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OVERESTIMATION OF DONATION AMOUNT IN CAUSE-RELATED MARKETING

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CONSUMER OVERESTIMATION OF DONATION AMOUNT

Abstract

Research evidence suggests that people are generally inclined to overestimate the effectiveness of their contribution to the public good. In the context of cause related marketing (CRM) campaigns, cognitive bias resulting from the complexity of the judgmental task involved in interpreting the donation information can lead to overestimation of the donation amount. However, previous research in this area of CRM has mostly been focused on CRM campaigns where a firm ties in with a single cause. This study aims to extend research in this area to further explore the impact of CRM portfolio characteristics (framing and size) on cognitive bias in consumer judgment and decisions. The experiment investigates whether the degree of consumer overestimation of the CRM donation amount varies with an increase in the size of a cause portfolio, as well as the impact of portfolio evaluation framing on overall consumer overestimation of the donation. Results revealed no significant effect of portfolio size nor portfolio framing in overestimation. However, there were indications that some interactions with regards to overestimation may exist between small and large portfolio sizes under medium negative affect conditions.

Keywords: cause-related marketing, donation amount, overestimation, portfolio size, framing

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Chapter 1. Introduction

Background

Cause related marketing (CRM) is described as a form of "collaborative philanthropy" (File & Prince, 1998), whereby social causes are supported by profit-oriented firms as a result of "customers' engaging in revenue-producing transactions with the firm (exchange of goods and services for money)" (Varadarajan & Menon, 1988). The resultant effect is a win-win-win situation for all participants of the partnership – brand value is created for the for-profit firm, funds are raised for the charity organization and consumers feel good about contributing to a cause that makes a difference (Adkins, 1999a)

CRM is one of the six major types of Corporate Social Responsibility (CSR), including Cause Promotions, Corporate Social Marketing, Corporate Philanthropy, Employee Engagement and Socially Responsible Business Practices (Kotler & Lee, 2011). The key distinction of CRM from the other five is its ability to establish a direct connection between consumer behavior and corporate contribution levels to a particular cause (Kotler & Lee, 2011). In their seminal work, Varadarajan and Menon (1988) define CRM as *"the process of formulating and implementing marketing activities that are characterized by an offer from the firm to contribute a specified amount to a designated cause when customers engage in revenue-providing exchanges that satisfy organizational and individual objectives"*.

American Express is credited with pioneering CRM, when in 1983 it launched a cause campaign event to raise funds for the restoration of the Statue of Liberty in New York (Varadarajan & Menon, 1988). The company raised $1.7 million within three months through its pledge to donate one cent for every transaction made with an American Express card, one dollar for every newly opened American Express account and one dollar for every vacation

worth $500 or more sold at an American Express travel store (Williams, 1986). The event yielded a 28% increase in card transactions and a 17% increase in new credit card accounts for American Express (Adkins, 1999b).

CRM has mushroomed since then. Major manufacturers, retail chains, and financial services companies, such as Wal-Mart, Ben & Jerry's, Avon, Barclay's, Cadbury, Kellogg's, Citibank, MasterCard International, RE/MAX, Procter and Gamble, The Home Depot, Target, Timberland, and McDonald's, all use CRM as a strategic marketing tool to influence customer behavior. It has been regarded as one of the fastest growing forms of marketing (Berglind & Nakata, 2005). Corporate cause related sponsorship spending in North America grew 20.2 percent between 2013 and 2018 to $2.14 billion, only behind Sports sponsorship, which grew 20.7 percent. A further 4.6 percent growth was predicted for 2019 (IEG Sponsorship Reports, 2013, 2018, 2019).

A 2010 Cone study exploring consumer attitudes and expectations of company support for social and environmental issues suggests that 83% of Americans endorse CRM (Cone, 2010), while a similar study performed in 2015 indicates that as many as 90% would switch, price and quality being equal, to a brand that supports a cause (Cone, 2015). The relatively high popularity of CRM strategies with consumers stems from the perception that CRM provides the means for consumers to leverage their relatively small contributions into major corporate donations to support charitable causes, thereby making a big difference with minimal transaction costs. Many large companies have jumped on the bandwagon of CRM. CRM has become a mainstream business strategy, and certain high visibility causes like breast cancer concerns, support for children and families and local community initiatives are drawing substantial attention (Meyer, 1999).

Many companies are compelled to adopt innovative approaches to differentiate their CRM programs to avoid being lost in the crowd. This is because consumers are becoming increasingly sophisticated at scrutinizing authenticity of cause related marketing campaigns (Anghel et al., 2011). According to a 2017 survey, when a company takes a stand on a social or environment issue, as many as 56% of American consumers are willing to do the research to find out for themselves if the efforts are consistent with the company's activity (Cone, 2017). For example, the Kentucky Fried Chicken (KFC) 'Buckets For The Cure' campaign was labeled a failure due to perceived lack of authenticity between the sustained cause and its activity. As part of the campaign, KFC donated 50 cents to the Susan G. Komen Breast Cancer Foundation for every bucket of chicken ordered by restaurant operators. The problem was that a bucket of KFC contains 2400 calories and 160 grams of fat. The program was abandoned due to complaints that KFC and Komen were promoting unhealthy food to raise money for health research (Minton & Cornwall, 2016). Similarly, Starbuck's 'Race Together' campaign was considered a fiasco (Procter, 2015). Race Together was an initiative from Starbucks and *USA Today* that was designed to initiate discussion, compassion and action around race relations in America. It failed because consumers perceived a lack of fit between the cause and the organization (Procter, 2015). Some of the various approaches adopted include forging exclusive alliances with causes, initiating worthy causes on their own (e.g., Canadian Tire Jump Start, a national charitable program that helps financially disadvantaged kids participate in organized sport and recreation; CIBC Children's Foundation, a national charity responsible for distributing funds raised on CIBC Miracle Day), tying in with less visible/popular causes or simultaneously tying in with a bundle of multiple causes in a branded portfolio (Varadarajan & Menon, 1988). This study will focus on the latter approach: portfolio of causes.

According to Varadarajan and Menon (1988), a firm's tie-in with a portfolio of causes is necessitated by the need to appeal to the intense commitment to one of the causes by small

sub-segments of its constituencies, and the need to reach multiple market segments and situations when causes have seasonal patterns of fund-raising efforts. The first known example of this approach is Mastercard's "Choose to Make a Difference" campaign in 1987, in which Mastercard users selected one of six cause-related institutions, to which money was allocated from a total of $2.0 million. The company agreed to donate money each time a MasterCard was used and the customers got to choose how the money was allocated among the six charities by filling out ballots in their MasterCard statements. The recipient charities were AMC Cancer Research Center, the National Committee for Prevention of Child Abuse, MADD (Mothers Against Drunk Driving), the Muscular Dystrophy Association, the National Association on Drug Abuse Problems, and the American Health Association (Marketing News, 1987). More recent examples of corporate support for a smaller portfolio of multiple causes includes RE/MAX Canada's support for Children's Miracle Network and Canadian Breast Cancer Foundation, whereby a portion of commission from every home sale is donated to a local affiliate of these two charities (Calgary Herald, 2014). Examples of 12 multiple cause CRM campaigns run by top Fortune 500 companies in the past decade in Figure 1 below demonstrates the prevalence of business involvement in CRM as a portfolio rather than the support of a single cause.

One important characteristic of branded cause portfolios is the way they are organized. Portfolios are organized around either localities or issues (Agrawal et al., 2016; Khalili, 2010). Cause portfolio presentation mode or framing influences how they are evaluated by the consumer. For example, locality focused CRM cause portfolios, such as the FedEx portfolio of Memphis-based charities and US-based Mastercard's "Choose to Make a Difference" campaigns, tend to be presented with a narrow decision frame. In this case, consumers are able to estimate donation amount based on an isolated evaluation of each cause in the portfolio in such a way that interactions among multiple constituents are ignored in the consumer decision

(e.g., Kahneman, 2003; Kahneman & Lovallo, 1993; Liu & Chiu, 2015). In contrast, issue focused CRM cause portfolios tend to be expressed with a broad decision frame, whereby the consumer will integrate the overall effectiveness of the combined cause portfolio in his/her estimation of the donation amount, as in the case of the Product RED initiative that supports exclusively the Global Fund to fight AIDS, Tuberculosis and Malaria. Each Product RED partner company (e.g., Hallmark, Dell, Apple, Motorola, Starbucks and Gap) is licensed to create a product with the Product RED logo and a percentage of the profit is given to the Global Fund in exchange for the opportunity to increase the company's own revenue through the Product Red products that it sells (Dadush, 2010).

Figure 1

Examples of 12 Multiple Cause CRM Campaigns Run by Top Fortune 500 Companies

Company (Campaign)	CRM description
Macy's (Scan-to-donate)	Donated up to a total of $250,000*, to DoSomething.org. to encourage young people to volunteer for good social causes, such as education, bullying and the environment, in their community. (Tsiros & Irmak, 2020)
Subaru (Share the Love Event)	Donates $250 for every Subaru sold or leased during a six-week period to the customer's choice of the following charities: ASPCAR, Make-A-Wish, Meals On Wheels Association of America , and National Park Foundation (SUBARU "Share the Love" (2015): www.media.subaru.com) (Lafferty, Lueth & McCafferty, 2016; Tsiros & Irmak, 2020)
Amazon (Amazon "Smile" campaign)	Donates 0.5% of the purchase price of products to the consumer's favorite charity, allowing the consumer to choose from nearly one million organizations (Lafferty, Lueth & McCafferty, 2016)
Walmart (12 Days of Giving)	Wal-Mart Foundation, donates to disaster relief efforts, education programs, immigration integration programs, and children's hospitals, among others (http://foundation.walmart.com) (Eilert & Robinson, 2020)
H&M (All for Children)	Donates 25% of the retail sales price to help UNICEF provide 40,000 children living in Dhaka, Bangladesh, with improved access to education and protection of their basic rights including prevention of child labor (Tsiros & Irmak, 2020).

Newell Rubbermaid (Community Investment Initiative)	Provides cash and in-kind contributions in three areas: providing infants and children with a positive start and the tools to succeed; education and professional advancement, including trade and technical schools (Tsiros & Irmak, 2020).
National Football League (Crucial Catch: Intercept Cancer)	Donates to American Cancer Society (ACS) ACS through the partnership directed toward support of three screenable cancers: breast, colorectal and cervical
Bank of America/ Apple/ Microsoft / Starbucks (Product RED initiative)	Donates to Global Fund to fight AIDS, Tuberculosis and Malaria (Tsiros & Irmak, 2020).
Whole Foods Market (Communities Campaign)	Whole Foods Market's three philanthropic foundations (Whole Planet, Whole Kids, Whole cities) have combined forces to raise awareness and funds, enabling shoppers to join the retailer in efforts to alleviate global poverty, improve children's nutrition and increase healthy food access in communities facing barriers (Tsiros & Irmak, 2020).
JCPenney (JCP CARES)	Every month the partner with a different charity to raise funds for that cause – strengthening communities through youth development, healthy living and social responsibility (Tsiros & Irmak, 2020).
3M Post-it (City of Hope)	Donates to help fund research and treatment in the fight against cancer, diabetes and other life-threatening diseases (Tsiros & Irmak, 2020).
RE/MAX Canada (Children's Miracle Network/Yard Sale for the Cure)	Children's Miracle Network and Canadian Breast Cancer Foundation (Calgary Herald, 2014),

Three clear themes have emerged in the study of CRM. According to Wu and Hung (2008), CRM research is focused around the perspectives of the three key actors in a CRM program:

- Sponsoring company – CRM objectives, selection, performance and external organizational impact

- Consumer – behavior, responses and attitudes towards CRM

- Non-Profit organization – Internal organizational impact of participation in CRM

In many studies, the CRM donation has been used as a reference point to explore the perspectives of these key actors, given its critical underlying impact on the tactical and strategic success of the company-cause-consumer interaction (Koschate-Fischer, Stefan & Hoyer, 2012; Müller, Fries & Gendenk, 2014). Grau, Garretson and Pirsch (2007) outline four areas involving these perspectives:

- Psychological characteristics of consumers driving the donation behavior

- Non-profit organization's characteristics influencing the donation

- Consequences of CRM on the donor firm, as well as the consumer

- CRM campaign donation structure characteristics

Consistent with the first area stated above relating to psychological characteristics of consumers, this research will explore how portfolio *size* and framing will impact cognitive bias in consumer estimation of CRM donation amount within the context of a branded portfolio of multiple causes.

Rationale for the Research

Extant research generally suggests that consumers have a favorable perception of CRM initiatives. One stream of research posits that CRM promotions positively influence consumer perception of the sponsoring firm's behavior and consumer purchase intentions (Carringer, 1994; Hajjat, 2003; Kroll, 1996; Murphy, 1997; Ross, Patterson & Stutts, 1992; Ross, Stutts & Patterson, 1990-1991; Smith & Alcorn, 1991; Webb & Mohr, 1998;). Another stream of research probes further to examine the impact of the structural components of CRM initiatives on consumer perception, focusing specifically on CRM donations.

Evidence suggests that, overall, a positive relationship exists between donation size, consumer acceptance of CRM campaigns and perceived efficacy of their contribution – i.e.,

perception of benefit accruing to the non-profit organization (Dahl & Lavack, 1995; Hajjat, 2003; Moosmayer & Fuljahn, 2010; Strahilevitz, 1999; Subrahmanyan, 2004).

Other studies posit that donation message framing plays a significant role in consumer perception of CRM campaigns. The central theme in these studies is that concrete or abstract framing of a CRM donation message directly impacts consumer choice with regards to a donation exchange, but with different outcomes (Das & Kerr, 2009).

According to Grau, Garretson and Pirsch's (2007) exploratory study of various elements of CRM campaigns, consumers prefer concretely framed donation information, because it offers more tangible details to enable them to calculate the donation amount for themselves and make an intelligent judgment for themselves as to whether their donation will make a difference. In contrast, abstract messages are perceived as least trustworthy and least preferred.

To gain a richer understanding of the effect of CRM donation message framing on consumer perception, research has examined consumer confusion related to abstract CRM donation message frames. Pracejus, Olsen and Brown (2004) elaborated on the types of donation message framing, expressing framing in three broad categories of quantifiers - vague, estimable and calculable. A vague quantifier is expressed in vague terms, providing the consumer with little idea as to what is the actual amount being donated (e.g., does not state what portion of proceeds will be donated). An estimable quantifier provides the consumer with only some information to calculate the actual donation amount, but still includes some unknowns (e.g., states the percentage of profit). A calculable quantifier provides tangible information that allows the consumer to calculate the actual donation amount (e.g., states the percentage of price). They concluded that abstract formats, expressed as a vague quantifier, leads to consumer overestimation of donation amount to a CRM campaign and that this bias

occurs due to cognitive differences in how each individual interprets abstract terms found in CRM donation messages when mapping them onto a numeric scale (Budescu & Wallsten, 1985; Fillenbaum et al., 1991; Wallsten et al., 1986).

Olsen, Pracejus and Brown (2003) focused on an estimable quantifier, arguing that two theoretical mechanisms – Profit-equals-price (PEP) and Profit Overestimation (PO) – drive consumer confusion and result in a near universal intuitive overestimation when donation amounts are presented as a percentage of profit. The PEP mechanism is based on the tendency of people to take computational shortcuts in a bid to simplify the complexity of an estimation task, thereby leaving out relevant information demanded for the task environment (Eddy, 1982). Thus, additional ambiguity is brought to bear when donations are presented as a percentage-of-profit. According to the research, percentage-of-profit is problematic because consumers require a two-step calculation to arrive at the actual amount of money donated: first estimate the profit as a percentage-of-price, and then calculate the amount donated as percentage of profit. Therefore, a subset of the consumer population entirely overlooks the step of estimating profit as only a small fraction of price and this leads to overestimation of the donation amount. This argument is also consistent with how representativeness heuristics are articulated in Kahneman and Tversky's (1974) seminal work on heuristics and biases, where they argue that sometimes the manner in which an object or event is represented makes one insensitive to relevant information that may lead to a contrary outcome, such that the information is overlooked in the process of simplifying the judgment of probabilities, and this leads to biased conclusions (i.e., overestimation). The PO mechanism, on the other hand, is based on the fact that consumers are often inclined to overestimate profit to an extreme extent (Bolton, Warlop & Alba, 2003), which is exacerbated by the fact that consumers are rarely provided actual profit information in CRM.

