Gordon Institute of Business Science
University of Pretoria

The effects of outcome framing on impact investment choices

Fatima Harvey

19388226

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DECLARATION

I declare that this article is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Fatima Harvey

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LIST OF ABBREVIATIONS

BFS	balanced financial and social outcome disclosure
BPT	behavioural portfolio theory
CFA	confirmatory factor analysis
DF	dominant financial outcome disclosure
DS	dominant social outcome disclosure
ESG	environmental, social, and governance
IMM	impact measurement and management
MBA	Master of Business Administration
MCAR	missing completely at random
MVA	missing values analysis
SAVCA	Southern African Venture Capital and Private Equity Association
SMA	SurveyMonkey Audience

COVER LETTER

Greg Shailer, PhD; Omrane Guedhami, PhD; Hao Liang, PhD
Section editors, Finance and Business Ethics
Journal of Business Ethics
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Dear Mr Shailer, Mr Guedhami, and Mr Liang,

I am writing to submit our manuscript titled, "The effects of outcome framing on impact investment choices", for consideration as a *Journal of Business Ethics* research article.[1]

Using an experimental design, we examined the effects of variability in outcome information framing on the decision-making process of impact investors. Our findings illustrate that outcome framing has a meaningful effect on the capital allocation decision investors, but does not influence risk perception or sense of understanding of an investment choice.

Given the emerging interest and importance of impact investment as a mechanism for addressing rising environmental, social, and governance needs, we believe that the findings presented in our paper will appeal to socially conscious investors who subscribe to the *Journal of Business Ethics*. Our findings will allow your readers to consider the ethical and practical implications of outcome framing within an inherently dichotomous field of investment.

This manuscript expands on prior research conducted and published by Lee et al. (2020) in the *Strategic Management Journal*.[2] This manuscript also examines similar topics and issues to those explored in the following papers published by the *Journal of Business Ethics*:

1. Höchstädter, A. K., & Scheck, B. (2015). What's in a name: An analysis of impact investing understandings by academics and practitioners. *Journal of Business Ethics*, *132*(2), 449–475.

[1] The *Journal of Business Ethics* is rated a level 3 journal by the 2018 AJG and category A by the 2019 ABDC Journal Quality List. The journal is Scopus, IBSS, and ISI indexed.

[2] Lee, M., Adbi, A., & Singh, J. (2020). Categorical cognition and outcome efficiency in impact investing decisions. *Strategic Management Journal*, *41*(1), 86–107.

2. Pilaj, H. (2017). The choice architecture of sustainable and responsible investment: Nudging investors toward ethical decision-making. *Journal of Business Ethics*, *140*, 743–753.
3. Phillips, S. D., & Johnson, B. (2019). Inching to impact: The demand side of social impact investing. *Journal of Business Ethics*. https://doi.org/10.1007/s10551-019-04241-5

Each of the authors confirms that this manuscript has not been previously published and is not currently under consideration by any other journal. Additionally, all of the authors have approved the contents of this paper and have agreed to the *Journal of Business Ethics* submission policies.

Corresponding author[3]
Fatima Harvey, research student
Gordon Institute of Business Science, University of Pretoria
26 Melville Rd, Illovo, Johannesburg, 2196, South Africa
19388226@mygibs.co.za
+1 (214) 736-9200

Additional contacts:

Kerrin Myres, senior lecturer
Gordon Institute of Business Science
University of Pretoria
26 Melville Rd, Illovo, Johannesburg, 2196
South Africa
myresk@gibs.co.za
+27 (11) 771 4000

Gavin Price, associate professor
Gordon Institute of Business Science
University of Pretoria
26 Melville Rd, Illovo, Johannesburg, 2196
South Africa
priceg@gibs.co.za
+27 (11) 771 4000

[3] Order of authors is proposed to be student, supervisor, co-supervisor

CHAPTER 2. LITERATURE REVIEW AND HYPOTHESES

2.1 Introduction

The primary aim of this study was to investigate how the framing of financial and social outcome information affected the decision-making process of impact investors. This chapter presents a review of theory and literature relevant to this study. To establish the research context, this chapter will first review existing knowledge on impact investing and available literature on practices of evaluation and information disclosure. Prospect theory was the theoretical basis for this study. Accordingly, prospect theory and its relevance to understanding the construct of framing and its impact on sense of understanding, perceived risk, and financial decision-making will be discussed. Further to the theory, literature relating to the constructs of sense of understanding and perceived risk will be presented. To achieve the aim of this study, research propositions were derived from existing academic literature, as presented in this chapter. To test these research propositions, nine hypotheses were formulated. These research propositions and hypotheses will be discussed in the following sections. Figure 1 below provides a framework of the core constructs to be addressed in this research.

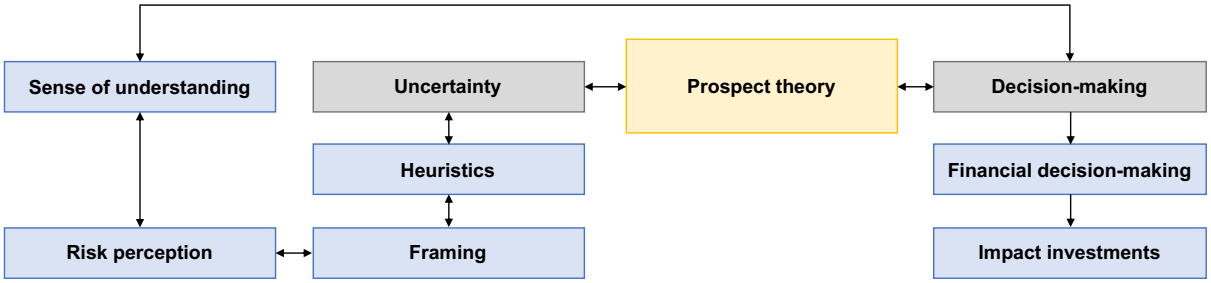

Figure 1: Framework for research

2.2 Impact investing

2.2.1 Background and market context

Impact investment is a funding mechanism within the emerging field of social finance (Santos, Pache, & Birkholz, 2015). It is conceptualised in literature as a spectrum of investment activity with the extremes being finance-first investors and philanthropists (Brandstetter & Lehner, 2015; Emerson, 2003; Nicholls, 2010). Impact investors are distinguished from environmental, social, and governance (ESG) or socially responsible investors by their practice of direct investment into

an enterprise, organisation, or fund to contribute to the achievement of their stated outcomes (Hornsby & Blumberg, 2013). Variability in social business models presents unique challenges to impact investors when assessing the financial and social risk of the business (Santos et al., 2015). The beneficiaries of impact investments are hybrid organisations that pursue financial and social goals (Brandstetter & Lehner, 2015; Lee, Adbi, & Singh, 2020). While they share a common purpose to maximise social impact, diversity in business models exists across these enterprises. Established literature has done well to create a typology for these numerous models (Santos et al., 2015) and four primary models can be outlined: market hybrids, blending hybrids, bridging hybrids, and coupling hybrids. Each of these models has unique management challenges that affect the potential synergies between financial and social returns, which are important to prospective investors (Santos et al., 2015). This variability further complicates the evaluation tasks for prospective investors.

2.2.2 Definition

The heterogeneity of terminologies related to impact investing is reflective of the diverse and dynamic nature of this emerging industry. An examination of existing studies reveals that a great amount of the previous academic effort on impact investment has focused on establishing definitional clarity (Agrawal, 2018; Höchstädter & Scheck, 2015; Mogapi, Sutherland, & Wilson-Prangley, 2019). As an illustration of this point, various terminology is applied to this field, including socially responsible investment, sustainable and responsible investment, social investment, socially conscious investing, and venture philanthropy. These terms are synonymous as a categorisation of a class of investments with both economic and social outcomes. However, important distinctions are found in asset class, geographic vernacular, identification and evaluation process, and the broadness of their qualification of social outcomes, with socially responsible investment encompassing the broadest screening and outcome criteria (i.e., companies with sustainability policies) (Brandstetter & Lehner, 2015; Höchstädter & Scheck, 2015; Pilaj, 2017). This study used the Global Impact Investing Network (GIIN, 2020c) definition, which states that "Impact investments are investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return". However, in establishing the foundation of knowledge for this study, it was concluded that since the definitional terms were principally synonymous in their investment outcome intention, all existing literature that covered complementary terminologies was considered relevant (Höchstädter & Scheck, 2015; Lee et al., 2020; Pilaj, 2017).

2.2.3 Evaluation and disclosure practices

Consistent and clear outcome information enables investors to design effective impact investment strategies. Calls for transparency in outcome reporting have become increasingly important for attracting additional capital into the impact investing market (Brandstetter & Lehner, 2015; Hand, Dithrich, Sunderji, & Nova, 2020). The field presents a challenge in the measurement of risk and return that is addressed insufficiently by traditional investment practices and tools (Brandstetter & Lehner, 2015; Vo, He, Liu, & Xu, 2019). The measurement of risk and return in traditional investment is well-understood and established in literature (Markowitz, 1999; Sharpe, 1964). Comparatively, the measurement of non-financial (i.e., social) return is an emerging practice characterised by variability and inconsistency (Brandstetter & Lehner, 2015). The efficiency of a portfolio for traditional investments is assessed by comparing the risk of monetary loss against the potential monetary return, with financial risk measured as a variance from the expected monetary return (Markowitz, 1952). The efficiency of impact investments is assessed based on impact generation, defined as "the potential for real change that an investment opportunity offers" (Hornsby & Blumberg, 2013, p. 88). These impacts can materialise directly on the beneficiaries, on the community, and on the social enterprise (Hornsby & Blumberg, 2013). Risk in impact investment considers *impact risk*, defined as the "measure of uncertainty that an organization will deliver on its proposed impact" (Brandstetter & Lehner, 2015, p. 94). In addition to financial uncertainty, impact investors are required to consider social uncertainty, impact risk, and the blended value of an investment in their choice process (Brandstetter & Lehner, 2015; Emerson, 2003; Scognamiglio, Di Lorenzo, Sibillo, & Trotta, 2019). Research on social risk has failed to reach a consensus on an optimal definition or model of measurement (Brandstetter & Lehner, 2015). The complexity of quantifying social risk makes it difficult to aggregate both financial and non-financial risk to develop an overall evaluation of risk for hybrid investments. Literature suggests that when "relevant non-financial risk is identified it should be considered as meaningfully higher than financial risk measure" (Brandstetter & Lehner, 2015, p. 98). This suggests that investors may consider social risk as meaningfully higher, or the elevated uncertainty may increase their risk aversion and decrease the attractiveness of an investment when presented with dominant social outcome information.

Early efforts to legitimise the industry focused on developing frameworks of opportunity identification and outcome measurement (Clarkin & Cangioni, 2015). The rising interest in impact investing has continued to encourage practitioner-led progress in the development frameworks and metrics for non-financial outcome measurement (Brandstetter & Lehner, 2015; Höchstädter &

Scheck, 2015). The evolution of the evaluation process for social impact originated with the practice of negative screening. This technique is still commonly applied by finance-first investors interested in diversifying their portfolio with ESG investments (Brandstetter & Lehner, 2015; Trinks & Scholtens, 2017). Negative screening entails purposefully avoiding investment in companies that engage in harmful or controversial activities (Trinks & Scholtens, 2017). However, the ethics of this approach have been called into question because exclusion may be subject to bias based on personal values and beliefs of investment managers, and queries the weight given to consider the empirical performance evidence (Trinks & Scholtens, 2017). Measurement has evolved to more positive screening and sophisticated approaches, which blend positive and negative screening, and involve numerous impact metrics, financial assessment, and ESG considerations (Bilbao-Terol, Arenas-Parra, Cañal-Fernández, & Bilbao-Terol, 2016). Impact investors have moved beyond screening strategies to the utilisation of comprehensive impact measurement and management (IMM) systems to benchmark and monitor investments. GIIN (2020a, 2020b) has made significant progress to consolidate IMMs through its IRIS+ and impact toolkit projects, but the quality of outcome information reported and collected is fundamentally important to the effectiveness of these IMMs.

Social impact reporting has been pioneered and advanced by social enterprises (Nicholls, 2009). This "bootstrapping" of social measurement has yielded a variance of metrics and tools in the sector. Research has demonstrated that the approach to impact measurement is heuristic and tailored to the strategic objective and audience of the enterprise or fund manager (Nicholls, 2009). While there is increasing adoption of the aforementioned global standards of measurement and reporting tools (e.g., IRIS+), there is still much variability in IMM systems (Lehner, Harrer, & Quast, 2019). Although the field of traditional finance has undergone evolutions in the models applied to portfolio measurement and undoubtedly will continue to evolve, advances in those standards of measurement are applied generally across the industry with minimal variability. In traditional finance, the requirements for the presentation and content of information are specified and enforced by regulation (Brandstetter & Lehner, 2015). The consistency of presentation and content of measurement enables an investor's sense of understanding and risk assessment in the portfolio management process (Long, Fernbach, & De Langhe, 2018). In contrast, reporting conventions and regulations for impact outcomes vary by geography, industry, and organisational structure (Nicholls, 2009).

While information variance can occur in the presentation of all types of information (Tversky & Kahneman, 1986), the current challenges in non-financial measurement create a distinct

opportunity for information variance in the impact investment field. Social outcome reporting is a voluntary practice and information disclosure related to social impact also has varying motivations (Fatemi, Glaum, & Kaiser, 2018). Fatemi et al. (2018) found that the intensity and variance in reporting tends to be primarily as a result of managerial motives (i.e., investor perception) and less about true performance. Their work further demonstrated that disclosure had a moderating effect on firm performance and value (Fatemi et al., 2018). Moreover, research has noted that variability in the type of information disclosed is a function of different disclosure motivations (Fatemi et al., 2018). Social entrepreneurs have displayed similar tendencies with disclosure practices, which they "exploit strategically to support their various mission objectives with key stakeholders" (Nicholls, 2009, p. 756). Practically, "reporting practices in social entrepreneurship attempt self-reflexively to enhance social mission rather than merely to respond to regulation, convention, or other isomorphic pressures" (Nicholls, 2009, p. 756). Vo, Christie, and Rohanna (2016) reported that impact analysts, the individuals responsible for financial and social outcome evaluation, "rely on both descriptive quantitative and qualitative data and analyses" (p. 480). Furthermore, the profile, experience and perceptions of the analyst influenced the evaluation approach (Vo et al., 2016). Therefore, while investors seek reliable information to evaluate the financial viability of investments, literature reveals the potential dilemma resulting from impact analysts' motivation to present information aimed at influencing decision-makers in their favour (Vo et al., 2016). Equally, it shows the significant influence investors have on how social enterprises and their impact analysts approach their work (Vo et al., 2016). What to measure and how to measure with regard to social impact is a persistent challenge within the field of social investment (Nicholls, 2009). Further complexity exists when investors seek to compare investments across sectors, as metrics are often incompatible (Nicholls, 2009).

2.3 Theoretical background and motivation

2.3.1 Prospect theory

When individuals are faced with choices in the context of uncertainty, "psychological tendencies" influence decision-making (Heutel, 2019; List, 2004; Tversky & Kahneman, 1986, p. S261). The practice of investing inherently operates within a context of uncertainty because future outcomes are unknown (Markowitz, 1991). Developed by Daniel Kahneman and Amos Tversky (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), prospect theory and its contemporary revision cumulative prospect theory examines the psychological influences on individual decision-making. A core tenant of prospect theory is the idea of a reference point (Kahneman & Tversky, 1979).

According to the theory, individuals tend to evaluate choices based on a reference point, rather than objective evidence, and to show preference for outcomes with higher certainty and lower risk (Barberis, 2013; Heutel, 2019; Kahneman & Tversky, 1979). The reference point represents a neutral outcome from which decisions yield a positive or negative deviation (Tversky & Kahneman, 1986). In practice, the reference point can be shifted by framing tactics, such as risk classification and positive and negative labelling (Tversky & Kahneman, 1986). The dynamic nature of the reference point leads decision-makers to be susceptible to variations in the outcome framing of choice options (Tombu & Mandel, 2015; Tversky & Kahneman, 1986).

2.3.2 Framing and heuristics

Variances in the framing of choice options create variability in choice preferences – a phenomena predicted by prospect theory that is referred to as the *framing effect* (Tversky & Kahneman, 1986). Decision framing refers to a decision-maker's perception of a decision's acts, contingencies, and outcomes (Tversky & Kahneman, 1981, 1986). Acts signify the options an individual has to choose from, contingencies are the probabilities of the outcomes as related to the acts, and outcomes refer to the consequences of the act (Tversky & Kahneman, 1981). When the outcome of simultaneous choices is presented differently, despite the choices having equivalent outcomes, individuals exhibit choice preferences, thereby demonstrating that the framing of outcome information influences their choices (Tversky & Kahneman, 1986). The presentation of the decision as well as individual norms, habits, and expectations influence the frame of the decision-maker (Tversky & Kahneman, 1986). These norms and habits develop into individual heuristics and bias (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Heuristics are useful mental shortcuts used to simplify complex decisions and form judgements in contexts of uncertainty (Tversky & Kahneman, 1974). Rather than assimilating varied outcomes information into a common frame, individuals default to the use of heuristics (Tversky & Kahneman, 1986). Benartzi and Thaler (2007) found that the heuristic strategy applied varies based on the complexity of the situation.

