability to create abnormal returns per unit of standard deviation of residual returns.

Regarding market timing ability, as we can see in Table 5, the market timing coefficient of our SR portfolio is 0.010 with a p-value of 0.003, which shows statistical significance at the 1% level. However, the market timing coefficients of C1 and C2 are 0.008 and 0.003 with p-values of 0.220 and 0.516, respectively, which shows that they are not statistically significant. As a result, we can conclude that when managers of our SR and matched portfolios do market timing, the portfolio manager of our SR portfolio is superior in this regard.

4.2.7 Tobin's Q and Leverage

As mentioned in Chapter 3, we can investigate whether SRI creates value in a portfolio by comparing the Tobin's Q of our SR and matched portfolios. As we can see in Table 5, while our SR portfolio has a mean Q ratio of 1.519, the mean Q ratios of C1 and C2 are 1.363 and 1.384, respectively. To test whether the difference between the mean Tobin's Q of our SR portfolio and that of the matched portfolios is significant, we perform a paired t-test.

The null and the alternative hypothesis can be seen in Equations 4.20 and 4.21, respectively.

$$H_0: T_{SR} = T_{MATCH} \tag{4.20}$$

$$H_1: T_{SR} > T_{MATCH} \tag{4.21}$$

In these equations, T_{SR} and T_{MATCH} are the mean Tobin's Q for our SR and matched portfolios, respectively. The t-statistic and the degrees of freedom are similar to the ones in Section 4.2.1. The null hypothesis states that the mean Tobin's Q of our SR and matched portfolios are equal, while the alternative hypothesis states that the mean Tobin's Q of our SR portfolio is higher than that of matched portfolios.

Based on the results in Table 5, the null hypothesis in Equation 4.20 regarding the difference between the Tobin's Q of our SR portfolio and that of matched portfolios will be rejected. As a result, our SR portfolio has statistically higher Tobin's Q compared to both matched portfolios, the differences being significant at the 1% level. Moreover, in 94% of the months in our study period, our SR portfolio possesses higher Tobin's Q compared to C1, and in 100% of the months it has higher Tobin's Q compared to C2. By performing a Sign test, we can investigate if these percentages indicate statistical significance. We get a p-value of 0.000 for comparing the Tobin's Q of our SR portfolio and C1, and a p-value of 0.000 for comparing the Tobin's Q of our SR portfolio and C2; both p-values indicate statistical significance. As we can see, the results of the paired t-test and the Sign test are consistent. As a result, in terms of Tobin's Q, our SR portfolio dominates both matched portfolios. Thus, we can conclude that SRI creates value in portfolios. Some investors and academics look at Tobin's Q as a measure to judge if an equity is overvalued or undervalued. They argue that a Tobin's Q higher than 1 is an indication of overvaluation and lower than 1 is an indication of undervaluation. Based on this view, since our SR and matched portfolios have Tobin's Q of higher than 1, they are overvalued. The price of an overvalued equity is expected to decrease in the near future.

As mentioned, although one reason for the higher Q ratio of our SR portfolio is the hypothesis that SRI creates value in portfolios, another explanation could be that our SR portfolio has a higher leverage ratio. To determine if the leverage ratio of our SR portfolio is significantly higher than that of C1 and C2, we perform a paired t-test.

The null and the alternative hypothesis can be seen in Equations 4.22 and 4.23, respectively.

$$H_0: L_{SR} = L_{MATCH} \tag{4.22}$$

$$H_1: L_{SR} > L_{MATCH} \tag{4.23}$$

In these equations, L_{SR} and L_{MATCH} are the mean leverage for our SR and matched portfolios, respectively. The t statistic and degrees of freedom are similar to the ones in Section 4.2.1. The null hypothesis states that the mean leverage of our SR and matched portfolios are equal, while the alternative hypothesis states that the mean leverage of our SR portfolio is higher than that of the matched portfolios.