These studies speak to the underlying rationale for the current research for a couple of reasons. Firstly, abstract donation message framing in the form of *vague* and *estimable* quantifiers accounts for close to 96% of donation message formats used in CRM campaigns (Pracejus, Olsen & Brown, 2004); therefore a study of their impact on consumer perception could easily be projected to CRM campaigns in general. Secondly, the issue of transparent portrayal of the actual amount being donated to CRM programs is receiving addition interest from regulators and academia (Dadush, 2010; Hartmann, Klink & Simons, 2015; Langen et al., 2011; Zheng, Zhu & Jiang, 2019). Studies indicate that the amount of the donation impacts choices between brands (Pracejus, Olsen & Brown, 2004). When this differential choice behavior occurs as a result of overestimation of the donation amount by the consumer, it presents a potential cause for consumer skepticism towards the objectivity of CRM claims (Webb & Mohr, 1998), with the further consequence of evoking decreased credibility of the company/brand, decreased purchase intention of the product and speculation about deception, which may lead policy makers to perceive a need for regulation (Darley & Smith, 1993; Edell & Staelin, 1983; Holbrook, 1978; Kim & Lee, 2009; Olsen, Pracejus & Brown, 2003). Lastly, this study is important because of the influence of portfolio size on audience outcomes when a CRM advertisement features multiple recipient charities. Recent research suggests that consumers are more likely to evaluate CRM campaigns lower when the cause portfolio is focused (i.e., supports one issue) versus diverse (i.e., supports many issues) because focused portfolio is perceived to have a weaker impact on the society (Eilert & Robinson, 2020; Kabongo, Chang & Li, 2013). Against this background, understanding determinants of consumer overestimation of the donation amount in the context of various CRM campaigns is important for taking conscious mitigation steps, both from an individual consumer perspective and from a public policy perspective.

Statement of the Problem

A Cone/Roper survey from 1999 indicated that eight out of 10 Americans prefer companies committed to a single specific cause for a long period of time rather than companies opting for multiple causes for a short period of time (Meyer, 1999). Obviously a different result may have been obtained had the double-barreled survey question been rephrased as the following: "Given an equal time period of commitment, do consumers prefer that companies commit to a single cause, or commit to a portfolio of several causes?" This description highlights the need for academic evidence regarding consumer attitudes toward CRM campaigns involving multiple causes (i.e., a cause portfolio).

Evidence from prior research indicates consumer confusion when the CRM donation information is expressed in abstract message frames (i.e., in vague or estimable formats), which causes consumers to systematically adjust donation estimates upwards. This is due to a cognitive bias related to inappropriate selection of an estimation strategy (Olsen, Pracejus & Brown, 2003; Pracejus, Olsen & Brown, 2004). However, most research studies examining this phenomenon had focused on CRM initiatives using only a single cause (Andrews et al., 2014; Barone et al., 2007; Strahilevitz & Myers, 1998; Winterich & Barone, 2011). Very few CRM research, to my knowledge and a search of article databases, has focused attention on the framing effect within a multiple cause bundle framework (Koschate-Fischer, Huber, & Hoyer, 2015; Eilert & Robinson, 2020). Today, more firms are using multiple cause CRM portfolios as a means of effectively reaching more diverse market segments (Lafferty, Lueth & McCafferty, 2016, Wei & Liou, 2020); hence, understanding how cognitive bias in consumer estimation of the CRM donation amount occurs in the context of a multiple cause portfolio is critical. Research to date has not reviewed multiple cause CRM portfolios with the explicit purpose of drawing inferences regarding cognitive bias in donation estimation.

Cognitive psychology suggests that there is a discrepancy between people's judgments when evaluating a decision problem in isolation and when considering a group of comparable decision problems (Redelmeier & Tversky, 1990). The decision frame that people adopt is influenced by the manner in which decision problems are presented to them (Langer & Weber, 2001; Liu & Chiu, 2015). This implies that when a portfolio is being evaluated for attractiveness, different outcomes will be reached depending on whether each cause is evaluated individually or as a group. People will give more weight to individual burdens and benefits of each unit when *segregated evaluation* criteria is provided, while more weight will be given to overall portfolio effectiveness when *aggregate evaluation* information is provided. These differences in portfolio evaluation approaches also have implications for a multiple cause portfolio in CRM, in terms of how to manage the fine balance between cause portfolio evaluation framing aimed at appealing to the narrow interests of various sub-segments of its constituencies versus framing the CRM donation message to ensure overall CRM portfolio attractiveness to the average consumer.

Cognitive psychology research on the anchoring phenomenon suggests that an individual's estimations can be biased by exposure to anchors or arbitrary cues and information that are irrelevant to the judgment that is being made (Brewer et al., 2007; Mussweiller & Englich, 2003; Tversky & Kahneman, 1974). Furthermore, studies have shown that anchors may not necessarily be numerical, but that physical quantities can also serve as anchors for physical judgments (Kruger, 1999; LeBoeuf & Shafir, 2006). Oppenheimer et al. (2008) further extend this position, suggesting that anchors can act cross-modally, such that physical quantities can bias numerical judgment. According to this research, the magnitude priming effect is the mechanism driving this cross-modal function of anchors. Magnitude priming in essence means that regardless of modality of judgment, people's exposure to large or small anchors may prime the notion of their general magnitudes

(e.g., "largeness" or "smallness") and that this activated sense of qualitative magnitude may bias consequent estimation performance in accordance with that activated size (Oppenheimer et al., 2008). This is also consistent with the view that people rely on a non-numerical sense of magnitude during estimation strategy selection (Brown, 1994; Conrad, Brown & Cashman, 1993) and the selected estimation strategy could, in turn, influence estimation bias (Olsen, Pracejus & Brown, 2003).

The view that magnitude priming causes anchors, such as physical quantities, to function cross-modally in influencing numerical estimation bias has implications for how portfolio size affects consumer estimation of corporate donation amount within CRM. A better understanding of how portfolio size impacts consumer perception of corporate donation amount will provide some guidance to marketers on how the overestimation bias might be minimized while, at the same time, help more causes to effectively implement a CRM campaign.

Research Questions

The effect of size on cognitive performance has received increasing research attention recently, distinguishing between group-size, problem-size and sample-size effects (Anderson, 1959, 1967; Boven & Epley, 2003; Groen & Parkman, 1972; Kaplan, 1981; Kaufmann & Betsch, 2009; Kerr, 1989; LeFevre, Sadesky & Bisanz, 1996; Shavitt, Sanbonmatsu, Smittipatana, & Posavac, 1999; Treen et al., 2016). The *group size* effect refers to a decrease in decision making efficiency when there is an increase in the size of the decision making group involved in allocating public goods (Kerr, 1989). Decision making efficiency tapers off when the optimal team size of five is exceeded (Treen et al., 2016). The problem size effect refers to an increase in solution latencies and error rates for simple addition problems with a larger solution size (i.e., 8+5 takes longer and is more error prone than 3+4), due to various aspects

of how stored arithmetic knowledge is represented in memory for cognitive processing (Groen & Parkman, 1972; LeFevre, Sadesky & Bisanz, 1996). The sample-size effect, on the other hand, refers to the sensitivity of judgment tasks to the size of the set of sampled information (Anderson, 1959, 1967; Boven & Epley, 2003; Kaplan, 1981; Kaufmann & Betsch, 2009; Shavitt, Sanbonmatsu, Smittipatana, & Posavac, 1999).

Further, studies have demonstrated that, under cognitive task such as estimation, people tend to perform better at estimating with problems of small magnitude than for problems of large magnitude (De Visscher et al., 2018). This is because people adjust their estimation strategies to the problem size. Solving problems of large magnitude require subtle interference from memory related similarities/overlap of physical trait which imposes additional steps, adds to complexity of the task and increases the likelihood of error (De Visscher et al., 2018; LeFevre, Greenham & Waheed,1993; LeFevre, Sadesky & Bisanz, 1996; Olsen, Pracejus & Brown 2003; tiberghien et al., 2019). Its implication for social campaigns is reinforced by Drumwright (1996), who stresses that social campaigns are more effective when they focus on fewer causes. Therefore, the following research question arises:

RQ1 **-** *Does cause portfolio size affect consumer overestimation of the CRM donation amount?*

In addition to the effect of size, the mode of representation (i.e., framing effect) of decision problems appears to have an effect on judgment outcome (Einhorn & Hogarth, 1981; Newell & Simon, 1972). Studies related to probability judgments clearly demonstrate the effect of mode of problem representation on judgement outcomes (Fischhoff, Slovic & Lichtenstein, 1978; Tversky & Kahneman, 1980). For example, Fischhoff, Slovic and Lichtenstein, (1978) conducted a study to demonstrate that information that people are exposed to has a tendency to distort their perception of hazard. In that study, they asked

respondents to judge completeness of a fault tree listing failures that could cause a car not to start when the ignition key was turned. Results indicated respondents evaluated completeness about the same when looking at the tree with full list of causes of starting failures, as when looking at tree with half of the causes deleted. Even trained automobile engineers were not immune to this distortion. They were just as insensitive to the deletions from the fault tree as lay people.

One important observation regarding studies examining the effect of decision problem framing on consumer judgment is that they distinguish between a content-driven framing effect and a structure-driven framing effect. Typically, in a single decision problem scenario, its content will drive the framing effect on consumer judgment. For example, studies analyzing single cause CRM have focused on the representation of the content of decision problems (i.e., message framing). Thus, framing the donation message in an absolute dollar amount versus the percentage of the cause related purchase price or profit that will go to a designated cause will directly impact the likelihood of consumer participation in a donation exchange (Das & Kerr, 2009). Pracejus, Olsen & Brown (2004) and Olsen, Pracejus and Brown (2003) extend this logic, demonstrating that ambiguity in the framing of the donation message will cause a near universal overestimation of the donation amount and will ultimately result in a differential choice in consumer participation in a donation exchange.

On the other hand, in a multiple decision problem scenario, the structural context will drive the framing effect on consumer judgment. Consumer and medical decision making research analyzing consumer judgment situations with multiple decision problems have focused primarily on structural context (i.e., joint versus separate framing and evaluation) to explain the framing effect on judgment and decision outcomes (Hsee, Leclerc, 1998; Ku & Hung, 2019; Kumar & Lim, 2008; Redelmeier & Tversky, 1992, Soman, 2004;

Venkatraman, Aloysius & Davis, 2006). This is because multiple prospects versus single prospect is the prevalent class of decision consideration that people are faced with across a broad spectrum of every-day life (Kahneman & Lovallo, 1993). For example, a decision not to wear a helmet on a single trip on a motorcycle is unlikely, in isolation, to have a significant consequence, but the decision to routinely avoid wearing a helmet is extremely likely to have fatal consequences in the long term. Health consequences of smoking a single cigarette on one night out with friends may be negligible, but a lifetime smoker faces a serious health risk (e.g., Read, Loewenstein, & Rabin, 1999). Langer and Weber (2001), Hsee et al. (1999) and Hsee and Leclerc (1998) posited that people make different judgments when individual problems are presented in isolation and evaluated separately versus when a group of problems is presented simultaneously and evaluated comparatively. According to Redelmeier and Tversky (1990), this effect is due to differences in relative weights given to the attributes, thus resulting in different outcomes.

In light of the above argument, the research question is:

RQ2- When donation amount is framed ambiguously, do consumers estimate the donation amount differently when evaluating a portfolio of multiple causes in a joint evaluation mode (i.e., presented simultaneously and evaluated comparatively) as compared with when considering a portfolio of multiple causes in a separate evaluation mode (i.e., presented in isolation and evaluated separately)?

In a seminal article entitled, "Small Wins: Redefining the Scale of Social Problems," Karl Weick argued that an effective strategy to solve social problems is "to recast larger problems into smaller, less arousing problems" in such a way that "people can identify a series of controllable opportunities of modest size that produce visible results and that can be gathered into synoptic solutions" (Weick, 1984, p. 40). In other words, limitations imposed by bounded

rationality cause people to define large social problems in a manner that ends up overwhelming them and impeding their ability to do anything about solving them. However, reframing larger problems downwards into smaller, more manageable pieces increases people's optimism in their own ability to take innovative actions to solve the problem. Bandura and Schunk (1981) described this self-optimism in one's own capabilities to produce results in specific judgment tasks as perceived self-efficacy, which is accompanied with higher performance. For example, trying to lose 50 pounds could be a daunting task, but reframing the scale of the weight loss as losing a pound each week, albeit a small win, could serve to motivate a person and improve chances of reaching the goal.

This underscores the likely impact of the interaction effect between size and framing mode on decision problem outcome. A large and growing body of research on number size framing further explained this interaction by pointing to the fact that people's sensitivity to attributes framed in small numbers tend to be more amplified. Consequently, an option is more favored when its superior attribute is framed with small numbers than when it is framed with large numbers (Chun-Tuan Chang & Yu-Kang Lee, 2008; Peng et al., 2013; Wong & Kwong, 2005). Thus, another research question is:

RQ3 -Does the framing effect interact with the size effect in consumer overestimation of the CRM donation amount in a multiple cause portfolio?

Chapter 2. Literature Review

This chapter will outline extant research that supports arguments for the relevance of cognitive psychology research toward understanding biases in individual decision making and criticism against its relevance. It will also present a review of literature of extant research on bias in individual decision making, as well as research on overestimation bias. An examination of ethical literature on Cause Related Marketing (CRM) will conclude the chapter.

Samuelson (1947) established the foundation of the normative theory of decision making in economics when he defined several assumptions about a rational individual's behavior in his seminal work *Foundations of Economic Analysis* (Carter et al., 2007). These assumptions are best articulated in Simon's (1955) description of a rational man (i.e., homo economicus), stating that he is:

> *. . . assumed to have knowledge of the relevant aspects of his environment which, if not absolutely complete, is at least impressively clear and voluminous. He is assumed also to have a well-organized and stable system of preferences, and a skill in computation that enables him to calculate, for the alternatives of action that are available to him, which of these will permit him to reach the highest attainable point on his preference scale.*

The rational perspective on decision making has an extensive following in neoclassical economics and is applied in game theory and expected utility theory (von Neumann & Morgenstern, 1947), subjective expected utility theory (Savage,1954), and the theory of rational expectations (Lucas & Prescott, 1971; Muth, 1961).

This rational perspective has been challenged on the basis that uncertainty and bounded rationality exist in decision making (Simon, 1955). Kahneman and Tversky (1973, 1979) later

demonstrated that human decision making may systematically deviate from rationality assumptions under uncertainty, therefore exhibiting biases, and that individual behavior in this case is best explained by cognitive psychology (Carter et al., 2007). This school of thought further argues that individuals often fail when it comes to judging probabilities, making predictions, or otherwise attempting to cope with uncertain decision environments in economics (Fischhoff, 1982b; Hogarth, 1987; Thaler, 2000). Simon (1957) argued that:

> *. . . the capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world – or even for a reasonable approximation to such objective rationality.*

According to Carter et al. (2007), despite strong support from many prominent researchers for intensification of research on deviations of actual behavior from the normative models of decision making, some have criticized this area as irrelevant.

The first argument is that these deviations from the rationality assumption are random in nature, therefore they will more or less cancel out at the aggregate level. These individual deviations do not necessarily disprove aggregate predictions of normative economic theory that assumes full rationality of all economic agents (Fama, 1970). However, Kahneman et al. (1982) and Einhorn and Hogarth (1981) have pointed out that these deviations from rationality in decision making, like biases under uncertainty, have a systematic pattern to them, even in the aggregate.