The notion of a psychological account is a useful concept in the evaluation of decision situations with compound or interrelated outcomes, such in impact investing. The psychological account is defined as "an outcome frame which specifies (i) the set of elementary outcomes that are evaluated jointly and the manner in which they are combined and (ii) a reference outcome that is considered neutral or normal" (Tversky & Kahneman, 1981, p. 456). Tversky and Kahneman (1981) proposed that individuals commonly evaluate a choice based on its direct consequences, as it requires less cognitive effort and is a more intuitive approach to decision-making. A more contemporary theory,

behavioural portfolio theory (BPT), has emerged in contrast to traditional investor theories (i.e., Markowitz, 1999; Sharpe, 1964) to explain investors' varying decision motivations (Bilbao-Terol et al., 2016; Shefrin & Statman, 2000). This theory extends prospect theory in combination with other established behavioural choice theories (Bilbao-Terol et al., 2016). Similar to the concept of a psychological account, BPT considers the use of mental accounts, which exist as a result of framing, to deal with several investment goals (Bilbao-Terol et al., 2016). This notion of psychological or mental accounts is useful to the current research as it provides a further theoretical tool to aid in understanding the competing motivations of impact investors.

When making choices involving monetary outcomes, psychologically driven risk behaviours are likely to yield outcome inefficient choices (Lee et al., 2020; Tversky & Kahneman, 1986). In the presence of adequate probability for gains and losses, individuals tend to display an aversion to risk when gains are at stake and an inclination towards risk when the choice involves losses (Tversky & Kahneman, 1986). Individuals display these behaviours even when choices yield identical outcomes (Tversky & Kahneman, 1986). When presented with the option to make a status quo decision or an incentivised alternative decision, Sautua (2017) found that individuals exhibit a status quo bias due to regret aversion and ambiguity-driven indecisiveness. The effects of variance in information on choice can also be explained by what Kahneman and Tversky (1986) describe as "nonlinearities of value and belief" (p. S257). This means that, since typical individuals do not instinctively make decisions based on actuarial probability distributions in their minds, much of the choice is based on mental representation (Tversky & Kahneman, 1986).

2.3.3 Framing and heuristics in financial decision-making

Extensive literature supports the usefulness of prospect theory in understanding investment behaviour (Barberis, Mukherjee, & Wang, 2016; Forbes, Hudson, Skerratt, & Soufian, 2015; Harrison et al., 2015; Meng & Weng, 2018; Qin, 2015). Individual reliance on heuristic thinking in financial decision-making, as well as the effects of heuristics on the efficiency and propensity to make investment decisions have been well-researched in recent years (Barberis et al., 2016; Benartzi & Thaler, 2007; Døskeland & Pedersen, 2016; Lee et al., 2020; Pilaj, 2017). Heuristic thinking is useful for investors' decision-making process, since they are exposed to large volumes of information, which may be cognitively overwhelming (Pilaj, 2017). For example, in their application of prospect theory to an investigation on investment outcomes, Barberis et al. (2016) demonstrated that historical stock returns were a significant factor in portfolio allocation decisions, and that past stock performance has a negative relationship with future performance. This outcome

is explained partially by loss aversion tendencies, which trigger investors to favour stocks with strong past returns and stable performance, causing these stocks to become overvalued and leading to weak future performance (Barberis et al., 2016).

2.3.4 Theoretical motivation

This study sought to extend the ideas of prospect theory to consider the effects of information variance on choice preference in a situation where both monetary and non-monetary information is considered. Prospect theory has broad applicability to contexts, irrespective of the unit of analysis (i.e., monetary incentives, human lives) (Tversky & Kahneman, 1981, p. 457). The seminal illustrations used to establish the principles of prospect theory focused on examples that discuss the violation of invariance when considering experiments with parallel monetary outcomes or human lives (Tversky & Kahneman, 1986). These illustrations did not consider mixed outcomes that presented a simultaneous choice between monetary and non-monetary outcomes. Døskeland and Pedersen (2016) investigated the effects of wealth framing and moral framing on social responsibility investment decisions. However, this experiment did not present wealth and morality information about the investment choice simultaneously. Kemel and Paraschiv (2018) examined choice preferences in social decisions and concluded that when choices involve human lives, individuals demonstrate risk aversion towards gains similar to that of decisions involving monetary outcomes, but display higher risk-seeking behaviour to losses than choices involving monetary outcomes. This study seeks to build upon the findings of Døskeland and Pedersen (2016), Kemel and Paraschiv (2018), and Lee et al. (2020) by considering both monetary and non-monetary outcome information in an evaluation of the effects of information framing in a decision-making process.

The nature of impact investment requires decision-makers to consider two reference points – financial and social – when evaluating risk and return. Conscious investors have long struggled to manage the tension between financial and social value (Emerson, 2003). Given its dual-purpose approach to outcomes, impact investing provides an interesting background against which to examine how individuals assess this reference point when considering financial and social gains and losses. More specifically, impact investing presents a unique context to examine framing effects as related to compound outcomes. Existing literature has identified this as an area that requires further theoretical development (Barberis, 2013). Vo et al. (2019) argue that "traditional investment and portfolio theories … are inadequate for decision-making and the construction of an optimized socially responsible investment portfolio" (p. 1). In their meta-analysis on impact

investment, Höchstädter and Scheck (2015) reported that "there have been repeated calls for academic research on impact investment" (p. 451). Literature also calls for further research to measure the "significance level to which [individual] investors tend to be influenced by identified behavioural bias" (Mittal, 2019, p. 12). Given the unique dual nature of utility in impact investment decisions, there is substantial opportunity to increase the body of knowledge regarding behaviour within this field through the lens of prospect theory.

2.4 Information variance and financial decision-making

Research affirms that financial decision-making is an inherently heuristic-based activity (Forbes et al., 2015). For instance, Wuebker, Hampl, and Wüstenhagen (2015) conducted an experiment to examine the impact of social networks on investment decisions. Their study confirmed that personal connections directly influence the decision-making process of venture capital investors, although this factor is moderated by investment experience (Wuebker et al., 2015). Investors rely on these personal ties to minimise market and industry uncertainty (Wuebker et al., 2015). An effect is magnified in geographies where investor networks are dense, such as in the United States (Wuebker et al., 2015). Several other experimental studies have explored the relationship between presentation and disclosure of information and investment decisions (Døskeland & Pedersen, 2016; Eccles, Ioannou, & Serafeim, 2014; Lee et al., 2020; Linciano, Lucarelli, Gentile, & Soccorso, 2018; Woike, Hoffrage, & Petty, 2015). Woike et al. (2015) designed a simulated decision-making model to determine how the manipulation of business plan outcome information influences the success of venture capital investment strategies. They concluded that investors who built their future strategies on a narrow base of feedback about prior business plan outcome information – namely only those they had invested in – performed worse compared with those who were exposed to a broader base of feedback (Woike et al., 2015).

Impact investors have a greater inclination to utilise heuristic decision-making (Lee et al., 2020). Following the emergence of the socially responsible asset classes, framing strategies have been used by entrepreneurs to create a distinct investor identity to differentiate and legitimise their products (Markowitz, Cobb, & Hedley, 2012). Frames serve to influence others' actions by establishing a comparison and call to action relative to the status quo (Markowitz et al., 2012). One such example is that impact investors use the heuristic technique of categorical labelling to form beliefs about the outcomes of impact-focused investment options (Lee et al., 2020). These beliefs have a greater influence on portfolio allocation decisions than the objective investment outcome information provided (Lee et al., 2020). Moreover, investor mindset may influence the decision

frame applied to outcome information. As a result of the array of social identities that exist across social finance actors, differences in the focus on value creation communication exist (Lehner et al., 2019). Social investors are more open to collaboration and inclusive communication, but traditional investors engaging in social financing still communicate using traditional finance terminology (Lehner et al., 2019). Furthermore, social investors display a strong preference for communicating non-financial impact in contrast to traditional investors, who commonly defer to communicating financial impact (Lehner et al., 2019). This also implies a bias towards the type of information that investors are likely to value in the assessment of their investments. In a complementary insight, Azmi, Mohamad, and Shah (2018) contended that when investors feel ethically obligated to the outcome of the investment, variance in the information related to the outcome of such socially oriented investments is likely to have a disproportionate impact on investor decision-making. Their work empirically demonstrated that when individuals invest in socially oriented funds, they display less sensitivity to negative returns so long as the monetary losses are sufficiently offset by the non-financial utility gained from the funds (Azmi et al., 2018). This finding offers insight into the strength of influence that non-financial utility has on investor decision-making. However, within this research's data set, this perceived risk seeking behaviour could also be attributed to low motivation to seek out alternative socially responsible funds due to limited options or the associated cost of switching investments (Azmi et al., 2018).

Some research has minimised the impact of information variance in influencing the outcome of financial decisions. In their study on the outcome efficiency of impact investment decisions, Lee et al. (2020) reported that a more structured presentation of outcome information was ineffective in improving efficiency of an investor's capital allocation decisions. However, by disclosing or suppressing the labels on a set of investment options, the authors demonstrated that investment decisions were influenced by the perceived value of that investment as determined by an investor's categorical cognition, rather than based on objective outcomes (Lee et al., 2020). This categorical labelling could be considered a form of outcome framing (Tombu & Mandel, 2015). In an experiment using wealth and moral framing for the advertisement of mutual funds, Døskeland and Pedersen (2016) demonstrated that framing influences investors' decisions and predicts their likelihood to seek out additional information. Investors exposed to a wealth frame, which showed a preference for financial outcome information, sought out further information, and invested more responsibility than individuals exposed to the moral frame, which has a preference for social outcome information (Døskeland & Pedersen, 2016). Furthermore, the decision action (i.e., the purchase of socially responsible mutual funds) was influenced by whether the individual had been exposed to wealth or moral framing (Døskeland & Pedersen, 2016).

An area that has received limited attention is the relationship between framing and capital allocation decisions in hybrid investments (Døskeland & Pedersen, 2016; Long et al., 2018). Lee et al. (2020) call for further research to examine "how impact investors consider the riskiness of financial versus social outcomes [and] respond to limited outcome information" (p. 103). Sautua (2017) calls for additional enquiry into how the introduction of information affects individuals in uncertainty-based decision-making. There is also a gap in existing literature on how variances in outcome framing affect perceived risk and decision-making in an impact investment context. Existing research focuses on non-hybrid investments or offers a choice of hybrid and non-hybrid investment options. Academic evidence of the effects of framing on decision outcomes has been established in previous sections, and it is implicit that the outcome of an investor's decision-making process is the capital allocation choice. Drawing from this existing literature, it is hypothesised that:

Hypothesis 1: Finance-dominant framing has an effect on the capital allocation decisions of impact investors.
Hypothesis 2: Balanced framing has an effect on the capital allocation decisions of impact investors.
Hypothesis 3: Social-dominant framing has an effect on the capital allocation decisions of impact investors.

2.5 Risk perception

2.5.1 Risk theory

It is well-accepted that investors are inherently risk-adverse and that, given the choice between two investments of equal outcome, they will choose the less risky option (Markowitz, 1952, 1999). The extensive body of knowledge on risk perception is organised around two ideologies: psychometric and decision theory (Long et al., 2018; Tombu & Mandel, 2015; Wilson, Zwickle, & Walpole, 2019). In psychometric risk, the dread factor – measured as the perceived consequences of a hazard – is the key influencer of an individual's risk assessment of that event, thus outweighing the reality of probability of event occurrence (Slovic, 1987; Wilson et al., 2019). According to decision theory, risk is perceived based on the given choice measured in comparison to all possible outcomes, often referred to as outcome variance (Kahneman & Tversky, 1979; Long et al., 2018; Tombu & Mandel, 2015).

Given the subjective nature of defining what an undesirable outcome is, there are numerous approaches to the measurement of risk perception (Tombu & Mandel, 2015). Risk perception in the psychometric approach can be measured using five categories: general unidimensional, probability and consequences, risk versus benefits, affect only, and probability only (Wilson et al., 2019). Based on their investigation of the existing body of work on risk measurement, Wilson et al. (2019) argued that perceived risk must be measured using a multidimensional measurement approach that considers affect and consequences. Their study confirmed that this approach to measurement was applicable across behavioural, social, and environment hazards (Wilson et al., 2019). Behavioural hazards were described as impacting oneself and being specifically hazardous to individual health and safety (Wilson et al., 2019). Comparatively, the measurement of risk in decision theory is more intuitive. Risk perception is based on evaluating the difference between an outcome to the individual and the actual outcome; or conceptualised differently, it considers the variance between the choice outcome and a reference point (Pollatsek & Tversky, 1970).

2.5.2 Framing and perceived risk

Variations in the framing of outcome variances strongly influence an individual's risk perception (Tombu & Mandel, 2015; Tversky & Kahneman, 1986). Outcome variance has been established as a significant contributing factor in assessing risk in decision-making (Tombu & Mandel, 2015). Debate exists as to whether risk perceptions can be deduced using decision-based outcome variance, or whether a psychological approach that is defined by the individual should be considered as a more effective approach (Tombu & Mandel, 2015). This dispute presents an opportunity for research to compare framing effects in a choice process with self-reported risk perception and risk attitude measures. Furthermore, framing can be characterised as either descriptor framing or outcome framing. Descriptor framing, as defined by Tombu and Mandel (2015), "refers to the selection of positive or negative descriptors to express options (e.g., the choice of using the terms *saved* or *die*)", and outcome framing "refers to variations in the positivity or negativity [termed the explicated valence] of the events that are explicated in a description" (p. 466).

Manipulating the way information is framed has been shown to influence decision-makers' attitudes and actions, specifically in the context of financial decision-making (Døskeland & Pedersen, 2016; Linciano et al., 2018). While financial costs and benefits and moral costs and benefits are considered in socially responsible investments, financially relevant information may

be more effective at reducing perceived uncertainty for investors (Døskeland & Pedersen, 2016). Linciano et al. (2018) posited that perceived risk is affected by the way financial information is presented. When the presentation of financial information is less visual and more verbal, investors tend to perceive those products as more complex and as a riskier investment decision (Linciano et al., 2018). While perceived complexity was identified as the primary driver of perceived risk, the study also demonstrated that individual characteristics like gender, financial literacy, and age can magnify the framing effects of information disclosure (Linciano et al., 2018). Moreover, impact investors may prioritise social outcome evidence in their decision-making process. Mogapi et al. (2019) found that impact investment decisions are greatly influenced by the impact lens or the perception of the strength of an investment's impact case. This influence was not diminished by the strength of the financial return, with fund managers rejecting financially sound opportunities due to weak expected social impact (Mogapi et al., 2019). Overall, social outcomes are viewed as incremental benefits and may not be sufficient to stand on their own against financial outcomes (Døskeland & Pedersen, 2016). When grouped with financial outcomes, social outcomes may be viewed as more advantageous if the reference point is social outcome information only; whereas when financial information is presented, the sensitivity to additional social outcomes information is minimal (Brandstetter & Lehner, 2015). Based on the relationships validated within existing literature, it is hypothesised that:

Hypothesis 4: Finance-dominant framing has a positive effect on the perceived risk of an impact investment decision.
Hypothesis 5: Balanced framing has a positive effect on the perceived risk of an impact investment decision.
Hypothesis 6: Social-dominant framing has a negative effect on the perceived risk of an impact investment decision.

2.6 Sense of understanding

Individual decision-making is guided by an individual's sense of understanding (Long et al., 2018). The sense of understanding construct differs from familiarity, in that the latter relates only to exposure to an entity or object and does not consider knowledge thereof (Long et al., 2018). Through the collection of data and information about a problem, individuals develop a subjective feeling of understanding that enables them to navigate uncertainty and take action in unfamiliar situations (Long et al., 2018). However, this heuristic judgement is a poor indicator of the objective risk of an investment (Long et al., 2018). Research has demonstrated that this sense of

understanding influences investor interest, confidence, and risk appetite, particularly in expert investors (Long et al., 2018). The measurement of understanding in the context of financial decisions presents a further challenge. According to Long et al (2018), "lack of calibration between subjective and objective understanding is a major problem in financial decision making" (p. 476). When sense of understanding is diminished, an investor's risk perception is negatively affected (Long et al., 2018). Literature also suggests that risk tolerance moderates the effects of diminished sense of understanding (Long et al., 2018). Consequently, it is hypothesised that:

Hypothesis 7: Finance-dominant framing has a positive effect on an investor's sense of understanding of a hybrid enterprise.
Hypothesis 8: Balanced framing has a positive effect on an investor's sense of understanding of a hybrid enterprise.
Hypothesis 9: Social-dominant framing has a negative effect on an investor's sense of understanding of a hybrid enterprise.

2.7 Research need

The emergent nature of impact investing exposes the field to unique vulnerabilities in asset misclassification and inconsistencies in outcome measurement, which influence an investor's perception of risk. Brandstetter and Lehner (2015) have called for a better understanding of the effects of variability in outcome presentation and reporting on impact investor decision-making to advance the field. While there is ongoing academic effort to develop integrated frameworks for the measurement of hybrid portfolios (Brandstetter & Lehner, 2015), what is still to be reconciled is how the presentation of expected financial and non-financial outcomes influences investors' perceptions of overall risk of the investment, given a specific financial or non-financial framing. Existing research has established the relationships between perceived risk and sense of understanding (Long et al., 2018) and explored the role of framing and heuristics in responsible investment decision-making (Døskeland & Pedersen, 2016; Forbes et al., 2015; Kemel & Paraschiv, 2018; Lee et al., 2020), while this study will examine the effect of outcome framing on capital allocation behaviour within the specific context of impact investments.