As we can see in Table 5, our SR portfolio has a mean leverage ratio of 22.516%, while C1 and C2 have mean leverage ratios of 21.530% and 19.684%, respectively, the differences being significant at the 1% level, which indicates that the null hypothesis in Equation 4.22 will be rejected. Moreover, in 80% of months in our study period, our SR portfolio has higher leverage compared to C1, and in 100% of months it has higher leverage compared to C2. We can perform a Sign test to investigate if these percentages indicate statistical significance. We get a p-value of 0.000 for comparing the leverage of our SR portfolio and C1, and a p-value of 0.000 for comparing the leverage of our SR portfolio and C2; both p-values show statistical significance. As we can see, the results of the paired t-test and the Sign test are consistent. As a result, our SR portfolio has significantly higher leverage ratio compared to both matched portfolios. We can argue that our SR portfolio's higher Tobin's Q can be partly due to its higher leverage. However, statistical significance does not necessarily imply economic significance. Since the difference in leverage ratios of our SR and matched portfolios is only a few percent, economically, such a small difference cannot have a significant effect on the valuation. As a result, we can almost be confident that the higher Q ratio of our SR portfolio is due to the ability of SRI in creating value.

4.2.8 Event Study

As mentioned in Chapter 3, to remove the possible effects of our study period, models, and data set on our conclusion regarding the effects of SRI on the performance of a portfolio, we perform an event study to investigate the response of the market to SRI. As mentioned, in this event study, we are dealing with two different events: being included in JSI, and being removed from JSI. To discover the effects of these events on the returns of companies, we described how to calculate AAR and CAAR. If these events have a positive effect on the return of companies, we expect to see significantly positive AAR and CAAR, and if the effect is negative, we expect to see significantly negative AAR and CAAR. If AAR and CAAR are not different from zero, we can conclude that these events are neutral. To test whether AAR or CAAR at any day in the event window is different from zero, we perform a one-sample t-test (Mackinlay, 1997).

The null hypothesis, the alternative hypothesis, the t statistic, and the degrees of freedom can be seen in Equations 4.24 to 4.27, respectively.

$$H_0: X_t = 0 \tag{4.24}$$

$$H_1: X_t \neq 0 \tag{4.25}$$

$$t = \frac{X_t}{S_t/\sqrt{N}} \tag{4.26}$$

$$DF = N - 1 \tag{4.27}$$

In these equations, X_t is the AAR or CAAR at day t during the event window, S_t is the standard deviation of AR or CAR at day t during the event window, and N is the number of included or excluded companies, which is equal to 51. The null hypothesis states that AAR or CAAR at day t in the event window is not different from zero, while the alternative hypothesis states that AAR or CAAR at day t in the event window is significantly different from zero.

The summary of results for AAR and CAAR can be seen in Table 6. As we see, AAR for inclusions are significant on days -3, 0, +3, +4, +8, +13, +14, and +17. AAR for exclusions are significant on days -15, -7, -6, +7, +8, and +19. Moreover, during the event window, we can see that in 42% of the days, AAR for inclusions are positive, and in 61% of the days, AAR for exclusions are negative. Since inclusion in JSI is deemed to be good news, we expect to see more than 50% positive AARs, while for exclusions, we expect to see more than 50% negative AARs. Although the results regarding inclusions are contrary to our expectations, the results regarding exclusions are in accordance with them. The positive AAR for inclusions on day -3, and the negative AAR for exclusions on days -15, -7, and -6 can be attributed to "information leakage." Moreover, the positive AAR for inclusions on days +3, +4, +8, and +13, and the negative AAR for exclusions on day +19 can be attributed to the late response of the market.

In Figure 2, only the statistically significant AARs (for both inclusions and exclusions) are shown. As we can see, there is no specific pattern in the movements of the AARs. As a result, we are not able to make a confident conclusion about the effects of being included in or being removed from JSI on the stock prices of these companies based on the results of AARs.