Another argument is that while individuals may be irrational at times, they can learn, and as they learn their actions will approach the traditional neoclassical models (List, 2004). This may be true in some cases (Krell & Grant, 2010); however, a number of biases, like the

failure to update expectations in a Bayesian manner, are relevant to individual learning in markets (Camerer, 1992, 1987; Carter et al., 2007; Ganguly et al., 2000).

Finally, a powerful argument regarding irrelevance of individual deviation from rationality on aggregate economic outcomes is that rational agents will drive irrational agents from the market because the former make higher profits, therefore the weight of their decisions on aggregate outcome will increase over time. This is not a very convincing argument, because a reduction in the quantitative weight of irrational traders cannot be guaranteed, even for the financial market (Fehr & Tyran, 2005). For example, if irrational traders take more risks than rational traders, it is possible that they may earn higher average returns which may ensure their survival in the long run (De Long et al., 1991). In fact, empirical evidence suggests that professional traders are more prone to behavioral biases than are nonprofessionals, as in the case of the professional traders from the Chicago Board of Trade who demonstrated a greater tendency for myopic loss aversion than ordinary students (Haigh & List, 2005).

In the same vein as the above stated points, what is perhaps the strongest argument in favor of the relevance of cognitive psychology research toward understanding biases in individual decision making was put forward by Tversky and Kahneman (1986). They state that these deviations from a rational normative theory of human behavior are "too widespread to be ignored, too systematic to be dismissed as random error, and too fundamental to be accommodated by relaxing the normative model".

Research on biases in human decision making based on cognitive psychology has found application in several business disciplines, including industrial and organizational psychology and management. This research draws upon the area of the psychology of decision-making (Beach & Connolly, 2005), judgment and decision-making (Shaban, 2005), and behavioral economics (Thaler, 1993) to better explore the effect of cause portfolio size and donation

framing on the cognitive bias at play when the consumer overestimates the CRM donation amount.

Overview of Biases in Decision Making

Thaler (2000) suggests that bounded rationality imposes limitations on information processing capabilities of *homo economicus*. Samuelson (1955) goes a step further to elaborate on the nature of this limitation, stating that the limitation is actually imposed on information gathering, computing abilities (Eddy, 1982) and memory (Arrow, 1986; Miller, 1956; Nordstrom et al., 1996; Slovic & Lichtenstein, 1971). In these 3 areas of information gathering, computing abilities, and memory, contrary to the assumptions of normative decision theory, a rational individual is unable to examine all possible alternatives in a complex decision environment under uncertainty, therefore forcing decision makers to use simplifying decision strategies or heuristics, which leads to decision biases (Hogarth, 1987; Tversky & Kahneman, 1974).

A systematic literature review of the ABI/Inform and EBSCOhost databases by Carter et al. (2007) revealed a total of 76 differently named decision biases or sources of decision biases. Based on the argument that previous attempts at categorizations of decision biases are based on subjective groupings, and none are mutually exclusive and exhaustive, they created a logical and manageable taxonomy of nine biases. These nine biases are believed to impact supply chain management decision making, so Carter et al. (2007) specified their effects on rationality, providing specific examples within the supply chain management context. Despite this important contribution to the study of decision biases, this taxonomy displays some weaknesses. One weakness that even the authors acknowledge is that the taxonomy has not been fully tested for external validity to establish that the classification exhaustively represents all biases that are present in day to day interactions (Carter et al., 2007). A second weakness of

the taxonomy is that continuous build-up of heuristic and bias research has caused emergence of an increasing list of new biases (Baron, 2002) and, coupled with the fact the interpretation of the term is gradually evolving over time (Gigerenzer, 2004), this has made it almost impossible to exhaustively capture all classifications of biases. Lastly, overestimation, which is considered a key bias, was conspicuously missing from Carter et al.'s (2007) review. However, Montibeller and von Winterfeldt (2015) elaborated on overestimation bias as a subset of overconfidence bias, distinguishing it as one of the group of biases which are difficult to correct given their tendencies to be resistant to logic and decomposition. Research has shown that people have been observed to engage in estimation strategies that involve calculations (Brown, 2002b; Brown & Siegler, 1993) and these computational short cuts can result in erroneous estimation strategies and subsequent overestimation bias (Olsen, Pracejus & Brown, 2003).

Another framework for understanding the cognitive mechanism underlying decision making biases was developed by Tversky and Kahneman (1974) in their seminal work *Judgment under Uncertainty: Heuristics and Biases.* They argued that people rely mainly on representativeness, availability and adjustment, and anchoring heuristic principles to intuitively assess the probability of uncertain events or predict the value of uncertain quantities, thus leading to various types of biases, including overestimation bias. However, despite the popularity of this argument and its success in stimulating streams of studies, thereby increasing the list of heuristics and biases and understanding of the terms, the ecological validity and logical soundness of the argument has been criticized by several subsequent studies (Cohen, 1981; Gigerenzer, 1996, 1991). For example, Gigerenzer (2004) criticized the terms used to describe these heuristics as common-sense labels and untestable models, which post hoc can account for almost everything, suggesting the need for a more testable model that describes process and conditions under which heuristics succeed or fail. Even the authors themselves,

Tversky and Kahneman, later modified their perspectives and suggested new interpretations on the strength of evidence from new research revealing new understanding of the terms (e.g., Kahneman & Fredrick, 2002 versus Tversky & Kahneman, 1974). The good news, however, is that several streams of research work on decision biases continue to be generated with a foundation in the three-heuristic perspective. Research across diverse fields has already begun to offer deeper insights into specific biases. For example, studies in international politics and strategic studies (Renshon, 2009), transportation management (Tal, 2008), biostatistics (Jeffries, 2008), cause marketing (Olsen, Pracejus & Brown, 2003; Pracejus, Brown & Olsen, 2004) and education (Mayer et al., 2006) have focused on overestimation bias.

Extant Research on Overestimation Bias

Extant research on overestimation bias generally focuses on three aspects – types of overestimation, underlying cognitive mechanisms and how to identify/mitigate potential bias.

In terms of the types of overestimation, the literature generally establishes two broad categories based on whether overestimation is explainable with or without reference to psychological biases (Garthoff, 1990). Literature also classifies three types of overestimation – conscious/rational, erroneous and biased overestimation (Renshon, 2009). Conscious/rational overestimation is said to occur as a result of deliberate upward adjustment of an assessment. Erroneous overestimation occurs when an assessment is made based on insufficient or misleading information (psychological bias is not a pre-condition for erroneous overestimation). Biased overestimation, on the other hand, occurs as a result of systematic upwards adjustment of an estimate as a result of cognitive bias (Olsen, Pracejus & Brown, 2003). A review of the literature suggests that biased overestimation is the least explored of the three types of overestimation (Renshon, 2009)

There appears to be a lack of consensus regarding the relationship between biased overestimation and over-confidence. Contrary to a widely held view in the judgment and decision making literature, Renshon (2009) differentiates biased overestimation from overconfidence and biased optimism. He contends that even though all three are systematic biases in decision making, the direction of biased overestimation runs exactly opposite to the direction of overconfidence and unrealistic optimism. Overconfidence and unrealistic optimism refer to "one's self-assessment relative to a target group" while biased overestimation refers to "overestimation of a target's capabilities relative to an objectively true level" (Renshon, 2009). That said, Renshon (2009) did not articulate what conditions affect the likelihood of biased overestimation to occur and what cognitive mechanisms underlie its occurrence. Contrary views describe overconfidence as an optimistic overestimation of the likelihood of a desired outcome, or one's judgment with no regard for factors limiting predictive accuracy (Griffin & Varey, 1996; Kahneman & Tversky, 1996; Perry, 2008).

When it comes to the second aspect of overestimation bias research - its underlying cognitive mechanisms, the literature indicates varied underlying mechanisms for overestimation bias, depending on the perspective of the researcher (Tal, 2008). For example, empirical findings from Mayer et al.'s (2006) analysis of overestimation of self-reported SAT scores among college students suggests motivated memory distortion (i.e., systematically overestimating their scores upwards) rather than memory deterioration (Kuncel, Credé & Thomas, 2005). However, the Mayer et al. (2006) study could not predict at what point the distortion occurs – whether at the time of information storage (i.e., change in student's memory representation of the scores) or at the time of reconstruction of the information (i.e., at the point of reporting the scores). Peracchio and Meyers-Levy (1997), on the other hand, used the resource-matching hypothesis (Anand & Sternthal, 1989) to predict that overestimation is a function of inefficient information processing during the interval between the periods of

information storage and retrieval. They pointed out that when the cognitive resources available are less than the cognitive resources required (RA < RR), subjects will resort to heuristic processing which could lead to overestimation. Finally, Olsen, Pracejus and Brown (2003) and Pracejus, Olsen and Brown (2004) point to errors in information retrieval (i.e., ignoring or improperly using a critical piece of information) as the exclusive reason for cognitive distortion which results in an overestimation bias occurring at the point of information retrieval, prior to processing. In two separate studies the authors concluded that confusion associated with expressing CRM donation information, either as a percentage of profit or a percentage of proceeds, leads many consumers to engage in inappropriate estimation strategy selection while attempting to take computational short cuts, resulting in near universal overestimation of the donation amount. Another important conclusion from this study is that even consumers who have had formal business training are not immune to this bias, hence participant motivation cannot account for this.

The third aspect of overestimation bias research focuses on how to identify/mitigate negative effect of this cognitive bias in decision making and is also referred to as debiasing research. Foundational literature on debiasing research is highly fragmented and narrow focused with many advocating intervention techniques for debiasing that work on some tasks but have limited success or even backfires on others (Arkes, 1991, Sanna et. al., 2002; Kaufmann et. al., 2010; Larrick, 2004). In addition to these techniques, debiasing research also focused on the positive influence of group cognitive diversity on debiasing judgement (Arkes et.al., 1987; Larrick, 2004; Meissner & Wulf, 2017). Overall, literature outlined three main categories of debiasing mechanism that has been perceived as efficacious in reducing biases: cognitive measures such as draw attention to the opposite perspective in order to examine evidence or scenarios which would not have been considered otherwise (Epley & Gilovich, 2005; Faro & Rottenstreich, 2006; Schulz-Hardt et al., 2002), motivational measures that

advocates for setting suitable incentives (Larrick, 2004) as well as technological measures (Hodgkinson et al., 1999; Meissner & Wulf, 2013). The technological measures comprise of cognitive mapping that involves breaking down and rebuilding the decision structure (decision process and related information) in order to align the decision task with decision makers' cognitive capabilities (Ashton & Kennedy, 2002) as well as scenario planning (Meissner & Wulf, 2013).

Similar to the literature described above, most of previous research on overestimation in CRM has been mostly confined to the single decision problem context (i.e., with a single cause organization) with few exceptions (Koschate-Fischer, Huber, & Hoyer, 2015; Eilert & Robinson, 2020). Varadarajan and Menon (1988), in their seminal work on CRM, describe the cause portfolio as one of the key types of CRM. Unfortunately, not much research has been focused on this type of CRM campaign. This study aims to fill this gap by focusing on overestimation of the CRM donation in the context of the cause portfolio.

Examination of Ethical Literature on Cause Related Marketing

Given the potential impact of consumer overestimation of the CRM donation on brand choice (Pracejus, Olsen & Brown, 2004), it is worth examining academic contributions on the topic of ethics in Cause Related Marketing research.

Ethics remains one of the frequently discussed topics in CRM research. A quantitative analysis of 246 articles on the subject of Cause Related Marketing in 46 journals from 1988-2013 performed by Guerreiro et al. (2016) indicates that ethics remains the second most frequently discussed long term topic behind "brand-cause fit" and has been in active discussion since 2002. One of the earliest conceptualizations of ethics as a dimension of Cause Related Marketing was proposed by Carroll (1979) in his three-dimensional model of corporate social

performance, where he suggests that obligations of firms to the greater society must be assessed along the range of economic, legal, ethical, and discretionary categories of business performance. It is on these bases that the firm must identify social issues (i.e., consumerism, environment, and discrimination) to align with and determine what philosophy it will choose to respond to these issues (i.e., reaction, defense, accommodation, or proaction). Choice of response philosophy will determine where the firm will position on the *do nothing* to *do much* continuum.

A key theme of the ethics studies in CRM research is whether CRM is less "ethical" or desirable than other forms of corporate donation such as philanthropy. Critics of CRM posit that expectation of commercial returns make CRM less ethical than philanthropy (Gurin, 1987; Schiller, 1988; Varadarjan & Menon, 1988). Advocates of CRM, on the other hand, argue that CRM and philanthropy are not inherently ethical, but must meet certain criteria of independent ethical standards derived from the realm of moral philosophies, such as teleology, based on the principle that if an act produces a desired result it is considered "ethical", and deontology, based on principle that a behaviour is "right", not because of its consequences, but because it complies with certain universal principles such as treating the individual as having inherent worth and not being exploited and treated merely as means to achieve ends (Baylin, Cunningham & Cushing, 1988).

Carroll (1991) further expanded, albeit indirectly, on this moral and ethical component of CRM, stating that a perception of conflict between a firm's "concern for profits" versus its "concern for society" is an oversimplification, but instead utilized three major ethical approaches to management – moral, amoral and immoral – to assist executives to reconcile their obligations to their stakeholders with those to the society in an ethical or moral fashion.

Criticism of CRM as being less "ethical" due to expectation of commercial returns has generated another stream of research related to consumers questioning the motivation of a firm for engaging in CRM. Although skepticism toward CRM appears to be declining, consumers remain critical of these efforts, often questioning whether a company's support of a social cause is designed to benefit the cause or the company ("Report: Consumers Swayed", 1997; Smith & Stodghill, 1994; Webb & Mohr, 1998).

Barone, Miyazaki and Taylor (2000) argued that effective influencing tactics used in CRM strategies can be used to manipulate consumer perception of underlying motivations for corporate sponsorship of CRM, which in turn influences consumer choice.

Building on the topic of potential impact of the degree of influence of CRM tactics and strategies to manipulate consumer choice, Olsen, Pracejus & Brown (2003) examined potential consumer confusion associated with the "percentage of profit" wording often used in expression of donation amount to CRM and concluded that it could lead to the systematic overestimation of donation values and thus consumer choice of a brand. This raises an ethical concern for marketing and public policy from a consumer protection perspective. They also explored several potential affirmative disclosures to minimize the problem.

Finally, another stream of ethics research in CRM explores the ethical conflicts that could occur in the partnership between a corporation and non-profit organizations, because the organizations involved have different objectives and goals (Andreasen, 1996; Farache, et al., 2007). These conflicts could include possible damage to the corporation's reputation when the non-profit organization oversteps ethical bounds (Andreasen & Drumwright, 2000), corporations spending more on publicising the CRM program than their actual financial contribution (Varadarajan & Menon, 1988), corporations "cherry-picking" attractive, risk-free, high-visibility causes at the expense of less popular, high-risk, low-visibility groups that need

the support more (Gurin, 1987; Varadarajan & Menon, 1988), exaggeration of corporate support which could lead individual donors to assume that specific causes no longer require donations due to corporate support via CRM campaigns when in reality direct donations are likely to be more beneficial (Polonsky & Wood, 2001), or CRM used to hide or legitimize harmful activities central to the firm's business (Bravo et al., 2012; Andreasen & Drumwright, 2000)

This research has implications from a public policy perspective, in the sense that it exposes to policy makers additional areas of focus in CRM practice, where regulation or a code of conduct is urgently needed.

Theoretical Framework

It is well documented that a multiple strategy perspective is applicable across diverse estimation tasks (Siegler, 1987). A multiple strategy perspective on decision behavior demonstrates that people's estimation strategy selection is contingent upon the task characteristics, particularly accessibility to task-relevant representative content in memory which can be retrieved and the nature of task-relevant information (Blair & Burton, 1987; Brown, 2002a).