In conclusion, this study's research problem is concerned with information framing and its effects on the decision-making process of impact investors. This research problem will be investigated through the research proposition and hypotheses identified in this chapter.

CHAPTER 4. RESEARCH METHODOLOGY

This chapter outlines the methodology and design for the research to be conducted in this study.

4.1 Choice of research methodology and design

This study's research philosophy was positivism, as the research aimed to produce credible and meaningful data based on the discovery of observable and measurable constructs (Saunders & Lewis, 2018). In line with this philosophy, existing theory was used as a basis to develop hypotheses, with statistical analysis then being applied to generalise the relationships and associations between the data variables. This study aligned with existing research in seeking to identify, measure, and compare variables affecting investor behaviour through a positivist lens (Døskeland & Pedersen, 2016; Lee et al., 2020; Long et al., 2018).

This research used a deductive approach. This approach involved testing an existing theoretical proposition, which contrasts with theory development through an inductive research approach (Saunders & Lewis, 2018). A conceptual model of the relationship between the research constructs, provided in Appendix A1, and the research questions for the study were derived logically from existing literature (e.g., Lee et al., 2020; Long et al., 2018), which supported a deductive approach.

This research was an explanatory mono-method quantitative study. The mono-method is characterised by using one data collection method (Saunders & Lewis, 2018). This method was undertaken by Døskeland and Pedersen (2016) in their study of the impact of framing on investor behaviour in socially responsible investments, and by Wuebker et al. (2015) in their study on the effects of status hierarchies and personal ties on venture capital decision-making. An explanatory approach seeks to study and explain casual relationships between variables (Saunders & Lewis, 2018). The purpose of this research was to examine the relationships between perceived risk, sense of understanding, and outcome information framing in the context of impact investment decision-making.

A single-factor experimental design was used to establish a causal relationship between the variables identified in this research (Kirk, 2012). An experiment is a highly structured strategy that isolates causal variables and enables the researcher to test of the robustness of a theory (Saunders & Lewis, 2018; Zellmer-Bruhn, Caligiuri, & Thomas, 2016). In describing the relevance of experimental research to international business, Zellmer-Bruhn et al. (2016) asserted that "the true

experiment is typically considered the only research method that can assess a cause and effect relationship" (p. 401). Academia has shown an increased interest in experimental research within the field of business (Døskeland & Pedersen, 2016; Kemel & Paraschiv, 2018; Lee et al., 2020; Long et al., 2018; Wuebker et al., 2015; Zellmer-Bruhn et al., 2016). Experimental design has been applied extensively to research in the field of behavioural economics and, more recently, to the emerging body of research on socially responsible and impact investing (Døskeland & Pedersen, 2016; Lee et al., 2020; Long et al., 2018; Wuebker et al., 2015). A post-test-only design was deemed acceptable for this study because it was possible for the researcher to establish the expected value of the mean that would be observed in the absence the dominant disclosure scenarios (Kirk, 2012).

Quality experimental design involves three critical elements: randomisation, replication, and local control (Kirk, 2012). This study used a self-administered web-based questionnaire through an online survey tool (SurveyMonkey) as the means of distribution for the experiment. The experiment followed a between-subjects design, where participants are exposed to multiple counterbalanced treatments using a completely randomised design (Hsu, Simmons, & Wieland, 2017). Web-based survey platforms and crowdsourcing tools are cited in academic literature as effective tools for administering randomised experiments (Hsu et al., 2017; Lee et al., 2020; Long et al., 2018).

This research was a cross-sectional study conducted at one period in time. This time horizon is appropriate for studying a specific topic at a particular time and can be used for qualitative and quantitative methods (Saunders & Lewis, 2018). The requirements for a longitudinal study would not have been conducive to the time constraints on this research project, further supporting the choice of a cross-sectional time horizon.

4.2 Population

The population considered for this study was professional and non-professional investors. In this study, investors were defined as individuals with formal academic qualifications in business (i.e., Master of Business Administration [MBA] and other business degrees), self-reported interest or knowledge in business and investing, or professional investment experience (Lipe, 2018). This population was selected to achieve the aims of this study, namely explaining the possible relationship between perceived risk, sense of understanding, and investment decisions. Furthermore, the population should enhance generalisability of the research findings. It is the prevailing view that impact investments are not limited to geographies, sectors, social-economic

demographics, or financial instruments (Clarkin & Cangioni, 2015; Höchstädter & Scheck, 2015). As such, this study required data from a broad heterogenous population of individuals capable of making investment decisions.

4.3 Unit of analysis

Given that the aim of this study was to investigate how the framing of financial and social outcome information affects impact investors' decision-making process, the unit of analysis for this study was individual professional and non-professional investors.

4.4 Sampling method and sample size

As a complete sampling frame of individual professional and non-professional investors was unavailable, this study used non-probabilistic sampling techniques. The sampling methodologies used were critical case purposive sampling and self-selection sampling from three groups: (1) individuals participating in SurveyMonkey Audience (SMA), (2) members of the Southern African Venture Capital and Private Equity Association (SAVCA), and (3) current MBA students in South Africa. Purposive sampling recruits participants based on judgement using specified criteria (Saunders & Lewis, 2018). Critical case purposive sampling is used to ensure a high likelihood of occurrence of the topic of interest within the sample identified (Saunders & Lewis, 2018). Self-selection sampling invites population members to identify themselves to participate in the research (Saunders & Lewis, 2018).

Web-based survey platforms and crowdsourcing tools have been used in existing research to recruit individuals from a heterogeneous population (Hsu et al., 2017; Lee et al., 2020; Long et al., 2018). Literature has also established that MBA students can be considered "reasonable proxies for nonprofessional investors", and properly screened survey marketplace participants "provide effort at levels at least as high as student experimental participants" (Lipe, 2018, p. 18). SAVCA is an industry body for professionals in private equity and venture capital, and its members are required to have high involvement and good standing within these fields; as such, individuals sampled from this population are capable of providing relevant data for this study.

The sample population was accessible to the researcher. SMA participants were solicited directly for participation in the experiment through an automated distribution directly from the SMA platform. The researcher is an MBA student at the Gordon Institute of Business Science (GIBS)

and used existing student-led social media platforms to distribute the request for participation. Additional social media platforms with interest groups focused on impact investment were also used to distribute the request for participation. Finally, e-mail addresses for all members of SAVCA were publicly available on their website. SAVCA leadership was notified of the intent to contact its members to request their participation in the academic research.

4.5 Measurement instrument

This study used a self-administered and self-completed web-based questionnaire. The questions were adapted from questionnaires used in previous academic studies. Refer to Appendix A2 for the questionnaire used in this study.

4.5.1 Sense of understanding

Sense of understanding was measured using a four-item scale adapted from the work of Long et al. (2018). The items were scored on a five-point rating scale, where 1 was "strongly disagree" and 5 was "strongly agree". The scale based on these four items has excellent construct reliability, as shown in Table 1 – Cronbach's alpha is 0.805 for Company A, 0.855 for Company B, and 0.894 for Company C (Hair, Black, Babin, & Anderson, 2019). Reliability is described as the degree to which the data collection methods and analysis procedures used produce consistent findings (Saunders & Lewis, 2018). Cronbach's alpha has been used to assess reliability in existing academic experimental design research focused on investor behaviour (Aspara, Chakravarti, & Hoffmann, 2015; Kemel & Paraschiv, 2018; Lee et al., 2020).

Conclusions drawn from experimental design procedures are susceptible to four primary sources of validity error: internal, external, construct, and statistical conclusion (Milligan & McFillen, 1984). Validity is a judgement of the degree to which empirical evidence and theoretical rationale support the method of measurement employed (Salkind, 2010; Saunders & Lewis, 2018). Internal validity is concerned with a cause-and-effect relationship between variables (Zellmer-Bruhn et al., 2016). The completely randomised design of the experiment served as the primary mitigation strategy against relevant factors that threatened the internal validity of this research – namely subject selection bias, demand characteristics, and causal ambiguity (Kirk, 2012; Salkind, 2010). A further threat, demand characteristics, was mitigated against by limiting the information on the purpose of the study within the informed consent. External validity refers to the generalisability of research results to other settings. The study mitigated external validity risk due to selection bias by

recruiting participants from a heterogenous population. The statistical conclusion of the findings of this study was ensured by obtaining a sample size consistent with the existing academic precedent. Construct validity was established by confirming both convergent and discriminant validity (Hair et al., 2019). Correlation matrixes for the three companies confirmed that all four items within the sense of understanding construct displayed correlations significant at the $p = 0.01$ level. A confirmatory factor analysis (CFA) performed for all three companies confirmed discriminate validity and validated that all four items loaded to one factor. The results of these validity checks are reported in Tables 1 and 2. On the basis of the correlation analysis and the CFA, the four items were combined and averaged into an aggregate sense of understanding variable (Hair et al., 2019).

Table 1: Sense of understanding correlation matrix (reliability and convergent validity)

	Company A					Company B					Company C				
Variable	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
1. I understand what [Company X] does.															
2. I can explain to others what Solar Solutions does.	0.499**					0.678**					0.689**				
3. I can make sense of the information presented about Solar Solutions.	0.331**	0.526**				0.574**	0.642**				0.682**	0.745**			
4. Solar Solutions' business is easy to understand.	0.469**	0.694**	0.525**			0.503**	0.563**	0.614**			0.576**	0.689**	0.686**		
5. Sense of understanding factor	0.706**	0.855**	0.763**	0.851**	**(0.805)**	0.824**	0.867**	0.845**	0.803**	**(0.855)**	0.842**	0.899**	0.893**	0.849**	**(0.894)**

Cronbach alpha reliabilities for variables are in parentheses
**Significant at the 0.01 level

Table 2: Confirmatory factor analysis

Kaiser-Meyer-Olkin and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.773
Bartlett's Test of Sphericity	Approx. chi-square	179.063
	df	6
	sig	0.000

Communalities

Component	Extraction	Extraction total	Component matrix	Total variance explained (%)
1. I understand what [Company X] does.	0.495		0.704	
2. I can explain to others what Solar Solutions does.	0.755		0.869	
3. I can make sense of the information presented about Solar Solutions.	0.55		0.741	
4. Solar Solutions' business is easy to understand.	0.739		0.859	
5. Sense of understanding factor		2.539		63.473

4.5.2 Perceived risk

Perceived risk was assessed using a one-item scale adapted from the work of Long et al. (2018) (e.g., "How risky would you rate an investment in Company X?"). Items were scored on a five-point scale ranging from 1 ("Very low/negligible risk") to 5 ("Very/extremely risky"). Risk perception is a well-established construct in literature and reliability of a unidimensional scale for perceived risk is in line with existing research (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012; Holzmeister et al., 2020).

4.5.3 Capital allocation

The financial decision was measured using a single-item capital allocation task. The measurement instrument was adapted from the work of Lee et al. (2018) and Long et al. (2018), which used probability distribution tasks and capital allocation tasks. The reliability of this unidimensional scale was assured using measurement items from high-quality academic literature (Litwin, 1995).

4.6 Data gathering process

To answer the proposed research questions, a post-test-only, between-subjects design experiment was designed. The experiment required participants to complete a capital allocation task that reflected critical features of an impact investment decision. Task design has been established as an effective approach to test investor behaviour (Døskeland & Pedersen, 2016; Lee et al., 2020; Long et al., 2018). Upon acknowledgement of their informed consent, participants were provided with a task briefing and instructions (see Appendix A3), which gave an overview of the context of the solar sector and guidance of what would be required of them in the experiment.

A pretesting of the experiment questionnaire was performed to assess the clarity and structure of the questions and usability of the eventual output data. Participants of the pretest provided feedback that the company profile information should be make accessible during the capital allocation task. Due to the design restriction of the SurveyMonkey online survey tool, it was not possible to recall the randomly assigned profiles for the participants for the capital allocation task. However, to accommodate this feedback, a note was inserted at the beginning of the task allocation section to advise participants that, should they wish to recall the company profiles, they could use the back button within the survey. If participants used this functionality, their previous responses would be saved, ensuring that no reanswering of questions was required. An additional point of feedback from the pretest was related to the risk profiles. To make the profiles more comprehensive, long- and short-term views were added for high- and low-risk tolerance. Other adjustments to question and response structure and verbiage were made based on pretest feedback requesting additional clarity and the condensing of Likert-scale responses.

4.6.1 Experiment structure

The experiment questionnaire was divided into three sections. In the first section, participants were asked to provide information on their education and business and investment interest and experience for sample qualification; these questions were adapted from Lee et al. (2020) and Lipe (2018). Furthermore, participants were asked to answer questions related to their industry knowledge and risk tolerance. Four risk profiles, which were adapted from the research of Long et al. (2018), were provided: (1) a short-term low-risk tolerance, (2) a long-term low-risk tolerance, (3) a short-term high-risk tolerance, and (4) a long-term high-risk tolerance. In the second section, participants were provided with company briefing information and asked to complete the questions relating to their risk perception and sense of understanding. These questions were adapted from the

research of Long et al. (2018). In the third section, participants were given a hypothetical financial endowment of USD$2 000 to allocate across three companies. Participants were required to spend the full USD$2 000 allocation. Similar studies support that this endowment amount limits naïve diversification behaviour and have used comparable hypothetical endowment values (Lee et al., 2020; Long et al., 2018). The capital allocation task question was adapted from the research of Lee et al. (2020).

4.6.2 Outcome treatments

Three companies were profiled for this experiment. To reduce bias due to familiarity, these companies were fictitious. Company profiles were positioned within the same industry, solar energy, and were adapted from publicly available information on the company websites of three real solar energy social enterprises: d.light (https://www.dlight.com/), M-Kopa (http://www.m-kopa.com/), and Orb Energy (https://ke.orbenergy.com/) (see also Acumen, 2017). The three profiles had differently worded company overview information, but essentially the same mandate and objectives. All three companies had nearly equivalent financial and social outcomes. Any differences in company overview, financial outcomes, or social outcomes were negligible. The structure and format of all company profiles was consistent, the company overview information was presented in paragraph format, and the outcome metrics were provided in a table. Information about the companies was presented to participants based on established categories of informational cues that investors use to evaluate potential investment opportunities (Woike et al., 2015). As per Woike et al. (2015), informational cues can be summarised into five categories:

> (a) product characteristics, (b) market characteristics, (c) the company's financial position and outlook, (d) the traits of the entrepreneur or management team, and (e) other cues such as the interest of another [investor] in a business plan under consideration or the ability of [an investor] to add value to a deal (p. 1706).

Variance in the company profiles was established through the framing of the metrics populated in the outcome tables. For each company, three outcome framing scenarios were developed: (1) dominant financial (DF) outcome disclosure, (2) dominant social (DS) outcome disclosure, and (3) balanced financial and social (BFS) outcome disclosure. Therefore, there were a total of nine possible treatments. In the DF scenario 1, financial outcome metrics were presented in the outcome table and social outcome metrics were provided in a brief sentence; in the DS scenario, social outcome metrics were presented in the outcome table and financial outcome metrics were provided

in a brief sentence; and in the BFS scenario, both financial and social outcome metrics were presented in the outcome table. These treatments are summarised in Table 3 below and the profiles provided to participants are shown in Appendix A4.

Table 3: Outcome treatments

	Dominant financial framing (scenario 1)	**Dominant social framing (scenario 2)**	**Balanced framing (scenario 3)**
Solar Solutions (Company A)	Treatment A1	Treatment A2	Treatment A3
Smart Solar (Company B)	Treatment B1	Treatment B2	Treatment B3
PV Projects (Company C)	Treatment C1	Treatment C2	Treatment C3

To assure validity, establish covariation, and control extraneous sources, participants were randomly assigned these outcome disclosure conditions (Brown & Melamed, 1990; Salkind, 2010; Zellmer-Bruhn et al., 2016). Profiles were randomly allocated using the SurveyMonkey "random assignment" A/B logic feature (SurveyMonkey, 2020). Using this feature, scenarios are randomly assigned to participants based on a set percentage of respondents. Every company profile was allocated independently and each company scenario was assigned equal weighting. Therefore, each of the three scenarios for every company was assigned to 33.3% of participants. Each participant had equal probability (33.3%) of being assigned any of the three scenarios for every company. Participants provided responses to all measures for only one scenario for each company.

4.7 Analysis approach

The data for this study was analysed by means of statistical techniques using the IBM SPSS analytics platform. Descriptive analyses were performed to provide statistics of the measures of central tendency and dispersion. Having confirmed that the measurement items had adequate reliability and validity, regression analysis was performed to quantify the relationship between constructs. This method is in line with the approach used by Long et al. (2018) and Rossi, Sansone, Van Soest, and Torricelli (2019). A regression analysis was performed independently for each company to allow the comparison of the results. The regression model considered two framing variables as independent variables, as it was necessary to establish a reference category for each regression due the creation dummy variables for the framing scenarios (Hair et al., 2019). Drawing from established statistical technique in experimental design, an ANCOVA was calculated to examine the effect of outcome framing on capital allocation, controlling for perceived risk, and sense of understanding (Hair et al., 2019).