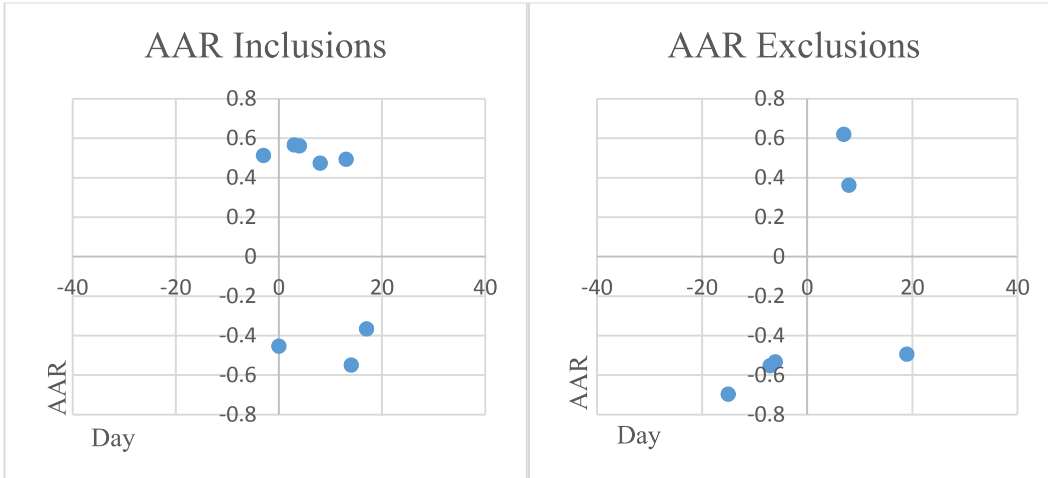

Figure 2: Significant AARs for inclusions (left), and significant AARs for exclusions (right)

CAARs show us a clearer picture. For inclusions, CAARs for none of the days in the event window are significant. This can suggest that inclusion in JSI is a neutral event, and market response to this event is insignificant. These results may not be in accord with our expectations. Since becoming a member of a SR index seems to be a positive event, we expect to see a positive response from the market. One possible explanation for the observed neutral reaction of the market to these included companies might be that good news commonly leaks much earlier. While companies usually try to hide any upcoming negative event until the last possible day, they tend to take an opposite approach when it comes to positive events. Contrary to included companies, we can clearly see that the reaction of the market to the excluded companies is significantly negative. As we can see in Table 6, CAARs for exclusions are significantly negative on days -6, -5, -1, 0, +1, +2, +3, +4, +5, +6, +7, +15, and +16. In Figure 3, in which only the statistically significant CAARs are depicted, CAARs around the event day form a clear pattern of negative numbers, which suggests that exiting JSI is a negative event from the point of view of the investors.