Evidence from previous research also suggests that estimation bias is systematically related to strategy selection (Olsen, Pracejus & Brown, 2003). Overestimation occurs when people engage in non-numerical strategies due to the process of converting a qualitative value to a numerical value (Brown, 1995; Brown, 2002a). Generally, non-numerical strategies involve either direct retrieval of a qualitative sense of magnitude or forming a qualitative sense of magnitude via memory assessment, then converting it into a number. If people lack a metric for this conversion, they can be quite inaccurate, typically leading to net

overestimation (Brown, 1995; Brown & Siegler, 1993; Conrad & Brown, 1994). A typical example of memory assessment involves the use of availability heuristics, where people's estimates are based on ease of information retrieval (Tversky & Kahneman, 1974).

One aspect of task relevant information that seems to have a specific strong effect on the outcome of non-numerical estimation tasks is the size of the task. In evaluating how survey respondents make frequency judgements to answer behavioral frequency questions, empirical findings suggest that when frequencies are high, people are not only likely to rely on non-numerical estimation strategies which lead to overestimation (Blair & Burton, 1987; Conrad & Brown, 1994; Conrad, Brown & Cashman, 1993), but that the absolute error increases with task size, i.e., event frequency (Brown, 1997). This is also consistent with Fiedler and Juslin's (2006) thesis that many cognitive biases can be explained in terms of sampling processes. Kaufmann and Betsch (2009) concur, suggesting that attributes of an information sample, such as its size, directly impact judgment. Furthermore, findings from Klemz and Gluca (2003) show that increased task complexity (i.e., increased number of task alternatives or attributes to be evaluated) leads to significant error in decision outcomes, even for experienced decision makers, due to the non-compensatory decision strategies they adopt in order to simplify their decision process.

The sample size effect provides a robust explanation of the sensitivity of intuitive judgment of samples involving multiple pieces of information (i.e., cause portfolios) to sample size and variance. It posits that summary judgment of a set of sampled information becomes more extreme with an increase in the size of the set (Kaufmann & Betsch, 2009; Boven & Epley, 2003; Evans & Bradshaw, 1986; Kaplan, 1981; Shavitt et al., 1999; Bar-Hillel, 1979; Anderson, 1967, 1959)

A stream of research has subsequently emerged to further elaborate on the underlying reason for the sensitivity of intuitive judgment to sample size. This research posits that people, as part of their intuition, adopt the statistical principle of the law of large numbers in everyday judgment situations (Evans & Pollard, 1985; Kruglanski, Friedland & Farkash, 1984; Nisbett, Krantz, Jepson, & Kunda, 1983; Nisbett & Ross, 1980; Piaget & Inhelder, 1975). This principle assumes that larger samples are perceived to yield a more reliable representation of its population characteristics than small samples (Hays, 1981; Sedlmeier & Gigerenzer, 1997); hence, increasing a sample size will cause enhanced weight to be assigned to it in subsequent quantitative judgments (Kaufmann & Betsch, 2009).

Drawing on findings by Pracejus, Olsen and Brown (2004) and Olsen, Pracejus and Brown (2003) that cognitive bias leads to near universal overestimation when donation information is expressed in ambiguous formats (i.e., with vague or estimable quantifiers), I therefore hypothesize as follows:

> *H1: When donation amount information is ambiguous (i.e., expressed as vague or estimable quantifier formats), consumer overestimation of donation amount will increase as size of the cause portfolio (number of causes) increases.*

This has significant implications for the composition of corporate CRM programs, since firms typically aim to support a portfolio of multiple causes in order to target different market or product segments or sub-segments at the same time (Varadarajan & Menon, 1988). Therefore, when a portfolio is composed of several causes, each perceived to represent roughly the same proportion of the consumer market segment, people's judgments will be sensitive to increases in the portfolio size.

The nature of a consumer's central tendencies offers a boundary condition for the effect of portfolio size on the degree of overestimation of a CRM donation. The concept of priming provides insight into this boundary condition. Priming describes a phenomenon, when a person's exposure to a stimulus subconsciously influences the person's response subsequent stimulus by providing a frame of reference. Previous research argues that intuitive judgments tend to assimilate irrelevant anchors (Kahneman & Tversky, 1974), concluding that anchors from one dimension or modality could, indeed, influence estimates of targets in another dimension or modality (Oppenheimer, LeBoeuf & Brewer, 2008). In essence, this means that people's exposure to a small or large quantity in one dimension can cross-modally prime the representation of magnitude in other dimensions, resulting in biased quantitative judgments and responses (Oppenheimer, LeBoeuf & Brewer, 2008; Smith & Price, 2010).

Another perspective on priming is the interaction between the degree of life satisfaction and the magnitude of affective priming in memory. Studies suggest a bidirectional relationship between affective priming effects and levels of life satisfaction (Robinson & Von Hippel, 2006). Moreover, the nature of this influence is such that people with higher levels of life satisfaction appear to have a strong association with larger positive affective priming effects partly due to a memory organization common among people who experience high levels of life satisfaction, whereby there is a strong interconnectivity of positive affective thoughts relative to negative (Robinson & Kirkeby, 2005; Robinson & Von Hippel, 2006).

Related to the concept of life satisfaction, or subjective well-being, is the concept of self-reported mood. The self-reported mood literature identifies two highly distinctive primary dimensions of mood – Positive Affect and Negative Affect (Watson & Clark, 1984; Watson & Tellegen, 1985). Positive Affect refers to a dimension of pleasurable engagement, high energy, full concentration stimulated by enthusiastic, alert and active mood state, while Negative Affect

is a dimension of subjective distress and unpleasurable engagement stimulated by a variety of aversive mood states (Watson, Clark & Tellegen, 1988). Many existing self-report instruments of subjective well-being (SWB) such as Satisfaction With Life Scale (SWLS) are unreliable, because they are subject to conscious distortion of response to the scale if respondents are motivated to do so and inadequate for assessing affective component of SWB (Pavot & Diener, 1993). On the other hand, Watson, Clark and Tellegen's (1988) 20-item mood scale that comprise the Positive and Negative Affect Schedule (PANAS) is well validated and cited by 12,300 scholarly papers (Kuesten et al., 2014). Therefore, PANAS is a more reliable measure.

Positive priming effects reinforce positive thoughts and experiences over time and this cascade of positive thoughts likely predisposes individuals to higher ratings of life satisfaction and well-being evaluations (Robinson & Kirkeby, 2005; Robinson & Von Hippel, 2006). For example, one positive thought (e.g., job security) is likely to trigger another one (e.g., stable finances) which in turn triggers another one (e.g., economic security, loving family relationships, good mental health, etc.), thus self-perpetuating a tendency for happiness that in turn gives rise to higher life satisfaction ratings. On the other hand, negative priming effect is demonstrated when exposure to consecutive negative stimuli (e.g., negative thoughts, sadness, anger) reinforces a greater degree of pessimism and avoidance behavior in everyday life of individuals, thus predisposing them to a lower ratings of life satisfaction and lower well-being evaluations (Carver & Scheier, 1998; Robinson & Kirkeby, 2005).

Schwarz and Clore's (1983) suggests that affective priming manipulations tend to induce bias in the interpretation of a judgment target. While Oppenheimer, LeBoeuf and Brewer's (2008) argued that biased quantitative judgments and responses can result from exposure to a small or large quantity in one dimension cross-modally priming the representation of magnitude in another dimension. Drawing on these two positions, one can

argue that given the same conditions, measuring consumers' positive (or negative) affect as measured by Positive and Negative Affect Schedule (PANAS) may result in varying degrees of overestimation (or underestimation) of the CRM donation amount. Thus, I propose that:

H2a: When the donation information is ambiguous (i.e., expressed in vague or estimable quantifier formats), the consumer's level of positive affect positively moderates the effect of the size of a given multiple cause portfolio on the extremity of consumer overestimation of the CRM donation amount.

H2b: When the donation information is ambiguous (i.e., expressed in vague or estimable quantifier formats), the consumer's level of negative affect negatively moderates the effect of the size of a given multiple cause portfolio on the extremity of consumer overestimation of the CRM donation amount.

The framing effect phenomenon has been receiving increasing attention in decision behavior research. The framing effect refers to how a different description or wording of a scenario (i.e., scenario decision frame) produces a different reasoning or behavioral preference, assuming all other objective information being equal (Frisch, 1993).

Cognitive psychology distinguishes between two primary decision frames by which the framing effect can occur: *distributional reasoning* and *case-specific reasoning* (Connie, John & Iyer, 2002). Distributional reasoning looks at a scenario in terms of its relevance to a broader context, with which there is a prior learning experience, then relies on normative or rule-based principles to draw on generalizations to analyze the current scenario. Case-specific reasoning evaluates each scenario independently, relying on costs and benefits to arrive at a decision (Reeves & Lockhart, 1993).

Typically, consumer decision behavior research has measured framing effects by comparing outcome choices (Dotson et al., 2012; Gamliel & Herstein, 2012; Levin & Gaeth, 1988), behavioral preferences (Braun, Gaeth & Levin, 1997; Gamliel & Herstein, 2007; Meyers-Levy & Maheswaran,1990), or moral reasoning processes (Connie, John & Iyer, 2002; Stanforth & Hauck, 2010) when examining two (negative and positive) frames of a scenario. Comparative analysis indicates conflicting outcome in these studies. For example, Levin and Gaeth (1988) and Dotson et al. (2012) studies demonstrated that diagnostic product experience dilutes impact of framing effects on consumer decision. On the contrary, Gamliel and Herstein (2007) study related to framing effects on consumer willingness to buy private brands suggested that relative to positive frame (save), negative frame (loss) results in higher consumer willingness to buy private brands.

Further, Braun, Gaeth and Levin (1997) study testing male and female responses suggested that framing effects were limited to female for whom framed attribute was specifically important. However, Connie, John and Iyer (2002) observed a different outcome showing that true framing effects are not likely to vary by gender. Meyers-Levy and Maheswaran (1990) attributes some of these conflicting outcomes in framing effects studies to people's use of either detailed versus heuristic processing in comprehending the message that is framed either positively or negatively. Their tendency to use detailed processing in determining their preference is greater when message information is of high personal relevance. However, tendency for heuristic processing is greater when the message information is of low personal relevance.

A stream of research has been undertaken in prospect theory research to account for various ways people encode compound joint outcomes -- "narrow framing" (Benartzi & Thaler, 1999; Kahneman & Lovallo, 1993), "choice bracketing" (Read et al., 1999), "mental

accounting" (Thaler, 1999), and "segregation/aggregation" (Langer & Weber, 2001; Redelmeier & Tversky, 1992). The central theme is that evaluating component outcomes either jointly (i.e., aggregated or consolidated) or separately (i.e., segregated or partitioned) may induce related differences in perceived value. For example, research on price framing for multiple component bundles finds that segregated pricing of individual components could raise salience of a component and its associated features, thereby increasing its weight in affect evaluation and choice (Chakravarti et al., 2002; Gilbrand, Gulitinan & Urbany, 2008). In contrast, most extant CRM research that examined the influence of the framing effect on the consumer decision making process had focused mainly on donation message framing in the context of a single cause (Das & Kerr, 2009; Grau & Garretson Folse, 2007; Grau, Garretson, & Pirsch, 2007; Olsen, Pracejus, & Brown, 2003; Pracejus, Olsen & Brown, 2004). Very few CRM research, to my knowledge and a search of article databases, has focused attention on the framing effect within a multiple cause bundle framework (Koschate-Fischer, Huber, & Hoyer, 2015; Eilert & Robinson, 2020).

Overall, it is suggested that an aggregated prospect frame leads to superior outcomes, but people are most likely to adopt segregated frames when faced with intuitive decision problems (Kahneman, 2003; Kahneman & Lovallo, 1993). This consequently results in isolated evaluation of components, often ignoring the overall portfolio context and leading to suboptimal results. Some studies suggest that this tendency for segregated framing occurs regardless of whether the context of the decision problem is at the individual or public level. On the other hand, Weick (1984) suggests focusing on small gains when addressing social dilemma problems, implying that dividing a large problem into pieces small enough for individuals to handle enhances the prospects of success. Hedonic optimizers would also normally adopt a narrow decision frame that segregates gains instead of a broad decision frame that combines all gains and appears to be optimal (Lim, 2006; Thaler & Johnson, 1990). In

fact, Langer and Weber (2001), in their analysis of a portfolio consisting of mixed lotteries, suggest a sensitivity of acceptance rates to the difference between narrow and broad presentation of the portfolios, even with similar risk profiles. They point out that narrow framing leads to segregated evaluation, which in turn results in lower overall evaluation of the portfolio. Therefore:

H3: When evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation leads to lower overall consumer overestimation of the donation amount, compared to aggregated framing of the same portfolio.

Evidence also suggests that under conditions of ambiguity where intuitive judgment is applied, framing effects are present for positively correlated investment portfolios (Steul, 2006). Perry (1985) also points out that this correlation rises as the portfolio size increases, thus implying a direct causal relationship between framing effect and portfolio size.

Drawing on Kahneman and Lovallo's (1993) conclusion that people intuitively adopt narrow framing which leads to suboptimal outcomes (i.e., lower estimates of donation amount), one can then assume a negative relationship between portfolio size and narrow framing. For example, in a decision-making environment under ambiguity, intuition leads people to frame the outcome narrowly by focusing on losses rather than gains, thus making it difficult to trade small losses for large gains. When evaluating a new gamble, the intuitive tendency toward narrow framing forces people to evaluate the gamble in isolation, instead of merging it with the risks they are already facing and checking whether the combination is attractive, thus missing out on the gamble's potential contribution to total wealth. This is particularly applicable in real-world situations where people fail to choose wise trade-offs by neglecting to consider diverse applications of the decision opportunity they are presented with. Voters, for

example, focus too much on the narrow interests of the small group to which they belong and neglect to consider the secondary effect of their interests potentially being represented by a minority group of legislators, which would reduce the likelihood of such interests being reflected in government decisions (Rickard, 2012). Therefore, my hypothesis states that:

H4: When evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation attenuates the effect of cause portfolio size on the extremity of consumer overestimation of the CRM donation amount.