4.8 Quality controls

Data quality was guaranteed using population screening criteria. The criteria ensured that sampled participants met the definition of an investor, as set forth in the sampling methodology. Furthermore, the use of an online platform to administer the experiment minimised the risk of bias due to researcher expectations and randomisation reduced the risk of environmental disturbances (Salkind, 2010). The intervention was timed and average task durations were compared against similar studies. This comparison revealed that the median completion time for this study's questionnaire was five minutes, which was less than comparative studies (Lee et al., 2020) that reported eight minutes and 11 minutes. The length of the questionnaires used for these comparative studies is unknown.

4.9 Research ethics

The researcher obtained ethical clearance from GIBS's Ethics Committee prior to starting the data collection (see Appendix A5). All participants were asked to acknowledge an informed consent statement prior to beginning the experiment questionnaire (see Appendix A6). Confidentiality was maintained through the collection of the data as no names or identifying information was requested, and through the reporting of the findings as only aggregate data was reported.

4.10 Data analysis

In total, 206 responses were collected from the SurveyMonkey online survey tool. Of these, eight responses were discarded immediately because participants did not consent to participate. Consented responses were first screened for their suitability based on the investor qualification criteria put forth by Lipe (2018). A missing values analysis (MVA) was conducted to identify missing data. One partial response was retained in the sample in which item-level data for the Company C scenario was incomplete. Failure to complete the questionnaire is a known process that results in missing data (Hair et al., 2019). This represented less than 1% of the final sample size, thereby making it acceptable to ignore the missing data and include the case response in the sample (Hair et al., 2019). A further 18 partial responses were retained in the sample in which all scenarios and their corresponding questions were completed, but the item-level data for the capital allocation task was incomplete. This missing data represented 14% of the final sample population. The results of the *t*-tests of the missingness confirmed that the missing data were missing

completely at random (MCAR) (Hair et al., 2019). Given that the missing data was MCAR, that it represented less than 20% of the final sample population, and that literature suggested a strong relationship between the variables, the missing values were replaced using the mean substitution imputation method (Hair et al., 2019). The MVA also identified missing values for the variable associated with MBA qualification. Nevertheless, this was anticipated as the question was only required if participants indicated that they had a master's degree or high qualification, thereby making it acceptable to ignore this missing data and include the case response in the sample. Based on these screening procedures, the final sample for this study was 133 participants, which was deemed sufficient based on existing literature and suggested sample size guidance for the multivariate techniques used to test the hypotheses (Hair et al., 2019; Lee et al., 2020).

Table 4: Data demographics

Variable	Frequency	Percentage
Educational qualification^	133	
MBA (Y/N)	71/36	
Gender (M/F)	84/49	
Age^^	133	
Energy sector investment experience		
None	43	32%
Less than 1 year	9	7%
1–2 years	23	17%
3–5 years	25	19%
6–10 years	22	17%
More than 10 years	11	8%
Knowledge of business and investing		
None at all	2	2%
A moderate amount	80	60%
A great deal	51	38%
Frequency of financial investments		
Never	7	5%
Infrequently	59	44%
Frequently	67	50%
Risk tolerance (high/low)	63/70	

^107 responses for "master's degree and above"
^^Mean age = 42.58; median age = 41.00; 25th percentile = 34.00; 50th percentile = 41.00; 75th percentile = 50.00

The sample demographics are reported in Table 4. Experience and knowledge of the investment, business, and the solar energy sector were characteristics of the target sample population for this study. Approximately 50% of the respondents had less than two years of energy sector investment

experience. However, nearly all respondents had at least a moderate amount of knowledge on business and investing, with just over one-third of participants responding that they had a great deal of knowledge. The majority of participants responded that they frequently had made investments in the prior year. Risk tolerance within the sample population was nearly even, with 47% of participants reporting a high-risk tolerance and 52% reporting a low-risk tolerance.

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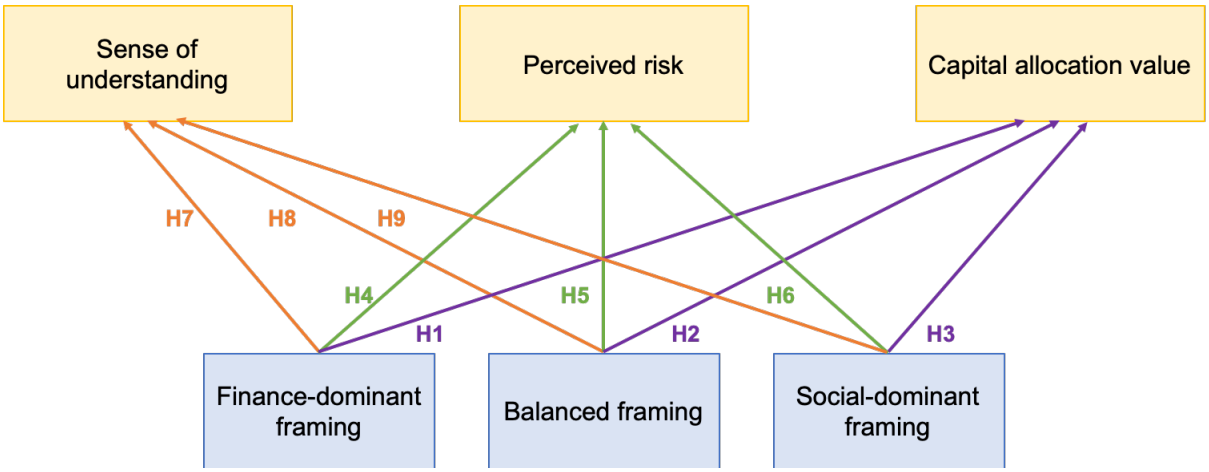
APPENDIX A

Appendix A1: Conceptual model



Appendix A2: Questionnaire

SECTION 1: DEMOGRAPHICS

(1) Please select your highest level of educational qualification. *(Adapted from Lee et al., 2020)*
□ No formal education
□ Primary school
□ Middle school
□ High school
□ Bachelor's degree
□ Master's degree or above *(If selected, participant routed to question 1a)*

(1a) Do you have a Master of Business Administration (MBA)? *(Adapted from Lee et al., 2020)*
□ Yes
□ No

(2) Please select your gender. *(Adapted from Lee et al., 2020)*
□ Female
□ Male

(3) Please enter your age. *(Adapted from Lee et al., 2020)*
_____

SECTION 2: INVESTMENT EXPERIENCE

(4) How many years of investment (formal or informal) experience do you have in the energy sector? *(Adapted from Long et al., 2018)*
□ None
□ Less than 1 year
□ 1–2 years
□ 3–5 years
□ 6–10 years
□ More than 10 years

(5) How much knowledge do you have of business and investing? *(Adapted from Lipe, 2018)*
□ Not at all
□ A moderate amount
□ A great deal

(6) How frequently have you made financial investments in the previous one year? *(Adapted from Lee et al., 2020; Lipe, 2018)*
□ Never
□ Infrequently
□ Frequently

(7) Which profile best aligns with your investment behaviour? *(Adapted from Long et al., 2018)*
□ You want predictability from your investments. You want to start investing to generate income to be withdrawn in 5–10 years. You are not willing to tolerate much risk, but do want your investments to make money.

□ You want to start investing to generate income to be withdrawn in 15–20 years. You are willing to tolerate a lot of risk in your investments and expect unpredictability and volatility, as long as you make money.

□ You want predictability from your investments. You want to start investing to generate income to be withdrawn in 5–10 years. You are willing to tolerate a lot of risk in your investments and expect unpredictability and volatility, as long as you make money.

□ You want to start investing to generate income to be withdrawn in 15–20 years. You are not willing to tolerate much risk, but do want your investments to make money.

SECTION 3: RISK AND UNDERSTANDING
(Questions below to be repeated for each company presented)

(#) How risky would you rate an investment in [Company X]? *(Adapted from Long et al., 2018)*
□ Very low/negligible risk
□ Low risk
□ Neutral
□ Moderately risky
□ Very/extremely risky

(#) I understand what [Company X] does. *(Adapted from Long et al., 2018)*
□ Strongly disagree
□ Disagree
□ Neither agree nor disagree
□ Agree
□ Strongly agree

(#) I can explain to others what [Company X] does. *(Adapted from Long et al., 2018)*
□ Strongly disagree
□ Disagree
□ Neither agree nor disagree
□ Agree
□ Strongly agree

(#) I can make sense of the facts I know about [Company X]. *(Adapted from Long et al., 2018)*
□ Strongly disagree
□ Disagree
□ Neither agree nor disagree
□ Agree
□ Strongly agree

(#) [Company X]'s business is easy to understand. *(Adapted from Long et al., 2018)*
□ Strongly disagree
□ Disagree
□ Neither agree nor disagree
□ Agree
□ Strongly agree

SECTION 4: CAPITAL ALLOCATION TASK

(#) Given the options of the three companies presented, you must divide your monetary endowment of USD$2 000. Please enter your choices below; the choices must equal USD$2,000. *(Adapted from Lee et al., 2020)*

Company A _____

Company B _____

Company C _____

Appendix A3: Task briefing and instructions

Globally, over 850 million people are still without access to electricity.[1] Energy demand is expected to continue to rise by around 1% per year until 2040.[2] At least half of this demand is expected to be met through cost-effective solar photovoltaic (PV) energy.[3]

You have consented to participate in an experiment focused on understanding investor decision-making preferences. The experiment consists of three sections: (1) participant information, (2) company information, and (3) investment allocation. The first section will ask you to provide information on your demographics, investment experience, and risk tolerance. Thereafter, you will be provided with company profiles for three hybrid enterprises in the PV energy industry. You will review the profiles and provide feedback on your level of understanding and risk perception for each enterprise. In the final section, you will be required to allocate a fictitious financial endowment of USD$2 000 across the three enterprises.

[1]International Energy Agency. (2019). *World Energy Outlook 2019*. Retrieved July 17, 2020, from https://www.iea.org/reports/world-energy-outlook-2019#

[2]International Energy Agency. (2019). *World Energy Outlook 2019: Executive summary*. Retrieved July 17, 2020, from https://iea.blob.core.windows.net/assets/1f6bf453-3317-4799-ae7b-9cc6429c81d8/English-WEO-2019-ES.pdf

[3]Ibid.

Appendix A4: Company profiles

Treatment A1

Company overview

Solar Solutions is a global leader and pioneer in delivering affordable solar-powered solutions designed for the two billion people in the developing world without access to reliable energy. Solar Solutions provides distributed solar energy solutions for households and small businesses that are transforming the way people all over the world use and pay for energy. Through its global distribution hubs, Solar Solutions is dedicated to providing the most reliable, affordable and accessible solar lighting and power systems for the developing world.

Product characteristics

Solar Solutions' groundbreaking solar lanterns and solar home systems come with an industry-leading two-year warranty and are Lighting Global certified. Solar Solutions has sold over 20 million solar products across 65 different countries and is a global brand that you can trust. Solar Solutions' products are water-resistant, weatherproof, and built to last over five years. The company employs top-tier engineers and designers to create products that improve the lives of customers.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Revenue	*$*	*1,209,247*
Contribution Margin		*30%*
Net Income	*$*	*60,462*
Total Assets	*$*	*12,257,343*
Total Shareholder Equity	*$*	*4,902,937*

In the last 12 years, Solar Solutions' products have transformed more than 100 million lives and provided solar lighting to 26 million school-aged children.

Treatment A2

Company overview

Solar Solutions is a global leader and pioneer in delivering affordable solar-powered solutions designed for the two billion people in the developing world without access to reliable energy. Solar Solutions provides distributed solar energy solutions for households and small businesses that are transforming the way people all over the world use and pay for energy. Through its global distribution hubs, Solar Solutions is dedicated to providing the most reliable, affordable and accessible solar lighting and power systems for the developing world.

Product characteristics

Solar Solutions' groundbreaking solar lanterns and solar home systems come with an industry-leading two-year warranty and are Lighting Global certified. Solar Solutions has sold over 20 million solar products across 65 different countries and is a global brand that you can trust. Solar Solutions' products are water-resistant, weatherproof, and built to last over five years. The company employs top-tier engineers and designers to create products that improve the lives of customers.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Lives empowered	*100 million*
Tons of CO_2 averted	*23 million*
Power generated from a renewable energy source	*221 GWh*
Saving in energy-related expenses	*$4.1 billion*
School-aged children reached with solar lighting	*26 million*
Productive hours created	*22 billion*

In 2019, Solar Solutions achieved USD$1.2 million in annual sales, with a net profit margin of 5% and an equity multiplier of 2.5.*

**equity multiplier = (average total assets / average shareholders' equity)*

Treatment A3

Company overview

Solar Solutions is a global leader and pioneer in delivering affordable solar-powered solutions designed for the two billion people in the developing world without access to reliable energy. Solar Solutions provides distributed solar energy solutions for households and small businesses that are transforming the way people all over the world use and pay for energy. Through its global distribution hubs, Solar Solutions is dedicated to providing the most reliable, affordable and accessible solar lighting and power systems for the developing world.

Product characteristics

Solar Solutions' groundbreaking solar lanterns and solar home systems come with an industry-leading two-year warranty and are Lighting Global certified. Solar Solutions has sold over 20 million solar products across 65 different countries and is a global brand that you can trust. Solar Solutions' products are water-resistant, weatherproof, and built to last over five years. The company employs top-tier engineers and designers to create products that improve the lives of customers.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Revenue	*$*	*1,209,247*	*Lives empowered*	*100 million*
Contribution Margin		*30%*	*Tons of CO_2 averted*	*23 million*
Net Income	*$*	*60,462*	*Power generated from a renewable energy source*	*221 GWh*
			Saving in energy-related expenses	*$4.1 billion*
Total Assets	*$*	*12,257,343*	*School-aged children reached with solar lighting*	*26 million*
Total Shareholder Equity	*$*	*4,902,937*	*Productive hours created*	*22 billion*

Treatment B1

Company overview

Smart Solar is the world's leading pay-as-you-go energy provider to off-grid homes. Smart Solar affordably powers homes and small businesses through connected technology. The company has developed a better way to provide affordable, safe and clean energy to millions of people living off the grid by unlocking solar, information, technology and finance. Thanks to the sun's rays and mobile technology, customers can light up their homes, charge their phones, and tune into the radio and TV.

Product characteristics

Smart Solar has developed a proprietary, patented technology platform that combines embedded cellular network and mobile payments to revolutionise asset financing in emerging markets. Solar Solutions' platform has been designed and built from the ground up by a talented team of software engineers, who continue to innovate and improve the system every day. Smart Solar's solar appliances and solar home systems come with a two-year warranty.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Revenue	*$*	*1,297,354*
Contribution Margin		*32%*
Net Income	*$*	*64,868*
Total Assets	*$*	*11,834,057*
Total Shareholder Equity	*$*	*4,930,857*

In the last eight years, Smart Solar's products have empowered over 100 million households and provided solar lighting to 28 million school-aged children.

Treatment B2

Company overview

Smart Solar is the world's leading pay-as-you-go energy provider to off-grid homes. Smart Solar affordably powers homes and small businesses through connected technology. The company has developed a better way to provide affordable, safe and clean energy to millions of people living off the grid by unlocking solar, information, technology and finance. Thanks to the sun's rays and mobile technology, customers can light up their homes, charge their phones, and tune into the radio and TV.

Product characteristics

Smart Solar has developed a proprietary, patented technology platform that combines embedded cellular network and mobile payments to revolutionise asset financing in emerging markets. Solar Solutions' platform has been designed and built from the ground up by a talented team of software engineers, who continue to innovate and improve the system every day. Smart Solar's solar appliances and solar home systems come with a two-year warranty.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Lives empowered	*101 million*
Tons of CO_2 averted	*27 million*
Power generated from a renewable energy source	*256 GWh*
Saving in energy-related expenses	*$3.8 billion*
School-aged children reached with solar lighting	*28 million*
Productive hours created	*21 billion*

In 2019, Smart Solar achieved USD$1.3 million in annual sales with a net profit margin of 5% and an equity multiplier of 2.4.*

**equity multiplier = (average total assets / average shareholders' equity)*

Treatment B3

Company overview

Smart Solar is the world's leading pay-as-you-go energy provider to off-grid homes. Smart Solar affordably powers homes and small businesses through connected technology. The company has developed a better way to provide affordable, safe and clean energy to millions of people living off the grid by unlocking solar, information, technology and finance. Thanks to the sun's rays and mobile technology, customers can light up their homes, charge their phones, and tune into the radio and TV.

Product characteristics

Smart Solar has developed a proprietary, patented technology platform that combines embedded cellular network and mobile payments to revolutionise asset financing in emerging markets. Solar Solutions' platform has been designed and built from the ground up by a talented team of software engineers, who continue to innovate and improve the system every day. Smart Solar's solar appliances and solar home systems come with a two-year warranty.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Revenue	*$*	*1,297,354*	*Lives empowered*	*101 million*
Contribution Margin		*32%*	*Tons of CO_2 averted*	*27 million*
Net Income	*$*	*64,868*	*Power generated from a renewable energy source*	*256 GWh*
			Saving in energy-related expenses	*$3.8 billion*
Total Assets	*$*	*11,834,057*	*School-aged children reached with solar lighting*	*28 million*
Total Shareholder Equity	*$*	*4,930,857*	*Productive hours created*	*21 billion*

Treatment C1

Company overview

PV Projects is a leading provider of solar energy systems. Unique to the solar industry, PV Projects is vertically integrated, manufacturing its own solar photovoltaic modules and solar water heating systems. PV Projects services residential and commercial customers, and works with banks and micro-finance institutions to enable customers to take solar loans. PV Projects was founded with the mission to make solar energy affordable, available, and hassle-free to customers looking for a better energy alternative.