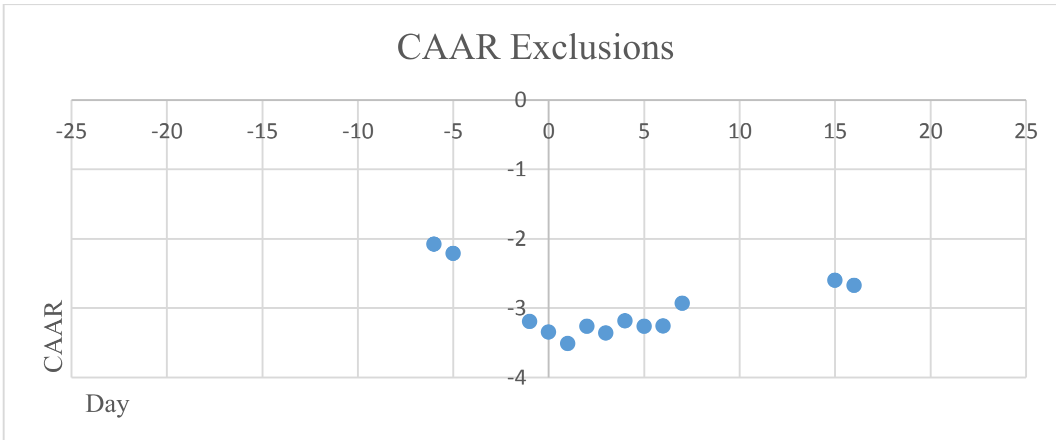

Figure 3: Significant CAARs for exclusions

4.3 Conclusion

Based on the results achieved from our research, we can conclude that our SR portfolio creates higher total return compared to the matched portfolios. Adjusting the total returns for different risk measures (total risk, downside risk, and market risk) indicates that our SR portfolio outperforms the matched portfolios on a risk-adjusted basis. Apart from the risk/return performance, our calculation of abnormal return based on CAPM and Fama-French model shows that our SR portfolio significantly outperforms the matched portfolios. We also compare the unsystematic risk, information ratio, and market timing of our SR and matched portfolios. In all these comparisons, our SR portfolio outperforms the matched portfolios. Our results regarding unsystematic risk also implies that SR companies are exposed to less controversial issues. By comparing the Tobin's Q of our

SR and matched portfolios, we conclude that our SR portfolio has a higher value creation ability. We also compare the leverage ratio of our SR and matched portfolios. The results show that although the differences between the leverage ratios are statistically significant, they are not economically significant. This suggests that the higher leverage of our SR portfolio cannot play an important role in its higher valuation. Finally, the results of our event study show that the market reaction to entering JSI is insignificant, while those companies that exit JSI experience a negative effect on their stock prices.

In conclusion, our study indicates that investing in socially responsible portfolios not only satisfies the ethical concerns of investors, but also leads to a superior risk-adjusted performance. However, we must be cautious about the magnitude of the outperformance. It could be partly due to our matching technique that does not allow any of our socially responsible companies be presented in the matched portfolios. As a result, the matched portfolios could be deprived from the good performance of some of the top-performing companies in our socially responsible portfolio.

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Appendix A – Sample of our SR and Matched Portfolios

In Table 9, the members of our SR portfolio and C1 in March 2003 with their NAICS code, industry, and total assets (in million CAD) can be seen.

Table 9: Members of our SR portfolio and C1 in March 2003

JSI member	NAICS	Total assets	C1 member	NAICS	Total assets
RIO TINTO ALCAN	331312	41420.58	CYMAT TECH	331314	28.91
ATI TECHNOLOGIES	334413	1546.97	HYDROGENICS CORP	334413	118.60
COGNOS INC	511210	979.59	DESCARTES SYS	511210	368.08
NOVA CHEMICALS C	325211	5721.45	CPI PLASTICS GRP	325211	109.02
HUDSON'S BAY CO	452112	4275.69	SEARS CANADA INC	452112	4139.20
ARCELORMITTAL DO	331221	3258.90	ESSAR STEEL ALGO	331221	1028.80
GEAC COMPUTER	541512	475.89	HUMMINGBIRD LTD	541512	494.59
FALCONBRIDGE LTD	212200	5409.00	LIONORE MINING	212200	873.92
FORTISBC HOLDING	221210	4921.30	CAN UTILITIES-A	221210	6096.50
PETRO-CANADA	211111	14774.00	CAN NATURAL RES	211111	14643.00
CREO INC	333244	1042.37	SHAWCOR LTD	333132	825.62
ZENON ENVIR	333319	238.14	GSW INC A	333319	262.97
LEITCH TECH CORP	334220	187.47	COM DEV INTL LTD	334220	111.74
AGRIUM INC	325311	2946.94	NU-GRO CORP	325314	130.15
ATS AUTOMATION	333999	713.87	SOLECTRON GLOBAL	333994	625.14
BROOKFIELD ASS-A	551111	21131.65	PARTNERS VALUE I	551111	236.91
BLACKBERRY LTD	334220	1276.18	COM DEV INTL LTD	334220	111.74
BCE INC	517110	39420.00	2737469 CANADA I	517110	5318.79
BALLARD POWER	334413	1082.36	HYDROGENICS CORP	334413	118.60
BANK OF MONTREAL	522110	256494.00	LAURENTIAN BANK	522110	16737.77
BANK OF NOVA SCO	522110	285892.00	LAURENTIAN BANK	522110	16737.77
CASCADES INC	322130	2927.00	CATALYST PAPER	322122	2816.40
CANFOR CORP	113310	2447.30	SINO-FOREST-CORP	113310	543.04
CAN IMPL BK COMM	522110	277147.00	LAURENTIAN BANK	522110	16737.77
CAN NATL RAILWAY	482111	17150.00	TRANSCANADA CORP	486210	20701.00
CANADIAN PACIFIC	482111	9956.70	AIR CANADA/OLD	481111	6910.00
CANADIAN TIRE-A	441310	4893.10	EMPIRE CO LTD A	445110	4516.10
DUPONT CANADA-A	325211	152.55	CPI PLASTICS GRP	325211	109.02
ENBRIDGE INC	221210	13945.00	CAN UTILITIES-A	221210	6096.50