Figure 2

Conceptual Framework
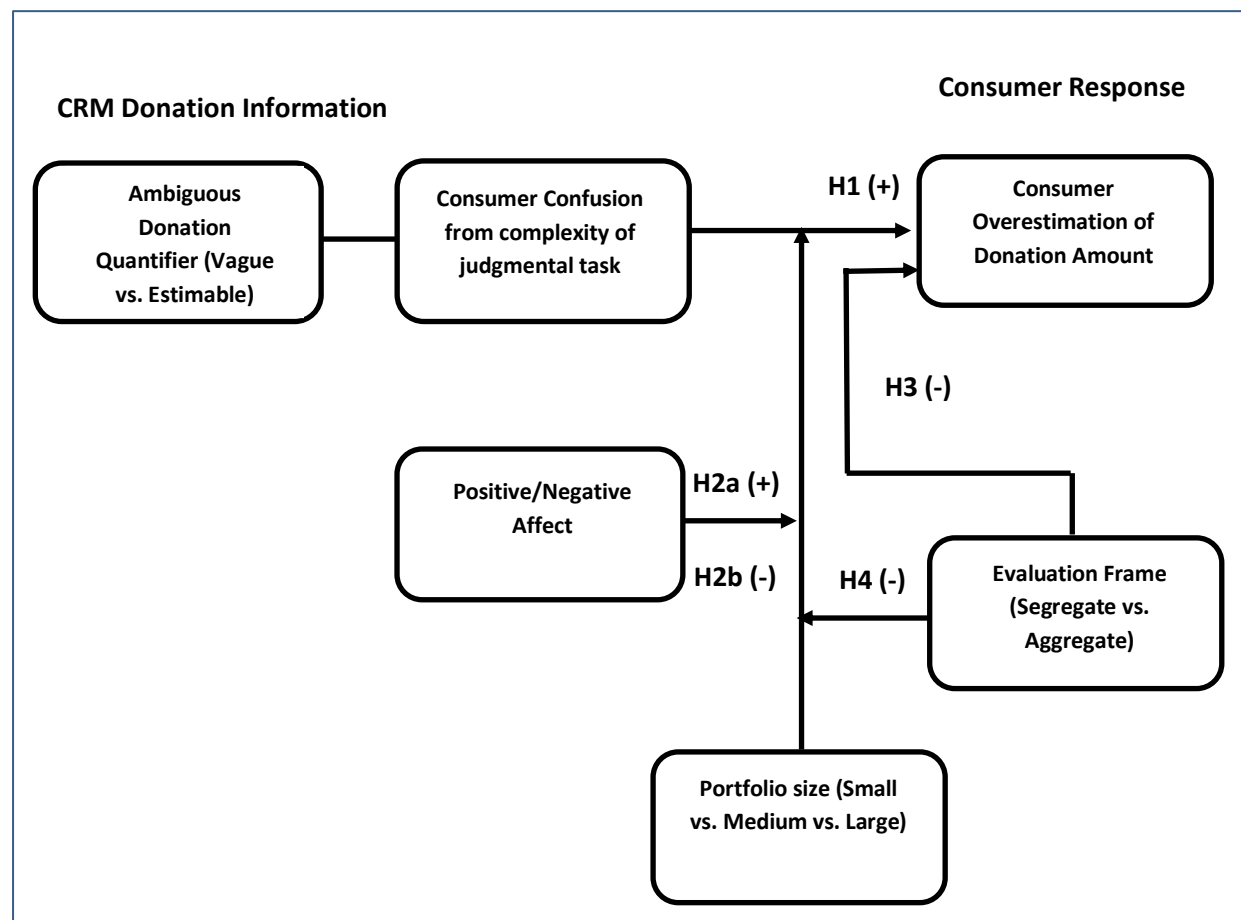
Definitions and Measures of Focal Constructs of Study

Focal constructs are defined and their measures described below

Figure 3

Focal Constructs Definitions

Variable	Definition	Measure
Donation Overestimation	Higher consumer estimate of CRM donation amount than actual resulting from consumer's confusion during attempt to interpret or map the ambiguous terms found in CRM donation messages onto a numeric scale because people take computational shortcuts in a bid to simplify the complexity of the estimation task, such that they overlook relevant information required for the task environment (Budescu & Wallsten, 1985; Eddy, 1982; Fillenbaum et al., 1991; Olsen, Pracejus & Brown, 2003; Wallsten et al., 1986).	Comparison of actual dollar amount of donation from similar CRM event and the scaled responses from the hypothetical CRM. All scaled response that are higher than the actual donation amount
Donation Quantifier	The way the company presents the CRM donation amount to the consumer (Grau, Garretson & Pirsch, 2007; Pracejus, Olsen and Brown, 2004) • Vague quantifiers provide consumers with almost no idea as to the actual amount being donated (i.e., generous donation will be made) • Estimable quantifiers give only a piece of information needed to calculate the donation amount (i.e., x% of percentage of profit will be donated) • Calculable describes donation amount in a manner allows consumers to calculate the actual amount being donated (i.e., x% of percentage of price will be donated)	Identified based on terms used to express quantity of donation amount in CRM campaign messaging
Portfolio Size	Number of causes involved when CRM campaign simultaneously ties in with a bundle of multiple causes in a branded portfolio (Varadarajan & Menon, 1988).	Count of causes listed in a branded CRM campaign portfolio
Positive/ Negative Affect	Self-reported primary dimensions of life satisfaction and well-being evaluations using mood states (Robinson & Kirkeby, 2005; Robinson & Von Hippel, 2006; Watson & Clark, 1984; Watson & Tellegen, 1985). Positive Affect refers to a dimension of pleasurable engagement, high energy, full concentration stimulated by enthusiastic, alert and active mood states, while Negative Affect is a dimension of subjective distress and unpleasurable engagement stimulated by a variety of aversive mood states (Watson, Clark & Tellegen, 1988).	20-item mood scale that comprises the Positive and Negative Affect Schedule (PANAS)

| Evaluation Frame | Expression in CRM campaign message of how CRM donation will be distributed to each cause in branded multiple cause portfolio either individually (segregate; i.e., donation to be split equally between charities) or as a group (aggregate; i.e., donation to be split unequally between charities) (Thaler, 1999; Langer & Weber, 2001) | Identified based on terms used to express how donation will be distributed to each cause in a multiple cause CRM campaign |

Chapter 3. Methods

A positivist philosophy is adopted for this research. Positivists believe that reality is independent of the researcher, hence it can be observed from an objective viewpoint without the researcher interfering in the phenomena being studied (Levin, 1988). Although there has been much debate about the appropriateness of the positivist paradigm for social science research (Hirschheim, 1985) when compared to the interpretivist perspective, its rich tradition in the performance marketing research is the key attraction. Experimental design is argued to be the best research design for establishing causal connections between variables because of its high internal validity (Bryman, Teevan & Bell, 2009). All the hypotheses described earlier will be tested using an experimental research design.

This chapter will outline methodology for testing the hypotheses proposed in chapter 1. The research design, survey instrument used for data gathering, as well as the response rate will be presented. The chapter then concludes by detailing our approach to data analysis for this study, criteria used to ensure validity and reliability of the research, as well as ethical consideration for the study.

Research Design

An Imagine Canada survey of 2,200 Canadian companies (Easwaramoorthy et al., 2006) indicates that social services, health and sports and recreation organizations are the most likely types of nonprofits to be supported by businesses and also that the top three causes that businesses support are children (68%), youth (55%), and people with physical disabilities (40%). Consequently, the 26 charities initially selected for the pretest for this experiment support children's health, recreation and social service issues. These 26 examples were chosen because they were the largest charities in each of these three categories, based on annual

donations. Charities that were local to a particular city were excluded from the list since the target participants for the pretest who are students at Athabasca University are from all across Canada. These 26 charities are listed as follows:

1. Children's Miracle Network

2. Make a Wish Foundation

3. Ronald McDonald House Charities

4. Sick Kids Foundation

5. Canadian Tire Jump Start

6. CIBC Children's Foundation

7. SOS Children's Villages Canada

8. Tim Horton Children's Foundation

9. Juvenile Diabetes Research Foundation Canada

10. World Vision Canada

11. Council on Drug Abuse (CODA)

12. Big Brothers Big Sisters of Canada

13. Boys and Girls Clubs of Canada

14. The Canadian Red Cross Society

15. CARE Canada, Bethany Care Society

16. Canadian Breast Cancer Foundation

17. Multiple Sclerosis Society of Canada

18. Canadian Cancer Society

19. Heart and Stroke Foundation of Canada

20. Canadian Wildlife Federation

21. The David Suzuki Foundation

22. World Wildlife Fund Canada

23. Tides Canada Foundation

24. The Nature Conservancy of Canada

25. MADD Canada

26. United Way of Canada

Pre-Test Methodology and Results

Prior to starting the experiment, a pretest was conducted to measure the perceived familiarity and favorability of each of the above-mentioned charitable organizations. The pre-test was also used to unveil any issues with the clarity and consistent interpretation of individual questions and ensure that the questions met their intended purpose (Burns et al., 2008).

Permission was obtained from the Athabasca University authorities to access respondents for the research. An invitation to participate in the pre-test, along with the link to the survey web site, was posted on the Athabasca University Student Portal. For Staff, a similar posting was put up on the Staff portal homepage. This provided access to a student, faculty and staff population of approximately 10,000 respondents. A minimum of 30 respondents were required for the pre-test. Every week, an automatic number generation was used to randomly select a series of 1:3 responses drawn from among volunteers for the study. Consequently, responses from 131 adults aged 18 and over were collected over an eight-week period.

Each of the 26 charities noted above was listed in the pre-test questionnaire, without providing a description of its mission/cause affiliation or assignment to a category. Respondents were asked to indicate whether they are familiar with the charity (*familiar* / *not familiar*) and whether they have a favorable or unfavorable opinion of each of these charitable organizations on a scale from 1 to 5 (where 5=*favourable*, 4=*mostly favourable*, 3=*no opinion*; 2=*mostly unfavourable*; 1=*unfavourable*). Demographic data (age, sex, and amount of

charitable giving per year) was collected as part of the pretest in order to ensure that there are no substantial differences in favorability and familiarity when comparing different demographic groups. A copy of the pretest questionnaire can be found in Appendix 1.

Pre-Test Sample Descriptor: For the pre-test, there were initially a total of 131 respondents. However, after deleting the questionnaires that had missing values or incomplete responses, 129 responses remained (98.5 percent of the original sample of 131 questionnaires). This is substantially more than the minimum 30 respondents that were required for the pre-test. Figure 4 indicates the demographics of the respondents. The gender distribution was 86% female and 14% male. The modal age range was 25- 34 years.

Figure 4

Demographics of the Pre-Test

AGE:	Male	Female	TOTAL:
18-24	n= 4 3.1%	n=18 14.0%	n=22 17.1%
25-34	n=10 7.8%	n=37 28.6%	n=47 36.4%
35-44	n=3 2.3%	n=33 25.6%	n=36 27.9%
45-54	n=1 0.8%	n=20 15.5%	n=21 16.3%
55-64	n=0 %	n=3 2.3%	n=3 2.3%
65+	n=0 %	n=0 %	n=0 0%
TOTAL:	n=18 14%	n=111 86%	n=129 100%

The gender distribution of the pretest sample drawn from Athabasca University students and staff indicating more female than male response is consistent with the student demographics numbers published on the AU website indicating 67% female student population as of 2010-2011 year (Athabasca University, AU at a Glance). However, there was no publicly available data related to gender distribution among from Athabasca University staff. That said,

preponderance of female response is also representative of the larger society and consistent

with a growing body of research on CRM, which suggests significantly more positive response

to CRM from women than men (Ross, Stutts & Patterson, 1991, 1992; Vilela & Nelson, 2016)

Figure 5 provides a ranking for all 26 charities, based on the Net favorability scores.

Favorability rating is a proven measurement technique used in polls or surveys to assess the

overall public sentiments towards a person, place or thing (Lavrakas, 2008). The rating is

commonly used in political polls to indicate if overall public opinion towards a politician is

favorable (positive), unfavorable (negative) or neutral. It is usually expressed in Net

Favorability score. The Net Favorability score was calculated by subtracting the unfavorable

opinions from the favorable opinions.

Figure 5

Charities Ranking Based on Pre-Test Results

Answer Choices	% Familiar (Have an opinion)	% With Favorable Opinion	% With Unfavorable Opinion	Net Favorable (%)	Net Favorability Ranking for HIGH familiarity (>50%)
Make a Wish Foundation	90%	86%	4%	82%	1
Ronald McDonald House Charities	94%	87%	6%	81%	2
Big Brothers Big Sisters of Canada	81%	80%	2%	78%	3
The Canadian Red Cross Society	89%	80%	9%	71%	4
MADD Canada	81%	76%	5%	71%	5
Boys and Girls Clubs of Canada	72%	71%	1%	70%	6
Canadian Wildlife Federation	68%	68%	0%	68%	7
Sick Kids Foundation	65%	65%	0%	65%	8
Heart and Stroke Foundation of Canada	79%	72%	8%	64%	9
Canadian Cancer Society	82%	70%	13%	57%	10
Multiple Sclerosis Society of Canada	59%	58%	1%	57%	11
Tim Horton Children's Foundation	67%	62%	5%	57%	12
World Wildlife Fund Canada	63%	58%	5%	53%	13
Canadian Breast Cancer Foundation	85%	68%	16%	52%	14
Children's Miracle Network	65%	58%	6%	52%	15
Canadian Tire Jump Start	62%	57%	5%	52%	16
United Way of Canada	65%	51%	14%	36%	17
The David Suzuki Foundation	59%	45%	14%	31%	18
World Vision Canada	70%	37%	33%	4%	19
Juvenile Diabetes Research Foundation Canada	44%	42%	2%	40%	20

The Nature Conservancy of Canada	31%	29%	2%	26%	21
CIBC Children's Foundation	15%	11%	5%	6%	22
Council on Drug Abuse (CODA)	14%	11%	3%	8%	23
CARE Canada, Bethany Care Society	13%	11%	2%	8%	24
SOS Children's Villages Canada	12%	8%	4%	5%	25
Tides Canada Foundation	7%	4%	3%	1%	26

Based on a median split on the Familiarity question and a median split on the Net Favorability Ranking, each charity was placed into one of the boxes in the Figure 6 below.

Figure 6

Favorability - Familiarity Matrix

High Favorability / Low Familiarity	**High Favorability / High Familiarity**
	Make a Wish Foundation
	Ronald McDonald House Charities
	Big Brothers Big Sisters of Canada
	The Canadian Red Cross Society
	MADD Canada
	Boys and Girls Clubs of Canada
	Canadian Wildlife Federation
	Sick Kids Foundation
Low Favorability / Low Familiarity	**Low favorability / High Familiarity**
CIBC Children's Foundation	Heart and Stroke Foundation of Canada
SOS Children's Villages Canada	Canadian Cancer Society
Juvenile Diabetes Research Foundation Canada	Multiple Sclerosis Society of Canada
Council on Drug Abuse (CODA)	Tim Horton Children's Foundation
CARE Canada, Bethany Care Society	World Wildlife Fund Canada
Tides Canada Foundation	Canadian Breast Cancer Foundation
The Nature Conservancy of Canada	Children's Miracle Network
	Canadian Tire Jump Start
	United Way of Canada
	The David Suzuki Foundation
	World Vision Canada

65%

50%

Charities with the highest Net Favorability Rankings which fall into the high favorability and high familiarity quadrants were selected and combined into portfolios of 2, 5,

or 8 charities. The two highest ranked charities were used for the 2-charity portfolio, the 5 highest ranked charities were used for the 5-charity portfolio, and the 8 highest ranked charities were used for the 8-charity portfolio. Consequently, 8 charities selected for the experiment based on the order of ranking are as follows:

Figure 7

Charity Portfolio Assignments

2-Charity Portfolio	5-Charity Portfolio	8-Charity Portfolio
1. Make a Wish Foundation 2. Ronald McDonald House Charities	1. Make a Wish Foundation 2. Ronald McDonald House Charities 3. Big Brothers Big Sisters of Canada 4. The Canadian Red Cross Society 5. MADD Canada	1. Make a Wish Foundation 2. Ronald McDonald House Charities 3. Big Brothers Big Sisters of Canada 4. The Canadian Red Cross Society 5. MADD Canada 6. Boys and Girls Clubs of Canada 7. Canadian Wildlife Federation 8. Sick Kids Foundation

Main Experiment

The primary purpose of the main experiment is to see if the degree of consumer overestimation of the CRM donation amount will vary with an increase in the size of a cause portfolio, thereby testing Hypothesis 1. The study also administered the PANAS (Positive and Negative Affect Scale) instrument, in order to test Hypothesis 2a and 2b.

Further, the experiment tested Hypothesis 3 by evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), to see how the portfolio evaluation framing (i.e., expressed in segregated frames or aggregated frames) impacts the overall consumer overestimation of the donation amount within the same portfolio size.

Segregated frames are expressed with a statement indicating equal split of donation amount between a specified number of charities, while aggregate frames are expressed as unequal split of donation amount. Respondents were allowed to self-select between the aggregate and segregate conditions.

The experiment also tests Hypothesis 4 by manipulating the cause portfolio size to see if the degree of consumer overestimation of the CRM donation amount varies with an increase in the size of a cause portfolio.

Method: To test hypothesis 1, the dependent variable is the overestimation of the CRM donation amount relative to the actual donation amount. The stimulus information is manipulated between-subjects according to a 3 (portfolio size: small vs. medium vs. large) x 3 (donation quantifier format: vague (ambiguous) vs. estimable (ambiguous) vs. calculable (non-ambiguous) full factorial design.

To test Hypothesis 2a and 2b, the PANAS instrument is used to measure positive affect and negative affect, to determine whether affect contributes to overestimation of donation amount.