Product characteristics

PV Projects has uniquely designed solar photovoltaic and solar water heating systems that are manufactured in-house, and sells, installs, and services these systems directly to better control the customer experience. PV Projects has installed industrial-scale solar water heating systems for multiple sites of a large multinational Fast-Moving Consumer Goods company and is rapidly expanding its operations.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Revenue	*$*	*1,204,874*
Contribution Margin		*31%*
Net Income	*$*	*60,244*
Total Assets	*$*	*11,560,315*
Total Shareholder Equity	*$*	*4,919,283*

In the last 10 years, PV Projects' products have averted more than 16 million tons of CO_2 and provided solar lighting to 124 million people.

Treatment C2

Company overview

PV Projects is a leading provider of solar energy systems. Unique to the solar industry, PV Projects is vertically integrated, manufacturing its own solar photovoltaic modules and solar water heating systems. PV Projects services residential and commercial customers, and works with banks and micro-finance institutions to enable customers to take solar loans. PV Projects was founded with the mission to make solar energy affordable, available, and hassle-free to customers looking for a better energy alternative.

Product characteristics

PV Projects has uniquely designed solar photovoltaic and solar water heating systems that are manufactured in-house, and sells, installs, and services these systems directly to better control the customer experience. PV Projects has installed industrial-scale solar water heating systems for multiple sites of a large multinational Fast-Moving Consumer Goods company and is rapidly expanding its operations.

Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Lives empowered	*124 million*
Tons of CO_2 averted	*16 million*
Power generated from a renewable energy source	*202 GWh*
Saving in energy-related expenses	*$4.0 billion*
School-aged children reached with solar lighting	*23 million*
Productive hours created	*19 billion*

In 2019, PV Projects achieved USD$1.2 million in annual sales with a net profit margin of 5% and an equity multiplier of 2.4.*

**equity multiplier = (average total assets / average shareholders' equity)*

Treatment C3

Company overview

PV Projects is a leading provider of solar energy systems. Unique to the solar industry, PV Projects is vertically integrated, manufacturing its own solar photovoltaic modules and solar water heating systems. PV Projects services residential and commercial customers, and works with banks and micro-finance institutions to enable customers to take solar loans. PV Projects was founded with the mission to make solar energy affordable, available, and hassle-free to customers looking for a better energy alternative.

Product characteristics

PV Projects has uniquely designed solar photovoltaic and solar water heating systems that are manufactured in-house, and sells, installs, and services these systems directly to better control the customer experience. PV Projects has installed industrial-scale solar water heating systems for multiple sites of a large multinational Fast-Moving Consumer Goods company and is rapidly expanding its operations.

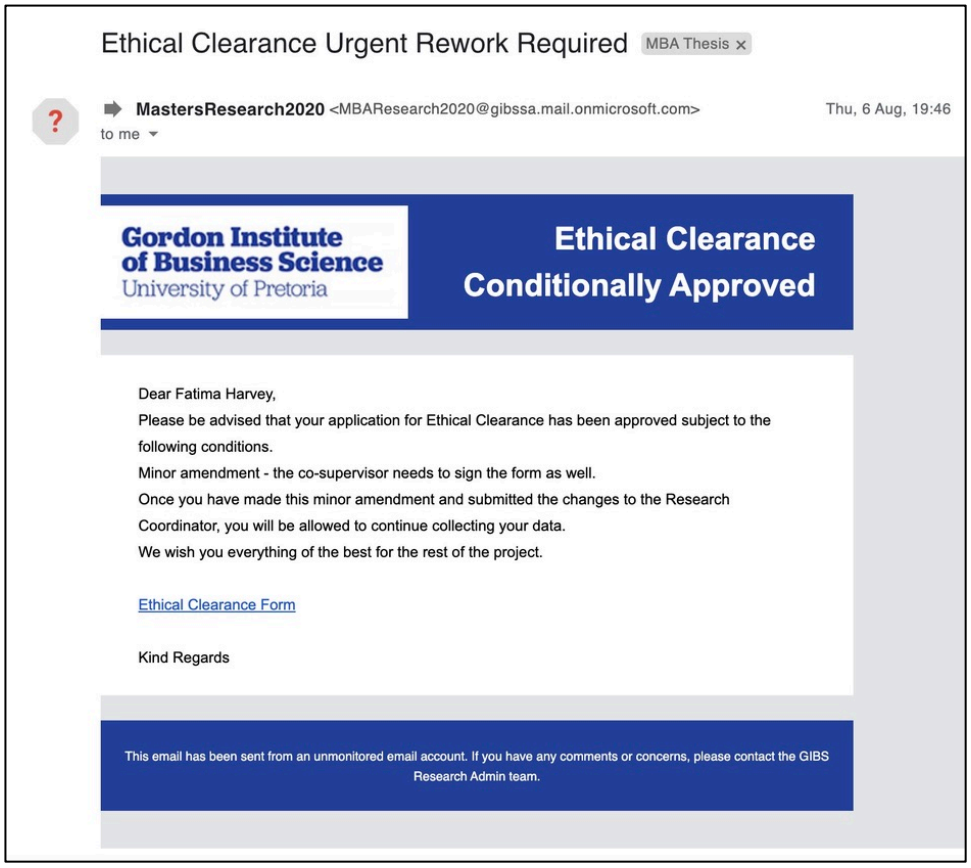
Market characteristics

The solar products and solar home system market are anticipated to grow at an average rate of 15% per year for the next five years.

Performance metrics

Revenue	*$*	*1,204,874*	*Lives empowered*	*124 million*
Contribution Margin		*31%*	*Tons of CO_2 averted*	*16 million*
Net Income	*$*	*60,244*	*Power generated from a renewable energy source*	*202 GWh*
			Saving in energy-related expenses	*$4.0 billion*
Total Assets	*$*	*11,560,315*	*School-aged children reached with solar lighting*	*23 million*
Total Shareholder Equity	*$*	*4,919,283*	*Productive hours created*	*19 billion*

Appendix A5: Ethical clearance



Ethical Clearance Urgent Rework Required MBA Thesis ×

MastersResearch2020 <MBAResearch2020@gibssa.mail.onmicrosoft.com> Thu, 6 Aug, 19:46
to me

Gordon Institute of Business Science
University of Pretoria

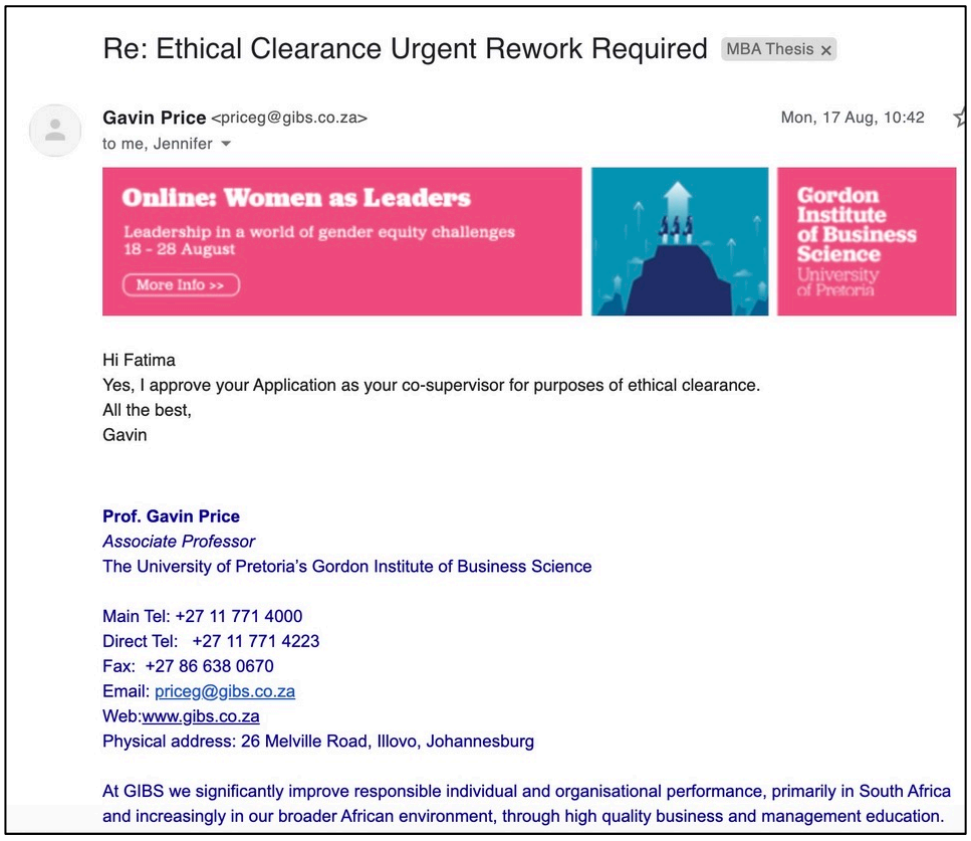
Ethical Clearance Conditionally Approved

Dear Fatima Harvey,
Please be advised that your application for Ethical Clearance has been approved subject to the following conditions.
Minor amendment - the co-supervisor needs to sign the form as well.
Once you have made this minor amendment and submitted the changes to the Research Coordinator, you will be allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.



Re: Ethical Clearance Urgent Rework Required MBA Thesis ×

Gavin Price <priceg@gibs.co.za> Mon, 17 Aug, 10:42
to me, Jennifer

Online: Women as Leaders
Leadership in a world of gender equity challenges
18 - 28 August
More Info >>

Gordon Institute of Business Science
University of Pretoria

Hi Fatima
Yes, I approve your Application as your co-supervisor for purposes of ethical clearance.
All the best,
Gavin

Prof. Gavin Price
Associate Professor
The University of Pretoria's Gordon Institute of Business Science

Main Tel: +27 11 771 4000
Direct Tel: +27 11 771 4223
Fax: +27 86 638 0670
Email: priceg@gibs.co.za
Web:www.gibs.co.za
Physical address: 26 Melville Road, Illovo, Johannesburg

At GIBS we significantly improve responsible individual and organisational performance, primarily in South Africa and increasingly in our broader African environment, through high quality business and management education.

Appendix A6: Informed consent statement

INFORMED CONSENT TO PARTICIPATE IN RESEARCH EXPERIMENT

This experiment is being conducted as part of a research study concerned with understanding the behaviours of investors when allocating impact capital to hybrid enterprises. Hybrid enterprises are entities that seek to optimise both financial and socials goals. Investing practices with these dual objectives are referred to as impact investments; however, other terms like socially responsible investment, sustainable and responsible investment, social investment, and venture philanthropy are generally synonymous and relevant for the context of this experiment.

The aim of this experiment is to understand your decision-making preferences as an investor. You will be required to review information about a set of hybrid enterprises and will then be asked to make investment choices by allocating a hypothetical financial endowment. This task should take you no more than 20 minutes.

You can withdraw from the experiment at any time without penalty. Your participation is anonymous; you will not be asked for any information that will identify yourself, and only aggregated data will be reported.

By participating in this experiment, you indicate that you understand these instructions and voluntarily participate in this research.

If you have any concerns, contact details of the researcher and research supervisors are provided below.

Researcher: Fatima Harvey (19388226@mygibs.co.za)
Supervisor: Kerrin Myres – senior lecturer (myresk@gibs.co.za)
Co-supervisor: Gavin Price – associate professor (priceg@gibs.co.za)

Appendix A7: Risk profiles

Profile A

You want predictability from your investments. You want to start investing to generate income to be withdrawn in 5–10 years. You are not willing to tolerate much risk, but do want your investments to make money.

Profile B

You want to start investing to generate income to be withdrawn in 15–20 years. You are not willing to tolerate much risk, but do want your investments to make money.

Profile C

You want predictability from your investments. You want to start investing to generate income to be withdrawn in 5–10 years. You are willing to tolerate a lot of risk in your investments and expect unpredictability and volatility, as long as you make money.

Profile D

You want to start investing to generate income to be withdrawn in 15–20 years. You are willing to tolerate a lot of risk in your investments and expect unpredictability and volatility, as long as you make money.

Appendix A8: Certification of additional support

25. APPENDIX 6 CERTIFICATION OF ADDITIONAL SUPPORT

(Additional support retained or not - to be **completed by all students)**

Please note that failure to comply and report on this honestly will result in disciplinary action

I hereby certify that (please indicate which statement applies):

- ~~***I DID NOT RECEIVE** any additional/outside assistance (i.e. statistical, transcriptional, and/or editorial services) on my research report:~~

  ……

- ***I RECEIVED** additional/outside assistance (i.e. statistical, transcriptional, and/or editorial services) on my research report*

  ……

If any additional services were retained– ***please indicate below which:***

☒ ***Statistician***

☐ ***Transcriber***

☒ ***Editor***

☐ ***Other (please specify:……)***

Please provide the name(s) and contact details of all retained:

NAME: ANDILE MTOTYWA……...

EMAIL ADDRESS: andile@bsri.co.za……

CONTACT NUMBER: +27 73 373 1453……

TYPE OF SERVICE: STATISTICIAN……

83

NAME: INDIA GONÇALVES

EMAIL ADDRESS: ihg.edit@hotmail.com

CONTACT NUMBER: +27 79 509 2002

TYPE OF SERVICE: EDITOR

NAME: ……...

EMAIL ADDRESS: ……

CONTACT NUMBER: ……

TYPE OF SERVICE: ……

I hereby declare that all *statistical write-ups and thematic interpretations of the results for* **my study were completed by myself without outside assistance**

NAME OF STUDENT: FATIMA HARVEY
……

SIGNATURE:
……

STUDENT NUMBER: 19388226

…… ……

STUDENT EMAIL ADDRESS: 19388226@mygibs.co.za

……

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Appendix A9: Plagiarism declaration

I declare that this article is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Fatima Harvey

1 December 2020

Appendix A10: Copyright declaration

Gordon Institute of Business Science
University of Pretoria

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA
Denkleiers • Leading Minds • Dikgopolo tša Dihlalefi

22.1 COPYRIGHT DECLARATION FORM

Student details			
Surname:	HARVEY	Initials:	FA
Student number:	19388226		
Email:	19388226@gibs.co.za		
Phone:	+1 (214) 412-0086		
Qualification details			
Degree:	MBA	Year completed:	2020
Title of research:	GIBS		
Supervisor:	Kerrin Myres and Gavin Price		
Supervisor email:	myresk@gibs.co.za / priceg@gibs.co.za		

Access

A.	My research is not confidential and may be made available in the GIBS Information Centre and on UPSpace.

I give permission to display my email address on the UPSpace website

Yes			No	

B.

	My research is confidential and may NOT be made available in the GIBS Information Centre nor on UPSpace.

Please indicate embargo period requested

Two years		Please attach a letter of motivation to substantiate your request. Without a letter embargo will not be granted.
Permanent		Permission from the Vice-Principal: Research and Postgraduate Studies at UP is required for permanent embargo. Please attach a copy permission letter. Without a letter permanent embargo will not be granted.

Copyright declaration

I hereby declare that I have not used unethical research practices nor gained material dishonesty in this electronic version of my research submitted. Where appropriate, written permission statement(s) were obtained from the owner(s) of third-party copyrighted matter included in my research, allowing distribution as specified below.

I hereby assign, transfer and make over to the University of Pretoria my rights of copyright in the submitted work to the extent that it has not already been affected in terms of the contract I entered into at registration. I understand that all rights with regard to the intellectual property of my research, vest in the University who has the right to reproduce, distribute and/or publish the work in any manner it may deem fit.

.

Signature:	Date: 1 December 2020
Supervisor signature:	Date: 1 December 2020

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APPENDIX B

Appendix B1: Author guidelines of the journal

Reference: Journal of Business Ethics. (2020). *Submission guidelines*. Retrieved October 15, 2020, from https://www.springer.com/journal/10551/submission-guidelines#Instructions for Authors_Manuscript Presentation

Manuscript presentation

The Journal of Business Ethics follows a double-blind reviewing procedure. Authors are therefore requested not to put their name(s) in the manuscript. Self-identifying citations and references in the article text should either be avoided or left blank when manuscripts are first submitted. Authors are responsible for reinserting self-identifying citations and references when manuscripts are prepared for final submission.

Online submission

Authors must submit their manuscripts online via the Journal of Business Ethics Editorial Manager website at: https://www.editorialmanager.com/busi/.

Authors are required to upload a title page with the author identifying information and a blinded manuscript with no author details.

- Title page
    - The title page should include:
        - A concise and informative title
        - Running head (short title)
        - The name(s) of the author(s)
        - The affiliation(s), address(es) and e-mail address (es) of all the author(s)
        - The institutional e-mail address, and telephone number(s) of the corresponding author
- Acknowledgements
    - Please include the acknowledgements and any other author identifying information in the title page.
- Blinded Manuscript
    - Abstract

- Please provide a short abstract of 100 to 250 words. The abstract should not contain any undefined abbreviations or unspecified references.