JSI member	NAICS	Total assets	C1 member	NAICS	Total assets
GLENCORE CANADA	212210	10797.25	LABRADOR IRON OR	212210	477.92
GENNUM CORP	334413	132.26	HYDROGENICS CORP	334413	118.60
HUSKY INJECTION	333511	1124.03	EXCO TECH LTD	333517	216.49
IGM FINANCIAL IN	523110	6291.70	PINETREE CAPITAL	523110	26.31
MANITOBA TELECOM	517110	1683.00	COGECO COMMUNICA	517110	1802.74
MAGNA INTL	336211	12788.68	INTIER AUTOMOT	336211	2777.23
MOORE WALLACE IN	339940	4174.74	MEGA BRANDS INC	339930	213.56
NATL BK CANADA	522110	84931.00	LAURENTIAN BANK	522110	16737.77
NORDION INC	621511	2565.00	CML HEALTHCARE I	621511	291.46
NORTEL NETWORKS	334210	21510.23	AASTRA TECH LTD	334210	272.25
NEXEN ENERGY ULC	211111	7717.00	CANADIAN OIL SAN	211111	4259.86
PRECISION DRILL	213111	2908.39	MULLEN GROUP LTD	213111	381.64
JEAN COUTU GRP-A	446110	1716.63	SHOPPERS DRUG MA	446110	3275.86
PENN WEST PETROL	211111	3309.66	ENERPLUS CORP	211111	2661.77
QLT INC	325412	822.92	AXCAN PHARMA INC	325412	735.89
ROGERS COMMUNI-B	517210	8465.50	TELESYSTEM INTL	517210	2162.03
ROYAL BANK OF CA	522110	403033.00	LAURENTIAN BANK	522110	16737.77
SHAW COMM-B	517110	7710.80	2737469 CANADA I	517110	5318.79
SUN LIFE FINANCI	524113	163295.00	GREAT-WEST LIFEC	524113	159150.00
SUNCOR ENERGY	211111	10501.00	REPSOL OIL & GAS	211111	11780.00
TELUS CORP	517110	17477.50	2737469 CANADA I	517110	5318.79
TRANSALTA CORP	221112	8482.00	ATLANTIC POWER	221112	604.70
TECK RESOURCES-B	212231	5375.00	CAN ZINC CORP	212231	26.75
TORONTO-DOM BANK	522110	273532.00	LAURENTIAN BANK	522110	16737.77
TOROMONT INDS	423810	856.18	VITERRA INC	423820	784.01
TEMBEC INC	322110	3818.80	CATALYST PAPER	322122	2816.40
THOMSON REUTERS	511110	24225.10	TORSTAR CORP -B	511110	1511.77
TROJAN TECH	333319	118.90	GSW INC A	333319	262.97
VALEANT PHARMACE	325412	2493.84	AXCAN PHARMA INC	325412	735.89
WESTPORT FUEL SY	336310	66.40	TESMA INTL INC-A	336310	1087.73
MICROSEMI SEMICO	334413	363.53	HYDROGENICS CORP	334413	118.60