To test Hypotheses 3 & 4, the dependent variable is the overestimation of the CRM donation amount relative to the actual donation amount. The stimulus information is manipulated within-subjects according to a 2 x 2 x 2 factorial design of cause portfolio size (small vs. large) and portfolio evaluation frame (segregated vs. aggregated) nested within the ambiguous donation quantifier factor (vague vs. estimable). Respondents were randomly assigned to only the cause portfolio size and ambiguous donation quantifier conditions, while they were allowed to self-select between the aggregate and segregate conditions.

Data Collection: Permission was obtained from the Athabasca University authorities to access respondents for the research. An invitation to participate in the research study, along with the link to the survey web site, was posted on the Athabasca University Student Portal. For Staff, a similar posting was put up on the Staff portal homepage. This provided the researcher with access to a student, faculty and staff population of approximately 10,000 respondents.

Additional permission was also obtained from the Athabasca University Ethics Review Board to access respondents from members of the public. An invitation to participate in the research study, along with the link to the survey web site, was posted on social media portals – WhatsApp, LinkedIn and Facebook.

The desired sample size of a minimum of 270 adults aged 18 and over was collected over an eight-week period. The rationale for this sample size is presented in the following statistical power analysis.

Sample Size - Power Analysis: An *a priori* power analysis was conducted to determine an appropriate sample size N that would be large enough to produce a power that is reasonably high, while maintaining statistical significance level α (maximum allowable probability of committing type I error) at a reasonably low value. This is done by controlling the probability of type II error β.

Figure 8

Description of Type I and Type II Errors

	Null hypothesis (H₀) is true	**Null hypothesis (H₀) is false**
Reject null hypothesis error	Type I error False positive	Correct outcome True Positive
Fail to reject null hypothesis	Correct outcome True Negative	Type II error False negative

The null hypothesis **H₀** to be rejected is that an increase in the size of the cause portfolio will not affect the overestimation of the donation amount.

It should be noted that type II error is the failure to reject null hypothesis H_0 when the null hypothesis is false, while type I error is rejecting the null hypothesis when it is true. Reducing the chance of type I error increases the chance of type II error and vice-versa (Bryman, Teevan & Bell, 2009). The power of a test is the probability that the hypothesis test will reject the null hypothesis when the null hypothesis is false.

Typically, type I error is considered a more serious error that needs to be avoided. Therefore, in this hypothesis testing, we control α at a pre-determined nominal value and choose a sample size that ensures β is minimized. In this case, the null hypotheses are tested using ANOVA at a statistical significance level of $p \leq 0.05$ with a desired power of the test at $1 - \beta = 0.8$. This in essence means that there are, at most, 5 chances in 100 of the sample showing a relationship not found in the rest of the population and there is an 80% chance of rejecting the null hypothesis when it is false.

The central limit theorem (CLT) states that for a random sample taken from a population, the distribution of the sample mean will be close to a normal distribution (assuming

the population has a normal distribution), provided the sample size is sufficiently large. Simulation studies indicate samples of 25 or more produce an approximately normal distribution (Groebner et al., 2005, Koundouri & Kourogenis, 2011; Sang Gyu Kwak, & Jong Hae Kim, 2017). Thus, CLT suggests that picking samples in groups of 30 or more will ensure a normal distribution within each group (Shirota & Suzuki, 2014; Chang, Wu, Ho & Chen, 2008; Moen & Powell, 2005). Consequently, a minimum of 270 participants is required for this investigation (i.e., 30 participants for each of the 9 experimental groups.

Further, as a statistical power analysis was performed for sample size estimation, based on the Low Favorability / Low Familiarity and High Favorability / High Familiarity responses from the pre-test (N=129). The effect size in this study was considered to be large (0.8) using Cohen's (1988) criteria. With an alpha = .05 and power = 0.80, the projected minimum sample size needed in each group with this effect size (GPower 3.1) is approximately N = 21. Thus, our proposed sample size of 30 will be more than adequate for the main objective of this study.

The questionnaires for the main experiment are shown in Appendix 2. As part of the online questionnaire, participants were presented with an experimental advertisement for an annual "Make–A-Difference" event by a fictitious computer retail store (Giga-Byte Computer Products Inc.) which features a photograph of a brand-name 15.6" notebook computer for $999.99. The advertisement and sale price are based on an actual advertisement for a comparable notebook computer placed by a popular Canadian retailer. In an effort to make the advertisement appear real, standard features of a notebook computer are displayed on the advertisement - Windows 10, 2-in-1 13.3" Touch-Screen Laptop, Intel Core i7 - 12GB Memory, 512GB Solid State Drive, Bluetooth; touch screen; backlit keyboard; HDMI output.

At the bottom of each advertisement a statement explaining the donation information is included. It reads:

"As part of our ongoing commitment to support programs related to children's health, recreation and social service issues in the communities where we do business, (phrase indicating donation information) will be donated to a portfolio of N charities from the following list of charities - (List of charities that fall into the high favorability–high familiarity quadrant will be provided)."

The phrase stating the donation information is either vague – "a generous donation", estimable – "10% of profits", or calculable – "10% of sales price".

In the vague condition, the donation amount is expressed as a generous donation. In the estimable condition, donation amount is expressed as 10% of profits. In the calculable condition, donation amount is expressed as 10% of sales price. There are three portfolio sizes: the first one includes two charities, the second one has 5 charities and the third one has 8 charities.

Figure 9

Vague CRM Donation Quantifier Advertisements Manipulated by Cause Portfolio Size

Figure 10

Estimable CRM Donation Quantifier Advertisements Manipulated by Cause Portfolio Size

Figure 11

Calculable CRM Donation Quantifier Advertisements Manipulated by Cause Portfolio Size

Figure 12

Design of Experiment for Testing Hypothesis 1

		Ambiguous Donation Information		Non-Ambiguous Donation Information
		Vague quantifier "generous donation"	Estimable quantifier "10% of profits"	Calculable quantifier "10% of sales price"
Portfolio size (N)	Small (2 charities)	A	B	C
	Medium (5 charities)	D	E	F
	Large (8 charities)	G	H	I

This is a between-subjects experiment, so each participant saw only one advertisement. Participants were allowed to view the advertisement for one minute, after which they proceeded to answer the rest of the online questionnaire.

Manipulation: Participants were randomly assigned to the 9 groups, with a minimum of 30 respondents in each group. Figure 12 shows that the 30 participants who are randomly assigned to Group A are assigned to the small portfolio test conditions for advertisements with vague donation information (generous donation), group B participants are assigned to the small portfolio test conditions for advertisements with estimable donation information (10% of profits), while group C are assigned to the small portfolio test conditions for advertisements with calculable donation information (10% of sales price). Groups, D, E, F, G, H and I will be allocated as shown in Figure 12.

Further, additional questions with varied portfolio evaluation frame and portfolio size are used in the questionnaire to test H3 and H4.

Figure 13 shows that the same participants are divided into eight groups based on preferences indicated in response to the questions indicating equal versus unequal split of donation amount among various sizes of portfolio of charities. These groups are I, J, K and L (aggregated groups), and groups M, N, O and P (segregated groups) respectively. Segregated groups are those who expressed a preference for donation statement indicating equal split of donation amount between a specified number of charities, while aggregate groups are those who expressed preference for donation statement indicating unequal split of donation amount.

Group I is assigned to the aggregated frame test conditions for advertisements with vague donation information - "generous donation, to be split 70:30 between 2 charities" - while group K is assigned to the aggregated frame test conditions for advertisements with estimable donation information - "10% of *profits*, to be split 70:30 between 2 charities".

Groups J, L, M, N, O and P are assigned to varying magnitudes of donation amount from a defined set for aggregated large portfolio of vague and estimable donation quantifiers, as well as for segregated large and small portfolios of vague and estimable donation quantifiers.

Figure 13

Design of Experiment for Testing Hypothesis 3 & 4

		Vague quantifier "generous donation"		Estimable quantifier "% of profits"	
		Small portfolio (N=2) (Nested)	Large portfolio (N=8) (Nested)	Small portfolio (N=2) (Nested)	Large portfolio (N=8) (Nested)
Portfolio evaluation frame	**Aggregate**	I (generous donation, to be split 70:30 between 2 charities)	J (generous donation, splitting the donation unequally between 8 charities so that the 1st charity receives about twice as much as the 8th charity)	K (10% of profits, to be split 70:30 between 2 charities)	L (10% of profits, splitting the donation unequally between 8 charities so that the 1st charity receives about twice as much as the 8th charity)
	Segregated	M (generous donation, to be split 50:50 between 2 charities)	N (generous donation, to be split equally between 8 charities)	O (10% of profits, to be split 50:50 between 2 charities)	P (10% of profits, to be split 50:50 between 8 charities)

The CRM portfolio to be used will include only 2 charities for the small portfolio and 8 charities for the large portfolio, as shown in Figure 13.

The questionnaire includes the PANAS instrument (Watson, Clark, & Tellegen, 1988), which is used to measure positive and negative affect. The PANAS data is used to undertake the analysis for H2a and H2b. The PANAS instrument is followed by a scale measuring attitude toward cause-related marketing (Kropp, Holden, & Lavack, 1999). This CRM scale is used to compare donation estimates between those who have highly favourable attitudes to CRM versus those with less favourable attitudes to CRM.

Then each respondent viewed the cause-related marketing ad from a hypothetical company called Gig-a-Byte. As described above, the ad has 3 versions that describe the charitable donation in either vague, estimable, or calculable terms (i.e., generous donation, 10% of the profits, or 10% of the sales amount). Each of these 3 versions of the ad further has 3 versions, indicating that donations will be provided to a portfolio of either 2, 5, or 8 charities. This results in 9 versions of the questionnaire, one for each of the 9 experimental conditions.

The questionnaire for each of the experimental conditions includes a brief description of Gig-a-Byte's cause-related marketing (CRM) program. It also included a textual description of the "Save-A-Child" event last year, stating that for every notebook computer purchased $10 was donated to charity with the Children's Miracle Network being the only charitable organization recipient, but at the request of customers, this year's event features donations to multiple children's charities.

After viewing this ad, respondents were asked to estimate the aggregate donation amount for each selected cause portfolio size. Overestimation of donation amount was then defined using both actual dollar amounts and the scaled responses. Actual dollar amount donated was $29,982. Hence all scaled responses besides the "less than $30,000" were considered overestimation of donation.

In total, the questionnaire took approximately 8 to 10 minutes for respondents to complete. For each portfolio size, results from the ambiguous conditions were compared to results from non-ambiguous conditions in order to verify the hypothesis that ambiguous conditions lead to overestimation.

As an incentive for participating in this survey, participants' computer IP address was to be used in a draw for a $100 gift certificate. Unfortunately, unforeseen technology challenges

made this impossible, so instead $100 was donated to Canadian Salvation Army at the conclusion of the data gathering.

Survey Instrument

In an effort to maximize both reliability and validity of the survey instrument used in this study and consequently quality and quantity of the responses, the instrument was designed based on the principles discussed in section 3.1. Several factors were taken into consideration in order to minimize response error.

First, the questionnaire included questions followed a logical flow. Second, in order to minimize respondent fatigue, the questionnaire was kept short enough that it could be completed in 8 to 10 minutes. All of the questions asked were either directly related to the research variables or served to assist the flow, in order to minimize respondent fatigue. Finally, survey questions related to respondent's personal details and attitude towards donation to charity were added to ensure that respondents had sufficient data or knowledge to answer the questions. The data was gathered in case further analysis may be required to explain if demographic or responsiveness to CRM moderates the effect of cause portfolio size on overestimation. Most of the questions were in a close-ended format, well-spaced with clear instructions presented on a series of linked pages (multiple-item screens) as recommended for self-administered internet-based surveys (Burns et al., 2008; Borque & Fielder, 2003).

Figure 14

Scales Used to Measure the Variables

Variable	Type of Measurement	Scale	Descriptive Statistics
Donation Overestimation	Ordinal, Treated as Continuous	6-point scale	Mean (SD)
Donation Quantifier	Nominal		Mean (SD)
Portfolio Size	Nominal		Mean (SD)
Positive / Negative Affect	Ordinal, Converted to Nominal (affect level)	PANAS scale	Mean (SD)
Evaluation Frame	Nominal	2- point scale	Mean (SD)

Response Rate

The survey instrument was self-administered, however respondents were made aware that participation was voluntary. A cover letter that explains the reasons for the research, its importance, and why the respondent was selected, as well as a guarantee of confidentiality, was included in the invitation to each respondent (Bryman, Teevan & Bell, 2009). The questionnaires were short and concise to ensure easy understanding. However, a given respondent's questionnaire was not included within the data set if the respondent did not answer a large proportion of the questions, or if it was clear that the questionnaire was not taken seriously by the respondent. According to Bryman, Teevan & Bell (2009, p 196), the response rate is calculated as:

$$\frac{\text{Number of usable questionnaires}}{\text{Total sample} - \text{unsuitable members of the sample}} \times 100$$

A response rate of 66% was achieved.

The central limit theorem suggests a normal distribution will be achieved, with a certain probability, when the sample size per cell is equal to 30 or higher (Shirota & Suzuki, 2014; Chang, Wu, Ho & Chen, 2008; Moen & Powell, 2005; Koundouri & Kourogenis, 2011), assuming the population distribution is normal. The sample size was further verified by statistical power analysis.

Data Analysis

An analysis of variance (ANOVA) was performed using SPSS, with results indicating sum of squares, degrees of freedom (df), mean square, F-value and significance (sig) values for each of the two factors in the design (donation and impact), the interaction effect between them, as well as for the error term (**e**).

The F-value, which is determined by dividing the mean square of each independent variable (and also their interaction) with the mean square of the residual, is to test the null hypothesis.

The F-test is applied to the responses by comparing the F-value of each against a tabulated value from an F-distribution table. If the F-value is greater than the tabulated value and the significance level $< 5\%$, then the null hypothesis is rejected.

In this experiment the dependent variable is donation overestimation. Independent variables donation quantifier and portfolio size were manipulated to determine whether increase in portfolio size increases consumer overestimation of donation amount. Independent variables donation quantifier and positive and negative affect levels were also manipulated to determine whether positive and negative affects moderate effect of increase in portfolio size on extremity of consumer overestimation of donation amount. Finally, independent variables donation quantifier and portfolio size were manipulated while participants were able to self-

select among types of independent variable portfolio evaluation frame to determine whether segregated framing portfolio evaluation either leads to lower overall consumer overestimation of the donation amount or attenuates the effect of cause portfolio size on the extremity of consumer overestimation of the CRM donation amount.

Validity and Reliability

Bryman, Teevan & Bell (2009) propose three criteria for evaluating the quality of any quantitative research – replicability, reliability and validity. Replicability refers to whether others can repeat part or all of a study and get the same results. It can be enhanced by ensuring that methods used in generating a set of findings are made explicit (Bryman, Teevan & Bell, 2009).

Reliability emphasizes consistency of a particular measurement technique to yield the same result if administered on different occasions (Bryman, Teevan & Bell, 2009). Generally, the three types of reliability includes: (1) stability of results of a measure over time, assuming the concept being measured did not change; (2) internal reliability which is concerned about whether multiple measures administered in one sitting are consistent; and (3) inter-observer reliability, which is concerned with consistency in decisions when two observers are used. This study is most concerned with internal reliability.

A key criticism of experimental design is that manipulations of independent variables happen over a short time period in experimental designs (Brannigan, 2004), but these variables affect everyday life over a much longer time period; therefore, there may be a discrepancy between short term and long term impacts. This criticism further indicates why reliability is important in experimental design.

Typically, there are two types of errors in a measurement – random errors (X_R) and systematic error (X_S). Reliability evaluates how much of the variation of a measure is due to random errors. However, a perfectly reliable measure (X_R=0) may still have systematic error. Therefore, reliability of a measure is a necessary, but not a sufficient, condition for validity (Brahma, 2009).