- Manuscript
  - The average length of an article is approximately 8,000 - 10,000 words (including references). Articles should be no longer than 12,000 words. Exemption may be made for studies based on qualitative data.
  - Please double-space all material, including notes and references. Quotations of more than 40 words should be set off clearly, either by indenting the left-hand margin or by using a smaller typeface. Use double quotation marks for direct quotations and single quotation marks for quotations within quotations and for words or phrases used in a special sense. Number the pages consecutively.
- Figures and Tables
  - Lines should not be thinner than 0.25pts and in-fill patterns and screens should have a density of at least 10 percent. For bitmap graphics, TIFF is the preferred format.
  - The following resolutions are optimal:
    - Black-and-white line figures – 1200 dpi; line figures with some gray or colored lines – 600 dpi; photographs – 300 dpi; screen dumps – leave as is. The letter size of any text in the figures must be large enough to allow for reduction. If a figure contains color, make absolutely clear whether it should be printed in black-and-white or in color.
  - Each figure and table should be numbered and mentioned in the text.
  - The approximate position of figures and tables should be indicated in the margin of the manuscript. Figures and tables should be accompanied by an explanatory legend. The figures legends should be grouped and placed on a separate page. In tables, footnotes are preferable to long explanatory material in either the heading or body of the table. Such explanatory footnotes, identified by superscript letters, should be placed immediately below the table.
- Section Headings:
  - First-, second-, third-, and fourth-order headings should be clearly distinguishable.
- Appendices:

- Supplementary material should be collected in an Appendix and placed before the Notes and Reference sections.

- Notes:
  - Please use endnotes only. Notes should be indicated by consecutive superscript numbers in the text and listed at the end of the article before the References. A source reference note should be indicated by an asterisk after the title. This note should be placed at the bottom of the first page.
- Cross-Referencing:
  - In the text, a reference identified by means of an author's name should be followed by the date of the reference in parentheses and page number(s) where appropriate. When there are more than two authors, only the first author's name should be mentioned, followed by "et al". In the event that an author cited has had two or more works published during the same year, the reference, both in the text and in the reference list, should be identified by a lower case letter like "a" and "b" after the date to distinguish the works.
- References
  - References to books, journal articles, articles in collections and conference or workshop proceedings, and technical reports should be listed at the end of the paper in alphabetical order. Articles in preparation or articles submitted for publication, unpublished observations, personal communications, etc. should not be included in the reference list but should only be mentioned in the article text (e.g., T. Moore, personal communication).
  - References to books should include the author's name; year of publication; title; page numbers where appropriate; publisher; place of publication, in the order given in the example below.
  - References to articles in an edited collection should include the author's name; year of publication; article title; editor's name; title of collection; first and last page numbers; publisher; place of publication, in the order given in the example below.
  - References to articles in conference proceedings should include the author's name; year of publication; article title; editor's name (if any); title of proceedings; first and last page number; place and date of conference; publisher and/or organization from which the proceedings can be obtained; place of publication, in the order given in the example below.

- References to articles in periodicals should include the author's name; year of publication; article title; full title of periodical; volume number (issue number where appropriate); first and last page number, in the order given in the example below.
- References to technical reports or doctoral dissertations should include the author's name; year of publication; title of report or dissertation; institution; location of institution, in the order given in the example below.

Appendix B2: Example of an article from the journal

Miralles-Quirós, M. M., & Miralles-Quirós, J. L. (2017). Improving diversification opportunities for socially responsible investors. *Journal of Business Ethics*, *140*(2), 339–351. https://doi.org/10.1007/s10551-015-2691-4

J Bus Ethics (2017) 140:339–351
DOI 10.1007/s10551-015-2691-4

Improving Diversification Opportunities for Socially Responsible Investors

María del Mar Miralles-Quirós[1] · **José Luis Miralles-Quirós**[1]

Received: 13 January 2015 / Accepted: 12 May 2015 / Published online: 19 May 2015

Abstract Socially responsible investment (SRI) has grown enormously and has expanded globally in recent years. It allows SRI investors to reduce their portfolio risk assumptions through international diversification. In this context, the aim of this paper is twofold (i) to examine price and volatility linkages among the most representative SRI indexes for North America, Europe, and Asia-Pacific employing a multivariate approach and (ii) to provide the out-of-sample performance of an optimal portfolio constructed on the basis of time-varying return and volatility forecasts from this specification approach. Our overall results show that using this technique, it is possible to reduce risk and out-perform the naïve rule, which is usually employed in this type of investment. These findings are relevant not only for academics but also for practitioners, especially for professional managers of SRI portfolios.

Keywords Socially responsible investment · International diversification · Information transmission · Optimal strategy · Naïve rule · Performance evaluation

JEL Classification G10 · G11 · G14

Abbreviations

BEKK	The model proposed by Baba, Engle, Kraft and Kroner
DJSI	Dow Jones Sustainability Indexes
ESG	Environmental, social and governance
GARCH	Generalized autoregressive conditional heteroskedasticity
SAM	Sustainable Asset Management
SR	Sharpe ratio
SRI	Socially responsible investment
VAR	Vector autoregression

✉ María del Mar Miralles-Quirós
marmiralles@unex.es

[1] Department of Financial Economics, University of Extremadura, Av. Elvas s/n 06071, Badajoz, Spain

Introduction

Socially responsible investment (SRI) refers to the practice of making investment decisions not only on the basis of financial performance, but also using environmental, social, and governance (ESG) criteria. Due to these extra considerations, SRI investors reduce their investment universe to those firms that adopt ethical principles. This results in a limit-to-diversification problem and, consequently, less opportunity to reduce investment risk. In recent years, this type of investment has grown enormously and expanded globally. In turn, this has enabled SRI investors to reduce their portfolio risk assumptions through international diversification.

Currently, SRI is a significant segment of international capital markets. It represents 16 % of the assets under management in the US, while in Europe and Asia-Pacific, the professionally managed assets of SRI portfolios have reached 5.9 trillion euros and 68.7 billion euros, respectively (Eurosif 2014). The development of SRI has been primary brought about by the increasing involvement of large institutional investors, such as pension and mutual funds, as well as traditional financial service providers. As a consequence, SRI indexes for different markets and geographical areas have been established to support and

promote SRI all over the world. These indexes represent a useful tool for SRI investors, who use them to identify target companies or regions for their SRI strategies.

The aim of this study is to use the most representative SRI indexes for North America, Europe, and Asia-Pacific to analyze price and volatility spillovers among these regions. This will enable us to construct an optimal portfolio in an international SRI context which alleviates SRI investors from the problems associated with a decrease in their diversification opportunities. For this purpose, we have chosen the Dow Jones Sustainability Indexes for each of the three regions: the DJSI North America, DJSI Europe, and DJSI Asia-Pacific over the 2004–2013 period.

There are a huge number of studies focused on understanding and quantifying the co-movements among conventional equity markets to determine the benefits of international diversification (Bekaert et al. 2009; Christoffersen et al. 2012, among others). However, only a few studies have investigated the linkages or spillovers among SRI markets. Roca and Wong (2010) exclusively analyze price interdependence among five SRI markets using a vector autoregressive (VAR) approach. Meanwhile, Tularam et al. (2010) provide evidence about the time-varying correlations between the Australian SRI market and other SRI markets worldwide using bivariate generalized autoregressive conditional heteroskedasticity (GARCH) models. Moreover, none of those studies have examined the practical application of those linkages for improving diversification opportunities for SRI investors. This study aims to address this gap in the SRI literature.

The contribution of this study to SRI literature is twofold. Firstly, we provide an in-depth analysis of the dynamic dependence in returns and volatilities among the three main SRI regions worldwide using a multivariate VAR–GARCH approach. Secondly, we examine the practical application of those linkages for portfolio optimization and trading strategy purposes in an out-of-sample period.

To that end, we compare our results with those obtained from a naïve strategy where the same fraction of the budget is invested into each stock market. We follow Christoffersen et al. (2012) who argue that, in order to quantify the international diversification benefit which derives from active asset allocation, it is necessary to compare it to an equally weighted portfolio. Moreover, the use of the naïve rule as our benchmark strategy can be justified on two additional grounds. Firstly, DeMiguel et al. (2009), among others, note that this strategy works surprisingly well out-of-sample. Secondly, this strategy is widely used by SRI investors because it is easy to implement as it does not require any estimate of either the variance of the asset returns or of any optimization procedure.

Our results show that it is possible to reduce risk and out-perform the common benchmark of reference with an optimal international diversification strategy which takes into account the cross-market return and volatility dynamics among SRI markets. The economic value of this allocation approach persists even when the costs associated with the daily rebalancing of each portfolio are considered and when portfolios are rebalanced on a weekly or a monthly basis. These findings are relevant not only for academics, but also for practitioners, especially professional managers of SRI portfolios.

The remainder of the paper is organized as follow. In "Literature review" section, we present a literature review. In "Methodology" section, we describe the methodology employed to construct and evaluate the proposed international diversification strategy. "Database" section describes the database employed. In "Empirical results" section, we present the empirical results. Finally, in "Conclusions" section, we provide the main conclusions.

Literature Review

The vast majority of researchers have focused on analyzing the performance of SRI funds or indexes in comparison to their conventional benchmarks. Although there are minor differences in their results, the overall evidence on the performance of SRI seems to show that there exist insignificant differences between SRI and conventional investment performance (Renneboog et al. 2008). Specifically, previous research studies which provide insignificant differences between ethical and conventional funds are those of Goldreyer and Diltz (1999), Cummings (2000), Bello (2005), Bauer et al. (2007), Gregory and Whittaker (2007), Jones et al. (2008), Cortez et al. (2009), Humphrey and Lee (2011), and Capelle and Monjon (2014), among others. Moreover, previous research studies about SRI equity indexes' performance with similar results are those of Sauer (1997), Statman (2000), Schröder (2007), Consolandi et al. (2008), and Managi et al. (2012), among others. We also highlight those studies focused on the analysis of SRI portfolios, such as Derwall et al. (2005), Kempf and Osthoff (2007), Hill et al. (2007), Humphrey et al. (2012), Brzeszczynski and McIntosh (2014). These analyze whether portfolios based on ESG screens may provide higher risk-adjusted returns than their conventional benchmarks.

Nevertheless, the main concern for professional managers of SRI portfolios is a lack of diversification which results in less opportunity to reduce portfolio risk assumptions. As we stated in the previous section, one way to alleviate this problem is through international diversification. However,

the benefits of international diversification depend upon the extent to which markets are linked.

In this context, Roca and Wong (2010) analyze the information transmission across five SRI markets (Australia, Canada, Japan, the UK, and the US) using daily DJSI data over the period 1994–2007 and observe that all SRI markets are significantly affected by each other. More precisely, they focus on the short-term interdependence among stock markets employing a VAR model to capture serial dependence across markets. This technique allows expected returns over every market index to depend linearly on past realized returns on every market index. This approach is general enough to capture any linear relation between market returns in consecutive periods, irrespective of whether its origin can be traced back to cross-covariances, autocovariances, or both. The overall results show that SRI markets respond to each other quite rapidly and within a short period of time. However, Roca and Wong (2010) conclude that this integration is still at a low level. This implies that there is still significant scope for SRI investors to diversify internationally across SRI markets.

Tularam et al. (2010) examine the relationship of the Australian SRI market with other SRI markets worldwide during the period 1994–2009. Their study focuses on time-varying correlations between markets to discover the extent of integration between them. To that end, they employ a multivariate GARCH technique to model the dynamic dependence structure of multivariate time series and, more precisely, to parameterize the dynamic equation of the conditional covariance. Their results indicate that the Australian market experiences a spike in correlation with the other markets especially during periods of market distress. Furthermore, they state that using these multivariate GARCH specifications, it is possible to extract more information about the interdependence among markets such as transmission of volatility or contagion risk and, more importantly, practical implications for active asset allocation.

This line of research has important implications for SRI investors because it gives them the opportunity to solve the classical allocation problem with forward-looking return and volatility forecasts obtained from these multivariate approaches. This is due to the fact that the practical application of Markowitz's (1952) portfolio theory requires implementing the expected return and the covariance matrix of the asset under consideration in the optimization programming problem. In this sense, the traditional approach has been based on computing the sample mean and covariance matrix of asset returns up to time t and uses them as the required inputs to the optimization program. However, this sample-based approach produces extreme portfolio weights that fluctuate substantially over time and perform poorly in an out-of-sample period as documented by Hodges and Brealey (1972), Michaud (1989), Best and Grauer (1991), and Litterman (2003), among others. Nowadays, the criticism of Markowitz's practical implementation persists. More precisely, DeMiguel et al. (2009) document that it is not possible to beat the naïve strategy using this classical sample-based approach.

The aim of this study is to analyze return and volatility spillovers among the three main SRI regions using a multivariate VAR–GARCH approach and to reflect the economic value of employing time-varying return and volatility forecasts from the multivariate model for international diversification purposes in a SRI context.

Methodology

This section is divided into three main sub-sections. Firstly, we present the multivariate model employed to estimate conditional returns and volatilities for the three SRI regional indexes. Secondly, we describe the methodology for the construction of the international diversification portfolios. Finally, we describe the criterion employed to evaluate the performance of the alternative strategies.

The Multivariate VAR–GARCH Approach

The econometric specification used in this paper has two components. Firstly, a vector autoregression with k lags is used to model the returns. This allows for autocorrelations and cross-autocorrelations in the returns:

$$R_{i,t} = c_i + \sum_{k=1}^{K} \sum_{\substack{i=1 \\ j=1}}^{3} \alpha_{ij} R_{i,t-k} + \varepsilon_{i,t}, \tag{1}$$

$$\varepsilon_{it} | \Omega_{t-1} \approx N(0, H_t), \tag{2}$$

where $R_{i,t}$ are the daily returns for the DJSI North America, DJSI Europe, and DJSI Asia-Pacific indexes, c_i and α_{ij} for $i = 1,2,3$, and $j = 1,2,3$ are the parameters to be estimated, $\varepsilon_{i,t}$ indicates the innovations for each index at time t following a normal distribution with a mean of 0 and variance H_t where Ω_{t-1} is the information set in $t-1$.

Secondly, to model the conditional variance–covariance matrix, a multivariate GARCH model is employed. The most widely used model is the BEKK representation, introduced by Baba et al. (1991).[1]

$$H_t = C'C + A'\varepsilon_{t-1}\,\varepsilon'_{t-1}A + B'H_{t-1}B, \tag{3}$$

where, in our case, C is a (3×3) lower triangular matrix with six parameters and A and B are squared (3×3)

[1] This specification has been the most popular in the literature. See Ortas et al. (2014) for an alternative use of this model in the SRI literature.

matrices of parameters. The elements of A capture the effects of shocks or events on volatility, while the elements of B capture the effects of past conditional variances measuring the diagonal parameters the effects of own past shocks and past volatility in both cases. The total number of estimated elements for the variance equations in our trivariate case is 24.

$$\begin{aligned} H_t = &\begin{pmatrix} c_{11} & & \\ c_{21} & c_{22} & \\ c_{31} & c_{23} & c_{33} \end{pmatrix} \begin{pmatrix} c_{11} & c_{21} & c_{31} \\ & c_{22} & c_{23} \\ & & c_{33} \end{pmatrix} \\ &+ \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \varepsilon_t \varepsilon' \begin{pmatrix} a_{11} & a_{21} & a_{31} \\ a_{12} & a_{22} & a_{32} \\ a_{13} & a_{23} & a_{33} \end{pmatrix} \\ &+ \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} H_{t-1} \begin{pmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{pmatrix} \end{aligned} \tag{4}$$

where

$$\varepsilon_t \varepsilon_t' = \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon_{3,t-1}^2 \end{pmatrix} \tag{5}$$

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix}.$$

Without using matrices we get the following forms for the conditional variances,

$$\begin{aligned} h_{11,t} = {} & c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 + a_{31}^2\varepsilon_{3,t-1}^2 \\ & + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ & + 2a_{31}a_{21}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{11}^2h_{1,t-1} + b_{21}^2h_{2,t-1} \\ & + b_{31}^2h_{3,t-1} + 2b_{11}b_{21}h_{12,t-1} \\ & + 2b_{11}b_{31}h_{13,t-1} + 2b_{31}b_{21}h_{23,t-1} \\ h_{22,t} = {} & c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + a_{32}^2\varepsilon_{3,t-1}^2 \\ & + 2a_{22}a_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{32}a_{12}\varepsilon_{1t-1}\varepsilon_{3,t-1} \\ & + 2a_{32}a_{22}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{12}^2h_{1,t-1} + b_{22}^2h_{2,t-1} \\ & + b_{32}^2h_{3,t-1} + 2b_{22}b_{12}h_{12,t-1} \\ & + 2b_{32}b_{12}h_{13,t-1} + 2b_{32}b_{22}h_{23,t-1} \\ \mathrm{h}_{33,t} = {} & c_{31}^2 + c_{32}^2 + c_{33}^2 + a_{13}^2\varepsilon_{1,t-1}^2 + a_{23}^2\varepsilon_{2,t-1}^2 \\ & + a_{33}^2\varepsilon_{3,t-1}^2 + 2a_{23}a_{13}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{33}a_{13}\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ & + 2a_{33}a_{23}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{13}^2h_{1,t-1} + b_{23}^2h_{2,t-1} \\ & + b_{33}^2h_{3,t-1} + 2b_{23}b_{13}h_{12,t-1} \\ & + 2b_{33}b_{13}h_{13,t-1} + 2b_{33}b_{23}h_{23,t-1}. \end{aligned} \tag{6}$$

Nevertheless, more recent studies document the relevance of considering the asymmetric effects of news on volatility for a better specification of the conditional variance–covariance matrix and the economic implications in terms of asset allocation (Kroner and Ng 1998). Following the extended approach of Glosten et al. (1993) proposed by Kroner and Ng (1998), and also used by Karmakar (2010), the model is specified as

$$\begin{aligned} H_t = {} & C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B + \eta' I(\varepsilon_{t-1<0}) \\ & \odot \varepsilon_{t-1}\varepsilon_{t-1}' \odot I(\varepsilon_{t-1<0})\eta, \end{aligned} \tag{7}$$

where $I_{(\varepsilon_{t-1<0})}$ is a 3×1 vector whose elements take value 1 if the corresponding innovation in vector ε_t is negative, and $\odot$ is the Hadamard (element by element) product which capture the different responses of volatility to negative shocks (bad news) or positive shocks (good news).