Appendix B – Python Code

The following Python code is used to find the matched portfolios for our SR portfolio.

```
import xlrd
no_JSI_cons=60

file_location = ""

workbook_data=xlrd.open_workbook(file_location)

data_JSI=[[],[],[]]

data_B=[[],[],[]]

sheet=workbook_data.sheet_by_index(0)

for i in range(no_JSI_cons):

    data_JSI[0].append(str(sheet.cell_value(i,0)))

    data_JSI[1].append(str(sheet.cell_value(i,1)))

    data_JSI[2].append(float(sheet.cell_value(i,2)))

sheet=workbook_data.sheet_by_index(1)

for i in range(len(filter(None,sheet.col_values(0)))):

    data_B[0].append(str(sheet.cell_value(i,0)))

    data_B[1].append(str(sheet.cell_value(i,1)))

    data_B[2].append(float(sheet.cell_value(i,2)))

NAICS=[]

for i in range(no_JSI_cons):

    NAICS.append([])

    for j in range(0,5):

        NAICS[i].append([])

for i in range(no_JSI_cons):

    for j in range(len(data_B[0])):

        N=str(data_JSI[1][i])
```

```
                digit=str(data_B[1][j])
                if digit==N:
                    NAICS[i][0].append(j)
                elif digit[:5]==N[:5] and digit[5:6]!=N[5:6]:
                    NAICS[i][1].append(j)
                elif digit[:4]==N[:4] and digit[4:5]!=N[4:5]:
                    NAICS[i][2].append(j)
                elif digit[:3]==N[:3] and digit[3:4]!=N[3:4]:
                    NAICS[i][3].append(j)
                elif digit[:2]==N[:2] and digit[2:3]!=N[2:3]:
                    NAICS[i][4].append(j)
for i in range(no_JSI_cons):
    for j in range(0,5):
        for k in range(len(NAICS[i][j])):
            for m in range(no_JSI_cons):
                if NAICS[i][j][k]!='N/A':
                    if data_JSI[0][m]==data_B[0][int(NAICS[i][j][k])]:
                        NAICS[i][j][k]='N/A'
for i in range(no_JSI_cons):
    for j in range(0,5):
        NAICS[i][j]=[x for x in NAICS[i][j] if x!='N/A']
differ=[]
for i in range(no_JSI_cons):
    differ.append([])
    for j in range(0,5):
        differ[i].append([])
        for k in range(len(NAICS[i][j])):
            differ[i][j].append(0)
for i in range(no_JSI_cons):
```

```
        for j in range(0,5):
            for k in range(len(differ[i][j])):
                differ[i][j][k]+=abs(data_JSI[2][i]-data_B[2][NAICS[i][j][k]])
for i in range(no_JSI_cons):
    for j in range(0,5):
        differ_NAICS=zip(differ[i][j],NAICS[i][j])
        differ_NAICS.sort()
        NAICS[i][j]=[NAICS[i][j] for differ[i][j],NAICS[i][j] in differ_NAICS]
for i in range(no_JSI_cons):
    NAICS[i]=NAICS[i][0]+NAICS[i][1]+NAICS[i][2]+NAICS[i][3]+NAICS[i][4]
match=[]
for i in range(no_JSI_cons):
    match.append([])
    match[i].append(NAICS[i][0])
    match[i].append(NAICS[i][1])
    match[i].append(NAICS[i][2])
portfolio_1=[]
portfolio_2=[]
portfolio_3=[]
for i in range(no_JSI_cons):
    portfolio_1.append(data_B[0][match[i][0]])
    portfolio_2.append(data_B[0][match[i][1]])
    portfolio_3.append(data_B[0][match[i][2]])
```