Validity, on the other hand, is concerned with the integrity of the conclusions of the research. Three main types of validity are construct validity, internal validity and external validity (Bryman, Teevan & Bell, 2009). Construct validity refers to the extent to which an indicator really measures the construct it is supposed to measure (Brahma, 2009). Internal validity measures the extent to which manipulation of the independent variables truly causes the observed changes in the dependent variable; therefore, it relates to factors of systematic error. External validity is concerned with the generalizability of results beyond the sample used in the study (Easterby-Smith, Thorpe & Jackson, 2008).

Construct validity is maximized when the researcher is able to rule out any possible rival explanation of the relationship between constructs (Podsakoff, et al., 2003). On the other hand, external validity is maximized when samples used are highly representative of the population under study and, by extension, more representative of the "real world". Internal validity is maximized when the experiment is able to eliminate or control the effect of all other factors on the dependent variable (Stewart, 2010a). Six extraneous factors that affect internal validity are history effect, maturation effect, testing effect, instrumentation effect, selection bias and mortality.

Bryman, Teevan and Bell (2009, p. 27), citing Cook and Campbell (1979), also identified five major threats to generalizability (external validity) of the findings. In the case of this model, the relevant threats are as follows:

- *Interaction of independent variable and history*: The Canadian economy was very buoyant at the time of this study in 2019, and as a result people may have been more generous and willing to support CRM causes. It remains to be seen whether the findings of this experiment will be generalizable if and when economic conditions change in the future.

- *Reactive effect of experimental arrangements*: Since most respondents are aware that they are participating in an experiment, their responses may reflect an effort to behave in a socially acceptable manner, rather than sincerity and spontaneity; this could affect the generalizability of the findings.

The proposed research design for this study will use much of the same structure as proposed by Bryman, Teevan and Bell (2009), which is to ensure replicability, reliability and validity.

Using the guidance from (Bryman, Teevan & Bell, 2009) replicability of the study was assured by providing a detailed description of the procedure for selecting respondents, administering data gathering instrument (self-completed questionnaires) in section 3.1 and description of the analysis of data in section 4.1. Internal reliability of each group of scaled was tested using Cronbach's alpha coefficient. Cronbach's alpha coefficient for questions was within the range of 0.700 – 0.895.

Further using the guidance from (Bryman, Teevan & Bell, 2009), a construct validity was performed. Overestimation of donation amount variable was tested for convergent and divergent validity with respect to other constructs in the questionnaire – age, gender, positive affect variable (excited), negative affect variable (upset). A weak correlation was observed with age and gender. On the other hand, a strong correlation with the positive affect variable (excited) was observed as well as a negative correlation with the negative affect variable (upset).

Ethical Considerations

This study involved human subjects so several principles were adhered to. Firstly, approval of the Athabasca University Research Ethics board was received before proceeding with this study. Secondly, consent of potential subjects was received before participating in the experiment and they were advised of all risks of participation (Bryman, Teevan & Bell, 2009). Finally, no harm to participants is expected or intended to occur as result of this study, and the identities and records of participants remain confidential (Bryman, Teevan & Bell, 2009).

Chapter 4. Results

Chapter 3 described the method used in collection of data for this research. This chapter will present descriptive statistics of the sample and results of the hypothesis testing.

Data Analysis

A minimum of 270 responses were required to ensure normal distribution of responses as per the central limit theorem, assuming the population is normally distributed (i.e., 30 responses for each of the 9 experimental cells for H1). This is further verified with statistical power analysis, which affirmed minimum sample required per experimental cell is 21. Overall, 350 survey responses were received.

As part of the methodology involved in using the internet questionnaire, respondents were randomly assigned to groups, which resulted in the frequency distribution shown in Figure 15

Figure 15

Distribution of Subjects in Experimental Cells

Distribution of Subjects in Experimental Cells			
	Vague quantifier "generous donation"	**Estimable quantifier "10% of profits"**	**Calculable quantifier "10% of sales price"**	**Total**
Small (2 charities)	n=34 9.7%	n=40 11.4%	n=38 10.9%	n=112 32.0%
Medium (5 charities)	n=43 12.4%	n=39 11.1%	n=39 11.1%	n=121 34.6%
Large (8 charities)	n=32 9.1%	n=53 15.2%	n=32 9.1%	n=117 33.4%
N Total	n=109 31.2%	n=132 37.7%	n=109 31.1%	n=350 100.0%

Because 120 of the 350 responses had some degree of missing data, most of the analyses that follow in this section are based upon a slightly smaller number of subjects. The decision was made to include the 120 questionnaires with some degree of missing data for testing interaction of cause portfolio size with overestimation (hypothesis 1), because most of the data missing were related to the PANAS scale (hypotheses 2) and portfolio evaluation frames (hypotheses 3 and 4). All response related to donation estimate were complete.

Hypothesis 1

H1: When donation information is ambiguous (i.e., expressed as vague or estimable quantifier formats), consumer overestimation of donation amount will become more extreme as size of the cause portfolio increases.

In order to test H1, an ANOVA was carried out. For the purposes of this ANOVA, the estimation of donation amount was treated as a continuous variable and was coded as follows: 1(less than $30,000), 2($30,000-$59,999), 3($60,000-$89,999), 4($90,000-$119,999), 5($120,000-$149,999), 6($150,000 or more) (Light & Margolin, 1971; Norman, 2010; Sullivan & Artino, 2013; Zumbo & Zimmerman, 1993). All estimation of donation amount coded as 2($30,000-$59,999), 3($60,000-$89,999), 4($90,000-$119,999), 5($120,000-$149,999), 6($150,000 or more) are considered overestimation. Only 6 participants did not overestimate the donation amount. The Mean values of each of these coded categories are used in the ANOVA and are listed in Figure 16.

The results of the 3 (portfolio size: small vs. medium vs. large) x 3 (donation quantifier format: vague (ambiguous) vs. estimable (ambiguous) vs. calculable (non-ambiguous) full factorial design, to test hypothesis 1 are shown in Figure 17. The main effect of donation

quantifier on overestimation yielded an F ratio of $F(2,321) = 5.99$ $p = 0.003$ indicating a significant difference of overestimation between vague ($M = 2.81$, $SD = 1.58$), estimable ($M = 2.95$, $SD = 1.43$) and calculable ($M = 3.46$, $SD = 1.34$) donation quantifiers. A Post Hoc Tukey test determined the Calculable Quantifier to be the driver of this effect. The main effect of portfolio size on overestimation yielded an F ratio of $F (2,321) = 0.98$, $p = 0.38$ indicating a non-significant difference of overestimation between small ($M = 2.96$, $SD = 1.46$), medium ($M = 3.04$, $SD = 1.48$) and large ($M = 3.20$, $SD = 1.48$) charities. The test of H1 to evaluate if interaction of donation quantifier and portfolio size causes overestimation to become more extreme yielded a non-significant F ratio of $F (4, 321) = 0.426$, $p = 0.79$.

Figure 16

Means and Standard Deviations – Hypothesis 1

Estimation of donation amount				
Cell Means: ANOVA	Vague quantifier "generous donation"	Estimable quantifier "10% of profits"	Calculable quantifier "10% of sales price"	Grand Mean
Small (2 charities)	Mean = 2.58 (s.d. = 1.54) n= 33	Mean =3.03 (s.d. = 1.50) n= 37	Mean = 3.26 (s.d. = 1.29) n= 35	Mean – 2.96 (s.d. = 1.46) n=105
Medium (5 charities)	Mean = 2.85 (s.d. = 1.56) n=41	Mean = 2.77 (s.d. = 1.42) n= 35	Mean = 3.49 (s.d. = 1.37) n= 37	Mean = 3.04 (s.d. = 1.48) n=113
Large (8 charities)	Mean = 3.00 (s.d. = 1.65) n= 31	Mean = 3.02 (s.d. = 1.39) n= 49	Mean = 3.66 (s.d. = 1.40) n= 32	Mean = 3.20 (s.d. = 1.48) n=112
Grand Mean:	Mean = 2.81 (s.d. = 1.58) n= 105	Mean = 2.95 (s.d. = 1.43) n= 121	Mean = 3.46 (s.d. = 1.34) n= 104	Mean = 3.07 (s.d. = 1.47) n=330

Figure 17

ANOVA Results – Hypothesis 1

Source	Sum of Square	*df*	Mean Square	F	Sig
Donation_ Quantifier	25.317	2	12.659	5.989	.003
Portfolio Size	4.141	2	2.071	.980	.377
Donation Quantifier x Portfolio Size interaction	3.603	4	.901	.426	.790

A visual inspection of the data back in Figure 16 suggests that there is a pattern of sequentially increased donation overestimation for the Small portfolio vs. Medium portfolio vs. Large portfolio, within both the Vague quantifier and Calculable quantifier conditions. However, this pattern does not seem to hold for the Estimable quantifier condition. In any case, the overall differences between different sized portfolios were insufficient to attain statistical significance.

H1 states that when donation information is ambiguous (i.e., expressed as vague or estimable quantifier formats), consumer overestimation of donation amount will become more extreme as size of the cause portfolio increases. However, these results mean that if compared to H1, responses received did not provide sufficient evidence to conclude that increase in cause portfolio size will cause consumer overestimation of donation amount to become more extreme when donation information is expressed in vague or estimable quantifier formats.

Figure 18

Plot of Estimated Marginal Means – Hypothesis 1
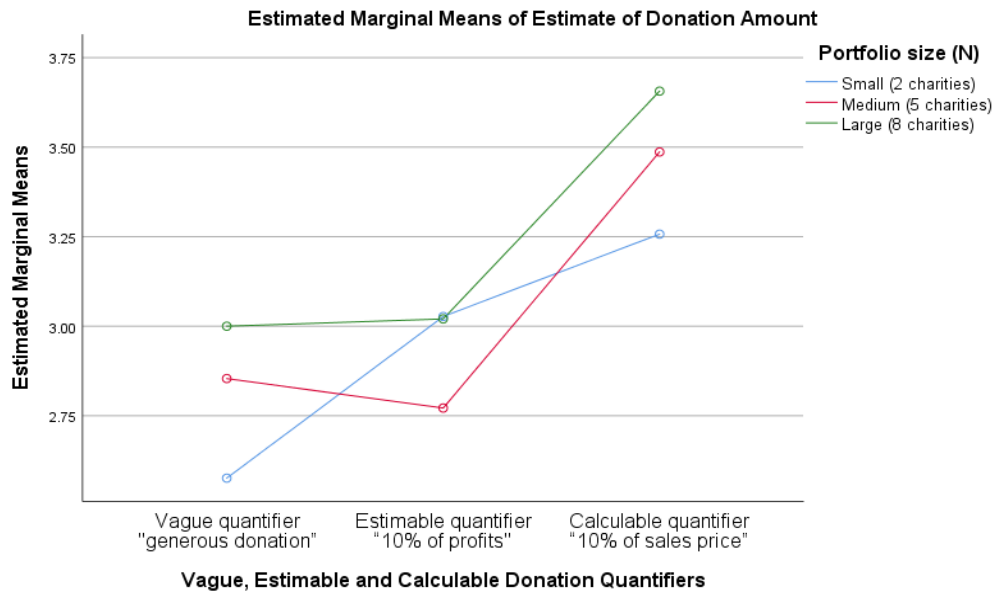
Hypothesis 2a & 2b

H2a: When the donation information is ambiguous (i.e., expressed in vague or estimable quantifier formats), the consumer's level of positive affect positively moderates the effect of the size of a given multiple cause portfolio on the extremity of consumer overestimation of the CRM donation amount.

H2b: When the donation information is ambiguous (i.e., expressed in vague or estimable quantifier formats), the consumer's level of negative affect negatively moderates the effect of the size of a given multiple cause portfolio on the extremity of consumer overestimation of the CRM donation amount.

A Factor Analysis was conducted to ensure that the PANAS scale actually loads onto two factors as it is intended to. Eigenvalues for the Factor analysis confirmed that PANAS is made up of only two components, with scale items for positive and negative affect aligning

CONSUMER OVERESTIMATION OF DONATION AMOUNT

with the appropriate component (see Figure 19 below). Scores for positive and negative affect are component scores.

Figure 19

PANAS Factor Analysis

Total Variance Explained

Initial Eigenvalues

Factor	Total	% of Variance	Cumulative %
1*	6.442	32.210	32.210
2	4.743	23.713	55.923

Extraction Method: Maximum Likelihood.

*1 in this model is negative affect, 2. Is negative affect.

Factor analysis confirms that Positive and Negative affect load one component each, separate from one another.

Rotated Factor Matrix

	Factor 1	Factor 2
Scared	0.831	0.008
Afraid	0.828	0.015
Nervous	0.768	0.030
Distressed	0.711	-0.191
Upset	0.704	-0.047
Ashamed	0.703	-0.081
Jittery	0.667	-0.033
Irritable	0.645	-0.174
Hostile	0.638	-0.079
Guilty	0.599	-0.058
Enthusiastic	0.026	0.839
Inspired	-0.069	0.820
Strong	-0.175	0.751
Excited	0.086	0.726
Attentive	-0.168	0.709
Active	-0.126	0.705
Determined	0.040	0.696
Interested	-0.094	0.685
Alert	-0.159	0.546
Proud	0.005	0.475

The following two graphs (Figure 20 and 21) show the distribution of scores for Positive affect and Negative affect. The Positive affect scale follows a normal distribution, while the Negative affect scale does not. The positive skewness displayed by Negative affect scale distribution is consistent with the tendency of the Negative affect data set as observed in previous research (Crawford & Henry, 2004; Merz et al., 2013; Watson et al., 1988). It suggests that people generally endorse greater levels of Positive affect (Mean = 30.3, SD = 3.8), compared to Negative affect (Mean = 20.7, SD = 3.5).

Figure 20

Positive Affect Distribution
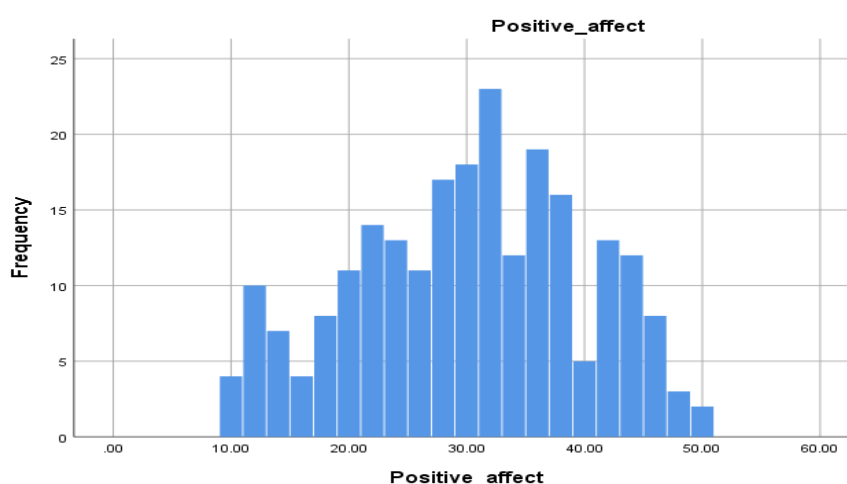
Figure 21

Negative Affect Distribution
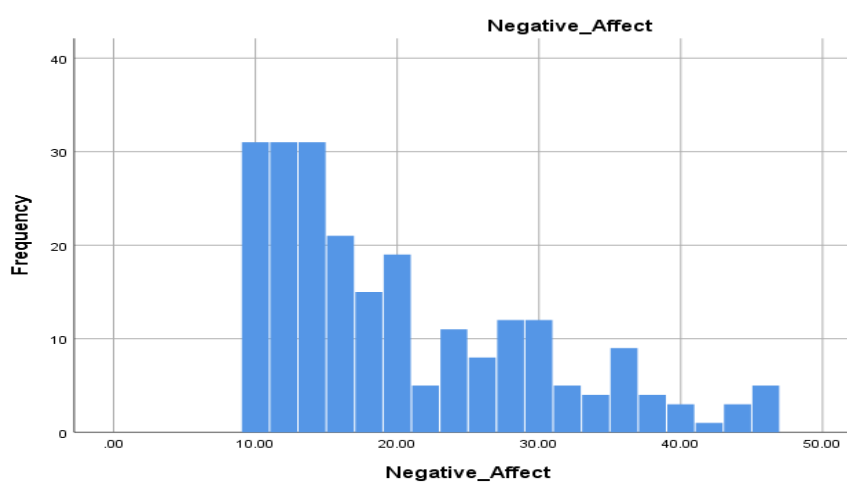
In order to use the PANAS scales in an ANOVA, the positive and negative affect scales were each subjected to a 3-way split. The lowest 1/3 of scores for each scale was labeled as "low", the middle 1/3 was labeled as "medium" and highest 1/3 was labeled "high". For positive affect this resulted in low scores falling at a value of 26 or below, medium values between 27-35, and high values at 36 and above. For negative affect this resulted in low values falling between 10-13, medium values between 14-24 and high values at 25 and above (see distribution of raw data and affect levels by IV category below in Figures 22-23). This approach makes it easy to estimate interactions in ANOVAs.