The model is estimated maximizing the likelihood function assuming normally distributed errors:

$$L(\theta) = -T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right), \tag{8}$$

where T is the number of observations and θ represents the parameter vector to be estimated.[2]

Optimal Portfolios

Multivariate VAR–GARCH estimates from the previous section can be applied for several financial purposes. In this study, we concentrate on international tactical asset allocation by constructing risk minimizing portfolios that compensate SRI investors from the foreseeable risk reduction opportunities associated with their investments.

According to the classical theory of optimal portfolio selection by Markowitz (1952), the mean–variance managers will allocate wealth among the three regional indexes to minimize portfolio variance subject to the constraint that the expected portfolio return attains a specific target R^*. We have to point out that volatile periods are generally associated with drops in market values. In these cases, investors will accept more risk to obtain non-negative returns. For that reason, we include in our optimization problem a non-negative expected return constraint. In

[2] Schüler and Schröder (2003) pointed out that by using this methodology, all of the estimations are conducted using Maximum Likelihood under the assumption that the residuals follow a normal distribution. However, as these authors also pointed out, this assumption is, in fact, not true because in most cases, the standardised residuals exhibit leptokurtosis. Thus, the application of the normal distribution leads to a so-called Quasi- or Pseudo-ML estimation. According to Weiss (1986), this application leads to a consistent estimation of the parameters if the equations for the (conditional) means and variances are specified correctly. Some authors tried to solve the problem by using different distributions. However, it was proven that when a distribution different from the normal one is used and this distribution is not the true one, then the estimates are, in most cases, not consistent. For that reason, we prefer to apply the normal distribution.

doing this, the problem which portfolio managers face is to find the optimal portfolio weights w_t which solve the optimization problem:

$$\begin{aligned} &\min_{w_t} w_t' \mathrm{H}_{t+1|t} w_t \\ &\text{s.t.} w_t' E\{R_{t+1}\} \geq R^* \\ &\qquad w_t' \mathbf{1} = 1 \\ &\qquad w_t \geq 0 \end{aligned} \tag{9}$$

where $\mathbf{1}$ is a vector of ones and the non-negativity constraints $w_t \geq 0$ mean that the portfolio manager is prohibited from making short sales.

Performance Evaluation

We consider the out-of-sample Sharpe ratio as the measure of portfolio performance. It is defined as the sample mean of out-of-sample excess returns over the risk-free asset,[3] divided by their sample standard deviation:

$$SR_p = \frac{\mu_p}{\sigma_p}. \tag{10}$$

Moreover, we have to point out that it is the most ubiquitous risk-adjusted measure used by financial market practitioners to rank fund managers and to evaluate the attractiveness of investment strategies in general.

Furthermore, to assess the statistical significance of the differences between the performance of the benchmark strategy ($\mathrm{SR}_{\mathrm{Naive}}$) and that of the model-based strategy (SR_p), we employ a bootstrap inference method. More precisely, the null hypothesis is H_0:$\{\mathrm{SR}_p - \mathrm{SR}_{\mathrm{Naive}} = 0\}$ for which we compute a one-sided p value following the methodology proposed by Ledoit and Wolf (2008).

Finally, to test whether our optimal portfolios produce economically significant profits, we calculate the portfolio performances after taking into account the costs associated with the daily rebalance of each portfolio considering not only transaction costs but also daily portfolio turnovers.

Following DeMiguel et al. (2009), we denote the share of wealth in area i before the portfolio is rebalanced at time $t+1$ as

$$\omega_{i,t^+} = \frac{\omega_{i,t}(1+R_{i,t+1})}{\sum_{i=1}^{N} \omega_{i,t}(1+R_{i,t+1})}. \tag{11}$$

When the portfolio is rebalanced, it gives rise to a trade in area i of magnitude $|\omega_{i,t+1} - \omega_{i,t^+}|$, where $\omega_{i,t+1}$ is the optimal portfolio weight on area i at time $t+1$ after rebalancing. Consequently, the total amount of turnover across all assets in the portfolio is

$$\tau_{t+1} = \sum_{i=1}^{N} |\omega_{i,t+1} - \omega_{i,t^+}|. \tag{12}$$

Moreover, if c denotes the proportional transactions cost, then the total cost to rebalance the portfolio is $c \times \tau_{t+1}$. Let $R_{p,t+1} = \sum_{i=1}^{N} R_{i,t+1}\omega_{i,t}$ denote the portfolio return from a given strategy before rebalancing occurs. The evolution of wealth invested according to that strategy is then given by

$$W_{t+1} = W_t(1+R_{p,t+1})(1-c\times\tau_{t+1}), \tag{13}$$

and the simple return net of rebalancing costs is $R^c_{p,t+1} = W_{t+1}/W_{t-1}$. Since the portfolio w_t is formed using only information available at time t and held for one day before being rebalanced at time $t+1$, the return $R^c_{p,t+1}$ represents the one-day out-of-sample return.

Database

As we described in the introduction section, we have selected for our research the Dow Jones Sustainability Indexes of North America, Europe, and Asia-Pacific which are offered cooperatively by the Sustainable Asset Management (SAM) and the Dow Jones companies. These indexes track the performance of the top 20 % of the 600 largest companies in the Dow Jones Total Market index that leads the field in terms of sustainability for their representative region. The DJSI North America includes Canadian and US companies, the DJSI Europe includes European companies (the UK, Switzerland, Germany, France, Spain, Italy, the Netherlands, Denmark, Sweden, Norway, Finland, Portugal, Ireland, Luxembourg, Belgium and Greece, in order of country allocation), and the DJSI Asia-Pacific includes Australian, Hong Kong, Japanese, Korean, New Zealand, Singaporean, and Taiwanese companies. The indexes include only companies that fulfill certain sustainability criteria better than the majority of their peers, applying a best-in-class approach.

The motivations behind our selection are twofold: firstly, the impact of the Dow Jones and SAM brands in the context of financial indexing and sustainability research, respectively,[4] and secondly, the availability of these index

[3] We employ the US Treasury Bill rate as the risk-free interest rate, obtained from Kenneth R. French's website.

[4] It is important to note that this index family has approximately USD 6 billion in assets under management in a variety of financial products including mutual funds, separate accounts, structured products and exchange-traded funds, and future contracts as reported in the 2012 results of the annual Dow Jones Sustainability Indexes review (http://www.sustainability-index.com).

series over a longer time horizon and across a global reach in an homogenous and comparable set.[5]

The data consist of daily returns (calculated as logarithmic differences) for the DJSI North America, DJSI Europe, and DJSI Asia-Pacific indexes for the period from December 31, 2003 to December 31, 2013.[6] All of them have the same dissemination time (17:59 EST)[7] avoiding the problem of non-synchronicity of the markets.

To avoid in-sample overfitting as well as spurious findings,[8] we use two non-overlapping sub-samples for the estimation and allocation stages: the first sub-sample (from December 31, 2003 to December 31, 2011—2,087 observations) is used for the estimation of the model, while the second sub-sample (from January 1, 2012 to December 31, 2013—520 observations) is used for the out-of-sample research.

Table 1 presents the summary statistics for these return series over the estimation period. An initial conclusion might suggest that the performance of the DJSI Asia-Pacific index as measured by mean daily return is better (0.0067 %) than the DJSI North America (0.0024 %) and the DJSI Europe (−0.0002 %). However, on the basis of the Anova test, we cannot reject the null hypothesis that all series in the group have the same mean since those differences are not statistically significant. On the other hand, due to the rejection of the null hypothesis of equality of variances among the return series, we can conclude that the DJSI North America index is less volatile (standard deviation of 1.27 %) than the other two indexes (1.48 and 1.60 % for DJSI Asia-Pacific and DJSI Europe, respectively). These preliminary results point out that it is important to study more accurately the covariance dynamics among these indexes. Further test produces similar results for these three series. Skewness and kurtosis values indicate that the distributions of returns for all the indexes are negatively skewed and leptokurtic. The Jarque–Bera statistic rejects the null hypothesis that the returns are normally distributed for all cases. The Ljung–Box statistic for up to 15 lags indicates the presence of significant linear and non-linear dependencies in the returns of all indexes. The ARCH test reveals that returns exhibit conditional heteroskedasticity, and the augmented Dickey and Fuller and Philips and Perron tests indicate that these time series are stationary. On the basis of the features observed in Table 1, a VAR–GARCH approach is appropriate to estimate the first and second moments of these indexes.

Empirical Results

This section is divided in two main sub-sections. The first one presents the in-sample estimates from the proposed model. The second one focuses on the out-of-sample application for international diversification purposes.

In-sample Results

The first step in the multivariate VAR–GARCH estimation procedure is to identify the best-fitting specification of the return series. This is particularly important as misspecifying the mean equation may lead to an incorrect estimation of the variance equation (Ewing and Malik 2005). Therefore, the conditional mean equations are defined as a VAR (5) process following the Akaike information criterion. Once the mean structure is identified, we jointly estimate the mean and variance specifications of the VAR–GARCH model to avoid the generated regressor problem according to Ewing et al. (2002).

Table 2 displays the estimated coefficients of the VAR model. As we can see, there are significant dynamic relationships in the return series of these three geographical areas. While the DJSI Europe and DJSI Asia-Pacific indexes are heavily influenced by movements in prices from North America, the DJSI North America index seems to be more driven by events in its own region. Thus, from a portfolio diversification point of view, the DJSI North America index provides greater profits.

Moreover, in Table 3, Panel A, we present the estimated coefficients of the asymmetric BEKK model. The low critical significance levels obtained for most of the parameter estimates (reported in parenthesis) reveal that this model is well suited. Furthermore, we show in Panel B that the null of cross-variance effects ($a_{ij} = b_{ij} \forall\, i \neq j$) is clearly rejected as well as the nulls of $a_{ij} = 0$ and $b_{ij} = 0$. For that reason, we cannot ignore cross relationships across all conditional moments and their symmetric shocks. We also observe that restrictions on cross-variance effects and asymmetric covariance are clearly rejected. As a consequence, cross relationships across all conditional moments and their shocks (symmetric and non-symmetric) cannot be ignored. Furthermore, the importance of considering asymmetries is further supported by the likelihood ratio statistic which is calculated as $\mathrm{LR} = 2[L(\Theta_1) - L(\Theta_0)]$ where $L(\Theta_1)$ and $L(\Theta_0)$ are the maximum log likelihood values obtained from

[5] Although nowadays the field of socially responsible indexes includes several families such as the Calvert Group, E.Capital, Ethibel, FTSE4Good, Humanix, Jantzi, KLD Analytics, and Vigeo, they are not included in our study because they are not available or they are available for shorter time horizons. In addition, these families differ in their construction methodologies, weighting criterion and component selection procedures, and so their inclusion in the analysis could make it difficult to extract concluding remarks.

[6] We use logarithmic returns multiplied by 100 to facilitate the convergence of the empirical models.

[7] Eastern Time (GMT-4).

[8] Data snooping occur whether the same sample is used for both estimation and allocation.

Table 1 Descriptive statistics

	DJSI North America	DJSI Europe	DJSI Asia-Pacific	Equality tests
Mean	0.002	−0.000	0.006	0.012 (0.98)
SD	1.275	1.602	1.481	39.66 (0.00)
Skewness	−0.393	−0.069	−0.315	
Kurtosis	12.859	9.952	8.431	
Jarque–Bera	8506.42 (0.00)	4205.19 (0.00)	2599.81 (0.00)	
Q (15)	56.468 (0.00)	43.332 (0.00)	16.199 (0.00)	
Q^2 (15)	2835.4 (0.00)	1750.1 (0.00)	2515.7 (0.00)	
ARCH (15)	728.98 (0.00)	493.09 (0.00)	669.43 (0.00)	
ADF (4)	−21.669 (0.00)	−21.650 (0.00)	−20.837 (0.00)	
PP (6)	−50.417 (0.00)	−46.587 (0.00)	−46.291 (0.00)	

This table presents descriptive statistics for the daily return series of the DJSI North America, DJSI Europe, and DJSI Asia-Pacific indexes over the in-sample period (2004–2011). The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. Q (15) and Q^2 (15) are Ljung–Box tests for 15th-order serial correlation in the returns and squared returns. ARCH (15) is the Engle (1982) test for the 15th-order ARCH. These three tests are distributed as $\chi^2(15)$. The ADF (4) and PP (6) refer to the Augmented Dickey and Fuller (1981) and Phillips and Perron (1988) unit root tests corresponding to the process with intercept but without trend. The p values of these tests are reported in parenthesis

Table 2 Estimates from the VAR specification

	DJSI North America		DJSI Europe		DJSI Asia-Pacific	
	Coeff.	p value	Coeff.	p value	Coeff.	p value
c_i	0.031	(0.10)	0.046**	(0.04)	0.012	(0.56)
$R_{1,t-1}$	−0.091***	(0.00)	0.482***	(0.00)	0.573***	(0.00)
$R_{1,t-2}$	−0.055*	(0.08)	0.143***	(0.00)	0.144***	(0.00)
$R_{1,t-3}$	−0.005	(0.88)	0.086**	(0.03)	0.085**	(0.01)
$R_{1,t-4}$	0.033	(0.31)	0.052	(0.17)	0.030	(0.37)
$R_{1,t-5}$	0.032	(0.28)	0.073*	(0.05)	−0.014	(0.66)
$R_{2,t-1}$	0.051**	(0.02)	−0.254***	(0.00)	0.207***	(0.00)
$R_{2,t-2}$	0.025	(0.29)	−0.076**	(0.02)	0.074**	(0.01)
$R_{2,t-3}$	0.000	(1.00)	−0.042	(0.17)	0.030	(0.29)
$R_{2,t-4}$	0.019	(0.43)	−0.012	(0.70)	0.015	(0.57)
$R_{2,t-5}$	−0.036	(0.10)	−0.047*	(0.09)	0.044*	(0.07)
$R_{3,t-1}$	−0.021	(0.28)	−0.029	(0.26)	−0.259***	(0.00)
$R_{3,t-2}$	−0.012	(0.55)	−0.043*	(0.09)	−0.136***	(0.00)
$R_{3,t-3}$	−0.042**	(0.03)	−0.053*	(0.05)	−0.046*	(0.07)
$R_{3,t-4}$	−0.029	(0.14)	−0.022	(0.40)	−0.021	(0.38)
$R_{3,t-5}$	−0.001	(0.94)	−0.019	(0.37)	−0.005	(0.80)

This table reports the mean equation estimations for the DJSI North America ($R_{1,t}$), DJSI Europe ($R_{2,t}$), and DJSI Asia-Pacific ($R_{3,t}$) return series (p values in parenthesis)

***, **, and * represent the levels of significance of 1, 5, and 10 %, respectively

the multivariate models with and without asymmetries, respectively. This statistic is asymptotically χ^2 distributed. In this case, $\mathrm{LR} = 2(-8313.054 + 8448.917) = 271.726$; thus, we can clearly reject the null hypothesis of no asymmetric effects even at the 1 % significance level.

Finally, for the purpose of robustness, we analyze the properties of the standardized residuals ($\in_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$) for each return series. Table 4 reports the main results of these specification tests. As we can observe, the mean value is close to zero in all cases with a standard deviation

Table 3 Estimates from the GARCH specification

Panel A: variance equation estimations

$$C = \begin{bmatrix} 0.106 & & \\ (0.00) & & \\ 0.020 & 0.137 & \\ (0.45) & (0.00) & \\ 0.157 & 0.163 & 0.276 \\ (0.03) & (0.01) & (0.00) \end{bmatrix} \quad A = \begin{bmatrix} 0.002 & 0.192 & 0.177 \\ (0.95) & (0.00) & (0.00) \\ 0.033 & 0.054 & -0.240 \\ (0.17) & (0.13) & (0.00) \\ 0.037 & 0.032 & 0.059 \\ (0.06) & (0.25) & (0.12) \end{bmatrix}$$

$$B = \begin{bmatrix} 0.954 & -0.003 & -0.084 \\ (0.00) & (0.81) & (0.00) \\ 0.013 & 0.971 & 0.091 \\ (0.21) & (0.00) & (0.00) \\ -0.012 & -0.044 & 0.833 \\ (0.47) & (0.07) & (0.00) \end{bmatrix} \quad G = \begin{bmatrix} 0.338 & 0.069 & 0.204 \\ (0.00) & (0.14) & (0.00) \\ -0.003 & 0.214 & -0.062 \\ (0.88) & (0.00) & (0.15) \\ -0.012 & 0.017 & 0.344 \\ (0.60) & (0.61) & (0.00) \end{bmatrix}$$

Panel B: testing restrictions on variance effects	χ^2	(p value)
H_0:$a_{ij} = b_{ij}\ \forall\ i \neq j$	279.617	(0.00)
H_0:$a_{ij} = 0$	415.337	(0.00)
H_0:$b_{ij} = 0$	134701	(0.00)
H_0:$\eta_{ij} = \eta_{ji}$	274.224	(0.00)
H_0:$\eta_{ij} = 0$	621.327	(0.00)

This table reports the estimations from the multivariate GARCH specification. Panel A shows the variance equation estimations with p values in parenthesis. Panel B shows the Chi-squared coefficients from some testing restrictions on variance effects (p values reported in parenthesis)

Table 4 Residual diagnostics

	DJSI North America	DJSI Europe	DJSI Asia-Pacific
Mean	−0.025	−0.026	−0.007
SD	0.988	0.993	0.990
Skewness	−0.527	−0.250	−0.136
Kurtosis	4.583	3.823	3.417
Jarque–Bera	313.50 (0.00)	80.366 (0.00)	21.479 (0.00)
Q (15)	8.997 (0.87)	8.826 (0.89)	3.365 (0.99)
Q^2 (15)	21.68 (0.12)	17.96 (0.27)	16.978 (0.32)

This table reports the residual diagnostics which include statistics for the standardized residuals. Q (15) stands for the Ljung–Box Q statistic for the standardized residuals up to 15 lags while Q^2 (15) stands for the Ljung–Box Q statistic for the squared standardized residuals up to 15 lags (p values reported in parenthesis)

of nearly one. We also observe a reduction in the kurtosis of the residuals compared to the original series. The Ljung–Box Q statistics for the 15th orders performed over the standardized residuals reveal a lack of serial autocorrelation and indicate the appropriate specification of the mean equations. Moreover, the Ljung–Box Q statistics for the 15th order in squared standardized residuals show that there is no series dependence in the squared standardized residuals, indicating the appropriateness of the fitted variance–covariance equations by the multivariate model.

While in Table 2, we observe the existence of significant interdependence among all these three geographical areas at price levels, in Table 3, the estimated parameters c_{ij}, b_{ij}, a_{ij}, and g_{ij} for all $i,j = 1,2,3$ cannot be interpreted individually. Instead, we present in Table 5 the estimated coefficients of the conditional variance equations for each index to interpret the non-linear functions of the parameters that form the intercept terms and coefficients of the lagged variances, covariances, and error terms. This allows us to more precisely analyze the existence of contagion risks among these three areas.

Relative to the DJSI North America, we observe in Table 5 that it is affected by its own volatilities lagged one period. The results from the DJSI Europe are very similar

Table 5 Conditional variance equations

	DJSI North America		DJSI Europe		DJSI Asia-Pacific	
	Coeff.	t value	Coeff.	t value	Coeff.	t value
$\varepsilon^2_{1,t-1}$	0.000	(0.02)	0.037**	(2.30)	0.032	(1.56)
$\varepsilon^2_{2,t-1}$	0.001	(0.49)	0.003	(0.54)	0.058***	(3.07)
$\varepsilon^2_{3,t-1}$	0.001	(0.67)	0.001	(0.40)	0.004	(0.55)
$\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	0.000	(0.05)	0.021	(1.23)	−0.085**	(2.25)
$\varepsilon_{1,t-1}\varepsilon_{3,t-1}$	0.000	(0.05)	0.012	(0.77)	0.021	(1.04)
$\varepsilon_{2,t-1}\varepsilon_{3,t-1}$	0.003	(1.08)	0.004	(0.88)	−0.029	(1.03)
$h_{11,t-1}$	0.911***	(34.4)	0.000	(0.09)	0.007**	(2.12)
$h_{22,t-1}$	0.000	(0.45)	0.943***	(27.1)	0.008**	(2.32)
$h_{33,t-1}$	0.000	(0.26)	0.002	(0.64)	0.695***	(14.7)
$h_{12,t-1}$	0.025	(0.91)	−0.007	(0.17)	−0.015**	(2.32)
$h_{13,t-1}$	−0.023	(0.52)	0.000	(0.16)	−0.140***	(4.41)
$h_{23,t-1}$	0.000	(0.37)	−0.086	(1.27)	0.153***	(5.03)
$\eta^2_{1,t-1}$	0.115***	(3.73)	0.005	(0.52)	0.042*	(1.69)
$\eta^2_{2,t-1}$	0.000	(0.05)	0.046**	(2.25)	0.004	(0.51)
$\eta^2_{3,t-1}$	0.000	(0.18)	0.000	(0.18)	0.119***	(4.29)
$\eta_{1,t-1}\eta_{2,t-1}$	−0.003	(0.10)	0.030	(1.23)	−0.026	(0.81)
$\eta_{1,t-1}\eta_{3,t-1}$	−0.008	(0.37)	0.002	(0.33)	0.141***	(3.15)
$\eta_{2,t-1}\eta_{3,t-1}$	0.000	(0.11)	0.007	(0.37)	−0.043	(0.97)

This table shows the estimated coefficients of the conditional variance for the DJSI North America ($h_{11,t}$), DJSI Europe ($h_{22,t}$) and DJSI Asia-Pacific ($h_{33,t}$) return series. The corresponding t values are given in parenthesis

***, ** and * represent the levels of significance of 1, 5 and 10 % respectively

but, in this case, its conditional volatility is also affected by North America shocks. Finally, the results related with the DJSI Asia-Pacific index show that not only is their conditional volatility affected by their own volatility but it is also affected by the shocks and volatility from North America and Europe. In order to check the suitability of the asymmetric GARCH model, we observe that the DJSI North America and DJSI Europe indexes are directly affected by their bad news, respectively. On the other hand, the DJSI Asia-Pacific index not only is directly affected by its bad news, but it is also directly affected by the bad news from North America and indirectly by the bad news from Europe.

Figures 1 and 2 present the plots of the conditional variance and covariance over time for the DJSI North America, DJSI Europe, and DJSI Asia-Pacific indexes. The figures show that conditional variances and covariances are not constant over time and have been especially volatile since the beginning of the international financial crisis. The highest rise was caused by the announcement of the Lehman Brothers bankruptcy in September, 2008. Additionally, Fig. 3 presents the evolution of the estimated

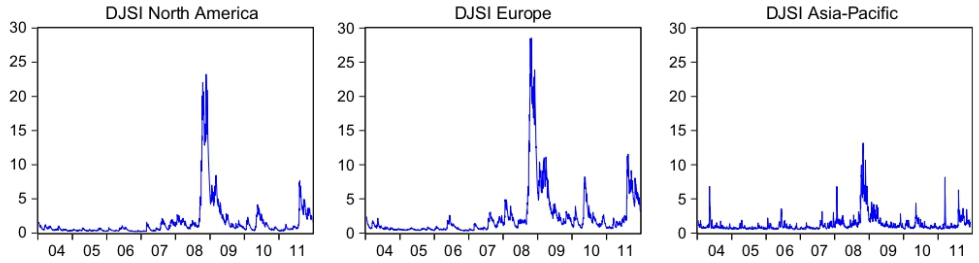

Fig. 1 Conditional variances

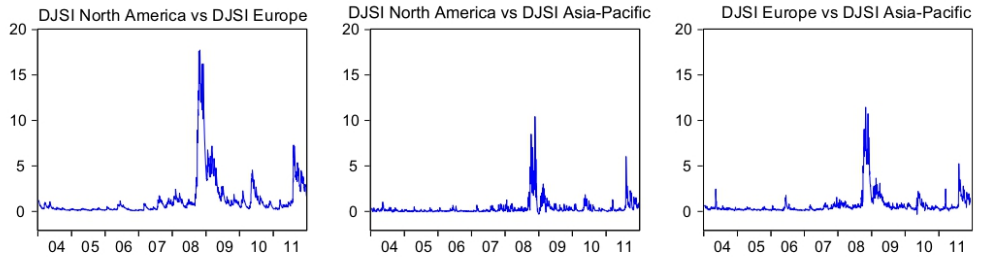

Fig. 2 Conditional covariances

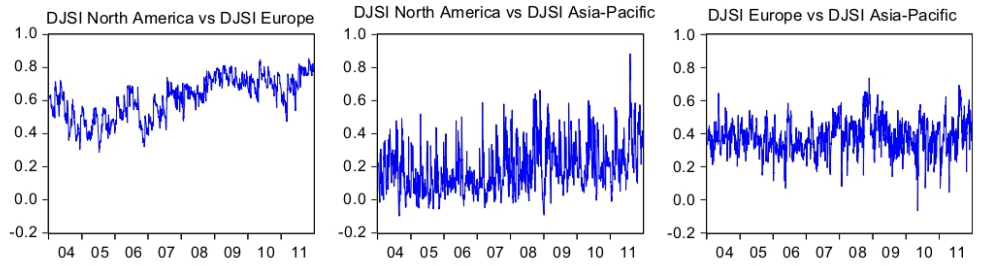

Fig. 3 Conditional correlations

correlation coefficients obtained from this model and shows that they vary considerably over time. This is especially important for the purpose of our research because optimal allocation is only relevant if conditional correlations fluctuate over time (de Goeij and Marquering 2009). Moreover, according to international portfolio diversification theory, the lower the extent of correlation between markets, the greater the benefits from international diversification. Therefore, higher profits from international diversification should be obtained from investing in the DJSI North America and DJSI Asia-Pacific indexes.

Out-of-sample Results

We consider the problem faced by an active SRI manager who rebalances her portfolios on a daily basis. To that end, with the estimated parameters of the estimated VAR–GARCH model, we forecast the return and the variance matrix of the DJSI North America, DJSI Europe, and DJSI Asia-Pacific indexes for the next trading day. We repeat this procedure 520 times (from January 1, 2012 until December 31, 2013) using a rolling sample of 2,087 observations in which the VAR–GARCH model is re-estimated each time. These forecasts are then used to determine the daily optimal weights for each index in the international portfolios proposed. Moreover, to examine the economic gains of constructing risk minimizing portfolios using this approach, we compare our results with those obtained following previous empirical evidence characterized by employing the naïve rule as our benchmark strategy.

Table 6 Out-of-sample performance evaluation

	Naïve rule	Optimal portfolio
Panel A: Portfolio weights		
DJSI North America	33 %	61.10 %
DJSI Europe	33 %	4.62 %
DJSI Asia-Pacific	33 %	30.63 %
Panel B: Performance evaluation		
Return	14.455	29.366
SD	11.738	10.249
Sharpe ratio	1.226	2.859
p value H_0:$\{SR_p - SR_{Naïve} = 0\}$		(0.00)

This table reports the out-of-sample performance evaluation of the optimal portfolio proposed in this study and the naïve rule, which serves as our benchmark strategy for comparison purposes. Panel A shows mean daily portfolio weights, and Panel B shows the annualized mean, the annualized standard deviation, and the annualized Sharpe ratios with the resulting bootstrap p value reported in parenthesis obtained using the methodology suggested in Ledoit and Wolf (2008)

Table 6 shows the out-of-sample results of the optimal portfolio as well as the naïve rule that serves as our benchmark strategy for comparison purposes. In both cases, the reported out-of-sample results include mean daily weights of the DJSI North America, DJSI Europe, and DJSI Asia-Pacific indexes; summary statistics of each portfolio in terms of annualized returns and annualized standard deviation; and the annualized Sharpe ratios with the resulting one-sided bootstrap p value of the equality of the Sharpe ratios using the methodology suggested in Ledoit and Wolf (2008).

While the naïve rule is a passive strategy in which investments are equally weighted in each geographical area, the optimal portfolio strategy computes the optimal weights on a daily basis using time-varying return and volatility forecasts from the VAR–GARCH model. As shown in Panel A of Table 6, this technique produces an optimal portfolio primarily composed of the DJSI North America and the DJSI Asia-Pacific indexes with a higher weight for the DJSI North America index. On the other hand, the weight of the DJSI Europe is close to zero. This indicates the relevant role of North America as a desirable target zone if investors want to reduce the risk of their investments in an SRI context with non-negative expected returns.

However, the main objective of this section is to provide an out-of-sample performance evaluation of the portfolios we have constructed. Panel B of Table 6 presents the performance evaluation of the naïve rule and the optimal portfolio in order to analyze the out-of-sample benefits of international diversification. As we can see, larger returns are obtained through the optimal portfolio based on a VAR–GARCH approach. The naïve rule not only yields smaller average returns but also higher standard deviations. Finally, in the last line of Table 6, we present the results from the annualized Sharpe ratios. These indicate that the best strategy in terms of risk-return trade-off is that based on the VAR–GARCH approach.

Fig. 4 Cumulative returns. This figure displays the cumulative returns over the out-of-sample period of the naïve strategy as well as the proposed portfolio based on the use of time-varying returns and volatility forecasts from a multivariate VAR–GARCH approach

Moreover, Fig. 4 displays the cumulative returns of the naïve rule and the proposed portfolio over the out-of-sample period. Again we note the better performance of the risk optimal portfolio based on the return and volatility forecast from a multivariate VAR–GARCH approach which produces positive and upward cumulative returns far higher than the naïve strategy.

However, before drawing some overall conclusions, we should point out our concern that the results presented above may differ if we consider transaction costs or may be driven by a specific choice of the portfolio rebalancing frequency or the benchmark strategy. For that reason, it is instructive to conduct a few robustness checks in order to control for these effects. To that end, we repeat the empirical exercise assuming transactions costs of 50 basis points and rebalancing portfolios on a daily, weekly, and monthly basis, a common practice among institutional investors. We also test whether these robustness checks provide significant higher Sharpe ratios than when employing a naïve rule based on investing the same fraction of budget into each SRI market. However, it would be more meaningful to show how the proposed strategy performs as compared to conventional stock markets. Therefore, we consider a "responsible" naïve rule as well as a "conventional" one as our benchmark strategies.[9]

As we observe in Table 7, the results of these robustness checks provide relevant conclusions. While the responsible naïve rule is outperformed by the conventional one, both of them are outperformed by the optimal one based on a VAR–GARCH approach even taking into account transaction costs or even when the portfolios are rebalanced less frequently. These results confirm the economic benefits of international diversification based on this technique for a socially responsible investor.

Our overall results reveal that SRI investors can achieve economic gains from optimal international diversification strategies. More specifically, SRI investors can reduce their risk assumptions and beat a naïve strategy by constructing optimal portfolios based on return and volatility forecast from a VAR–GARCH specification. Finally, we conclude that these results are robust for the presence of transaction costs and the choice of portfolio rebalancing frequency.

[9] To that end, we consider the benchmark indexes for North America, Europe, and Asia-Pacific provided by Dow Jones STOXX.

Table 7 Robustness checks

	Benchmark strategies after transaction costs		Optimal strategy after transaction costs		
	Conventional	Responsible	Daily rebalancing	Weekly rebalancing	Monthly rebalancing
Return	12.936	11.835	26.006	17.892	14.960
SD	11.246	11.609	10.171	9.776	10.528
Sharpe ratio	1.145	1.014	2.551	1.824	1.415
p value H_0:{$SR_p - SR_{Conventional} = 0$}		(0.00)	(0.00)	(0.00)	(0.00)
p value H_0:{$SR_p - SR_{Responsible} = 0$}			(0.00)	(0.00)	(0.00)

This table reports the out-of-sample performance evaluation after transaction costs of the benchmark strategies (a conventional naïve rule as well as responsible one) and the optimal portfolio considering daily, weekly, and monthly rebalancing frequencies. In each case, we provide the annualized mean, the annualized standard deviation, the annualized Sharpe ratios with the resulting bootstrap p value reported in parenthesis obtained using the methodology suggested in Ledoit and Wolf (2008)

Conclusions

The aim of this study has been to provide a practical technique which allows SRI investors to alleviate their limit-to-diversification problem and reduce their portfolio risk assumptions through international diversification.

To that end, this paper initially examines price and volatility spillovers among the most representative SRI indexes for North America, Europe, and Asia-Pacific using a multivariate VAR–GARCH approach. These initial results indicate the existence of significant interdependence among all three regions at price and volatility levels, although the DJSI North America index seems to be more driven by events in its own region.

Moreover, in order to analyze the economic implications of these initial results, we provide the out-of-sample performance of an optimal portfolio constructed on the basis of time-varying return and volatility forecasts from this specification approach. Our overall results indicate that using this technique produces an optimal portfolio primarily composed of the DJSI North America and the DJSI Asia-Pacific indexes with a higher weight for the DJSI North America index. Most importantly, this portfolio provides better results in terms of risk-return trade-off than a naïve strategy based on responsible or even conventional markets. Finally, we highlight that these results are robust for the presence of transaction costs as well as the choice of portfolio rebalancing frequency.

These findings are relevant not only for SRI academics, adding a new point of view to the SRI literature, but also for practitioners and policy makers. More precisely, the results of our study are relevant for financial authorities who are concerned about financial contagion risks as well as for those international organizations that promote SRI and may reduce these problems through international regulation. Moreover, this study provides practical contributions to individual and institutional investors, who increasingly consider ESG criteria in their investment decisions, while also seeking profitability; but more especially for asset management firms that create and manage portfolios for SRI investors and may use this technique to add value to their strategies.

Overall, it can be stated that the main objective of the study has been attained. However, the observed results are suggestive of further research. In particular, it would be of interest to provide international diversification strategies based on alternative techniques and compare them to the profitability reached by actual professional managers of SRI funds.

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