Figure 22

PANAS Positive Affect Sub Scores

Positive Affect Scale	Mean (SD)
Low Positive Affect	18.9 (5.0) n= 82
Medium Positive Affect	30.9 (2.5) n= 80
High Positive Affect	41.0 (3.9) n=68
Grand Mean:	30.3 (3.8) n=230

Figure 23

PANAS Negative Affect Sub Scores

Negative Affect Scale	Mean (SD)
Low Negative Affect	11.2 (1.2) n= 81
Medium Negative Affect	18.1 (3.2) n= 84
High Negative Affect	32.9 (6.2) n=65
Grand Mean:	20.7 (3.5) n=230

In order to test hypothesis 2a and 2b, a 3 (small, medium, large portfolio size) x 3 (low, medium, high affect level) ANOVA was performed. For this analysis, ambiguity was collapsed across vague and estimable because initial ANOVA analysis indicates similar results from both ambiguous variables. For hypothesis 2a, regarding the moderating influence of positive affect on portfolio effect of overestimation extremity, the results are as follows: The Mean values of each of these coded categories are used in the ANOVA and are listed in Figure 24 below.

Figure 24

PANAS Positive Affect Scores

	Low Positive Affect	Medium Positive Affect	High Positive Affect	Grand Mean
Small (2 charities)	3.26 (0.99) n=19	2.82 (0.94) n=39	2.71 (1.25) n=7	2.94 (1.00) n=65
Small (2 charities)	3.26 (0.99) n=19	2.82 (0.94) n=39	2.71 (1.25) n=7	2.94 (1.00) n=65
Medium (5 charities)	2.83 (1.47) n=28	3.23 (1.15) n=52	3.82 (1.33) n=11	3.29 (1.21) n=81
Large (8 charities)	4.20 (1.30) n=5	3.15 (1.29) n=52	3.53 (1.38) n=17	3.31 (1.23) n=74
Grand Mean	3.33 (1.18) n=52	3.09 (1.16) n=143	3.46 (1.36) n=35	3.03 (3.7) n=230

The main effect of positive affect level on overestimation yielded an F ratio of $F_{(2, 199)} = 1.40$, $p = 0.25$. indicating a non-significant difference in overestimation between low, medium and high positive affect. The test of H2a to evaluate if interaction of positive affect level and portfolio size positively moderates effect of portfolio size on overestimation yielded a non-significant F ratio of $F_{(4, 199)} = 1.37$, $p = 0.25$

Figure 25

ANOVA Results – PANAS Positive Affect

Source	Sum of Square	*df*	Mean Square	F	Sig
Positive Affect	3.920	2	1.960	1.401	0.249
Positive Affect x Portfolio Size Interaction	7.682	4	1.920	1.373	0.245

Figure 26

Plot of Estimated Marginal Means – PANAS Positive Affect
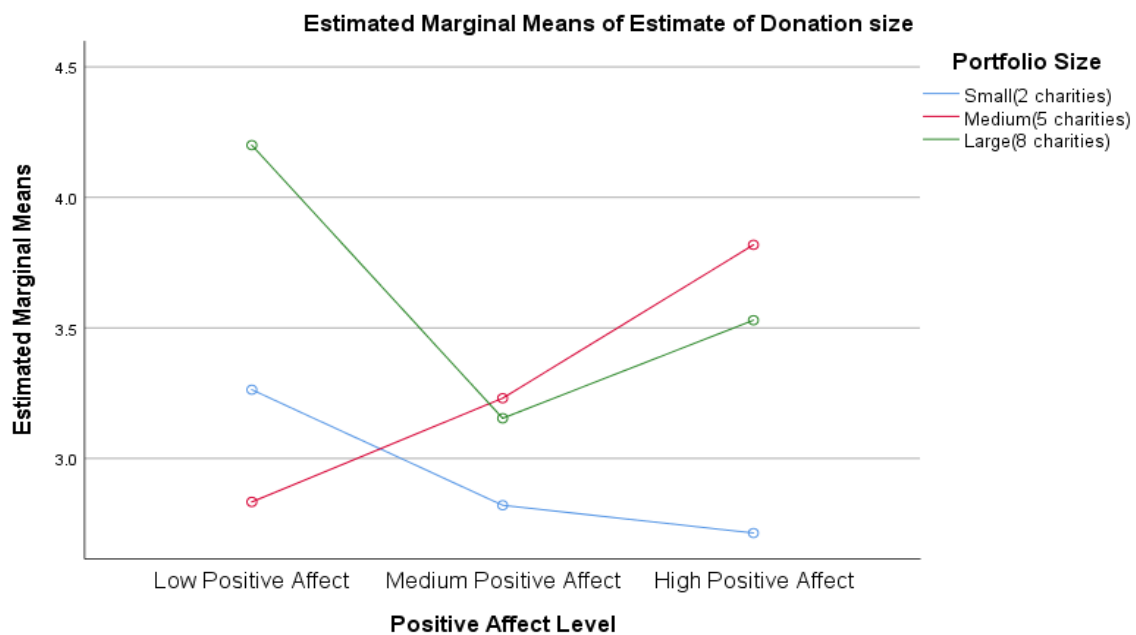
For hypothesis 2b, regarding the moderating influence of negative affect on portfolio effect of overestimation extremity, the results are as follows: The Mean values of each of these coded categories are used in the ANOVA and are listed in Figure 27 below (see Figure 29 for visual depiction of results).

**Figure 27**

PANAS Negative Affect Scores

	Low Negative Affect	Medium Negative Affect	High Negative Affect	Grand Mean
Small (2 charities)	3.00 (1.00) n=7	2.87 (0.98) n=32	3.04 (1.06) n=25	2.95 (1.00) n=64
Medium (5 charities)	4.00 (1.63) n=27	3.26 (1.18) n=53	2.80 (0.92) n=10	0.27 (1.22) n=90
Large (8 charities)	4.07 (1.54) n=14	3.27 (1.22) n=49	3.00 (1.35) n=13	3.37 (1.34) n=72
Grand Mean	3.79 (1.48) n=48	3.17 (1.15) n=134	2.98 (1.10) n=48	3.21 (1.21) n=230

The main effect of negative affect level on overestimation yielded an F ratio of $F_{(2, 201)} = 3.22$ $p = 0.04$, indicating a significant difference of overestimation between low, medium, and high negative affect. The interaction of negative affect level and portfolio size yielded a non-significant F ratio of $F_{(4, 201)} = 0.97$, $p = 0.43$.

H2 states that when donation information is ambiguous (i.e., expressed as vague or estimable quantifier formats), consumer's level of positive affect positively moderates the effect of the size of a given multiple cause portfolio on the extremity of consumer overestimation of the CRM donation amount and consumer's level of negative affect negatively moderates the effect of the size of a given multiple cause portfolio on the extremity of consumer overestimation of the CRM donation amount. However, these results mean that if compared to, responses received did not provide sufficient evidence to conclude that interaction effects of positive or negative affect exists with regard to overestimation. That said, some interactions with regards to overestimation may exist between small and large portfolio sizes under medium negative affect conditions.

Figure 28

ANOVA Results – PANAS Negative Affect

Source	Sum of Square	df	Mean Square	F	Sig
Negative Affect	9.052	2	4.526	3.216	0.042
Negative Affect x Portfolio Size Interaction	5.456	4	1.364	0.969	0.425

Figure 29

Plot of Estimated Marginal Means – PANAS Negative Affect
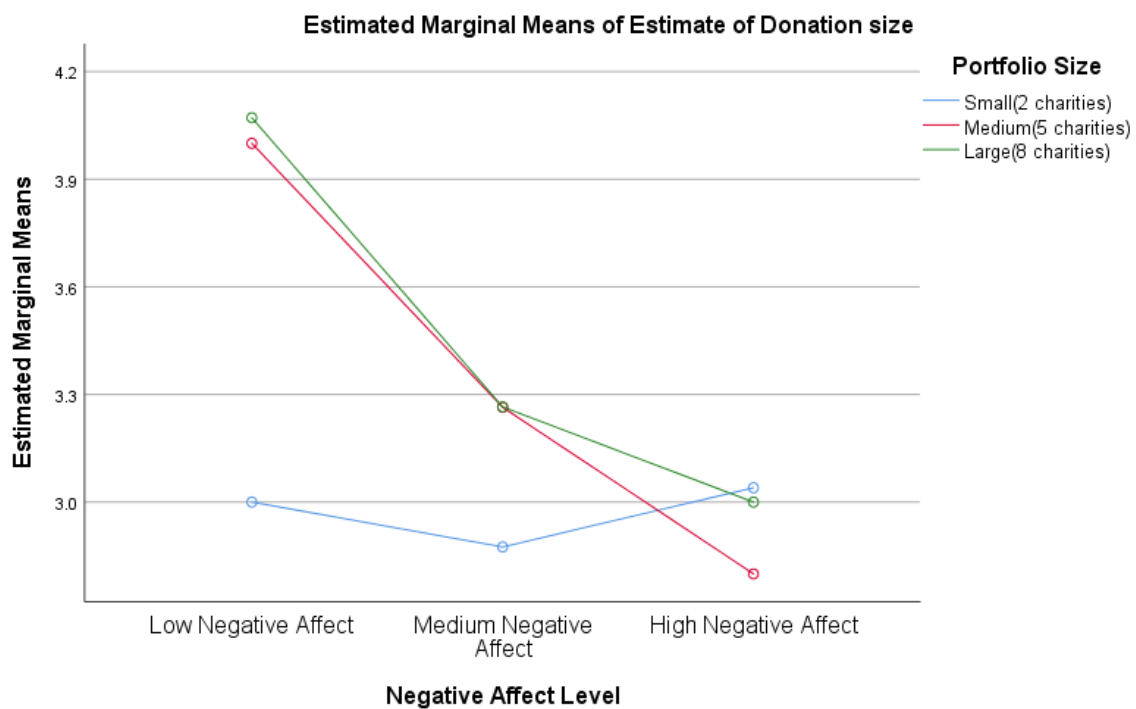
Hypothesis 3 & 4

H3: When evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation leads to lower overall consumer overestimation of the donation amount, compared to aggregated framing of the same portfolio.

H4: When evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation attenuates the effect of cause portfolio size on the extremity of consumer overestimation of the CRM donation amount.

In order to test hypotheses 3 and 4, a 2 x 2 x 2 factorial design of cause portfolio size (small vs. large) and portfolio evaluation frame (segregated vs. aggregated) nested within the ambiguous donation quantifier factor (vague vs. estimable) was used. However, the portfolio evaluation frame (segregated vs aggregate) was a variable in which respondents indicated whether they preferred a donation be split 70:30 (aggregate) or 50:50 (segregate). The vast majority of respondents preferred the segregate option, likely due to the fact that it seems the most fair. This resulted in experimental cells which did not have a sufficient number of respondents (i.e., there should ideally be at least 30 subjects in each experimental cell). Therefore, the ANOVA has been carried out, but it needs to be treated with caution because of the small cell sizes for the aggregate portfolio evaluation frame variable.

The ANOVA results are as follows: The Mean values of each of these coded categories are used in the ANOVA and are listed in Figure 30.

Figure 30

Means and Standard Deviations – Hypotheses 3 &4

		Vague Quantifier	Estimable Quantifier	Grand Mean
Small (2 charities)	Segregate	2.97 (0.99) n= 30	2.94 (1.03) n= 33	2.95 (1.01) n= 63
	Aggregate	2.50 (0.71) n= 2	2.00 (0) n= 2	2.25 (0.50) n=4
	Sub Grand Mean	2.94 (0.98) n= 30	2.89 (1.02) n= 35	2.91 (1.00) n=67
Large (8 charities)	Segregate	3.64 (1.39) n= 28	3.24 (1.28) n= 45	3.40 (1.33) n=73
	Aggregate	3.50 (0.71) n= 2	2.33 (1.53) n= 3	2.80 (1.30) n= 5
	Sub Grand Mean	3.63 (1.35) n= 30	3.19 (1.30) n= 48	3.36 (1.33) n= 78
Grand Mean	Segregate	3.29 (1.24) n= 58	3.12 (1.18) n= 78	3.19 (1.21) n= 136
	Aggregate	3.00 (0.82) n= 4	2.20 (1.10) n= 5	2.56 (1.01) n= 9
	Sub Grand Mean	3.27 (1.22) n= 62	3.06 (1.19) n= 83	3.15 (1.20) n= 145

Note: sample size is down to 145 due to 5 groups of participants (3 groups of 2, 5 and 8 cause portfolios with calculable quantifier conditions; 2 groups of 52 cause portfolio with vague and estimable conditions) being excluded as they are not relevant to the hypothesis being tested

The main effect of evaluation frame (segregate vs. aggregate) yielded an F ratio of $F(1,137) = 2.20$, $p = 0.14$ (shown in Figure 31), indicating no significant difference in overestimation between segregate (M = 3.19, SD = 1.21) and aggregate (2.56, SD = 1.01) collapsed across donation quantifier factor and charity size (hypothesis 3). The main effect of donation quantifier factor yielded an F ratio of $F(1,137) = 1.59$, $p = 0.21$, indicating a non-significant difference between vague (M = 3.27, SD = 1.22) and estimable (M = 3.06, SD = 1.19). The main effect of portfolio size on overestimation yielded an F ratio of $F(1,137) = 1.94$, $p = 0.17$, indicating a non-significant difference between small (M = 2.91, SD = 0.99) and large (M = 3.36, SD = 1.33) charities. The interaction effect of donation quantifier factor x evaluation frame x charity size on overestimation (hypothesis 4) yielded a non-significant F factor of $F(1, 137) = 0.03$, $p = 0.86$, interaction effects of donation quantifier factor x portfolio size, portfolio size x eval frame and donation quantifier factor x eval frame also yielded non-significant results (Figures 32-35. provides the individual non-significant 2-way interactions).

These results mean that responses received did not provide sufficient evidence to support H3 which states that when evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation leads to lower overall consumer overestimation of the donation amount, compared to aggregated framing of the same portfolio.

Responses received neither provided sufficient evidence to support H4, which states when evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation attenuates the effect of cause portfolio size on the extremity of consumer overestimation of the CRM donation amount.

Figure 31

ANOVA Results – Hypotheses 3 & 4

Source	Sum of Square	df	Mean Square	F	Sig
Donation Quantifier Factor	2.239	1	2.239	1.588	0.210
Portfolio Size	2.740	1	2.740	1.943	0.166
Evaluation Frame	3.096	1	3.096	2.195	0.141
Donation Quantifier Factor x Portfolio Size	0.551	1	0.551	0.391	0.533
Donation Quantifier Factor x Evaluation Frame	0.788	1	0.788	0.558	0.456
Portfolio Size x Evaluation Frame	0.063	1	0.063	0.045	0.832
Donation Quantifier Factor x Portfolio Size x Evaluation Frame	0.045	1	0.045	0.032	0.859

Figure 32

Plot of Estimated Marginal Means – Hypotheses 3 & 4 (Portfolio Size vs. Quantifier)
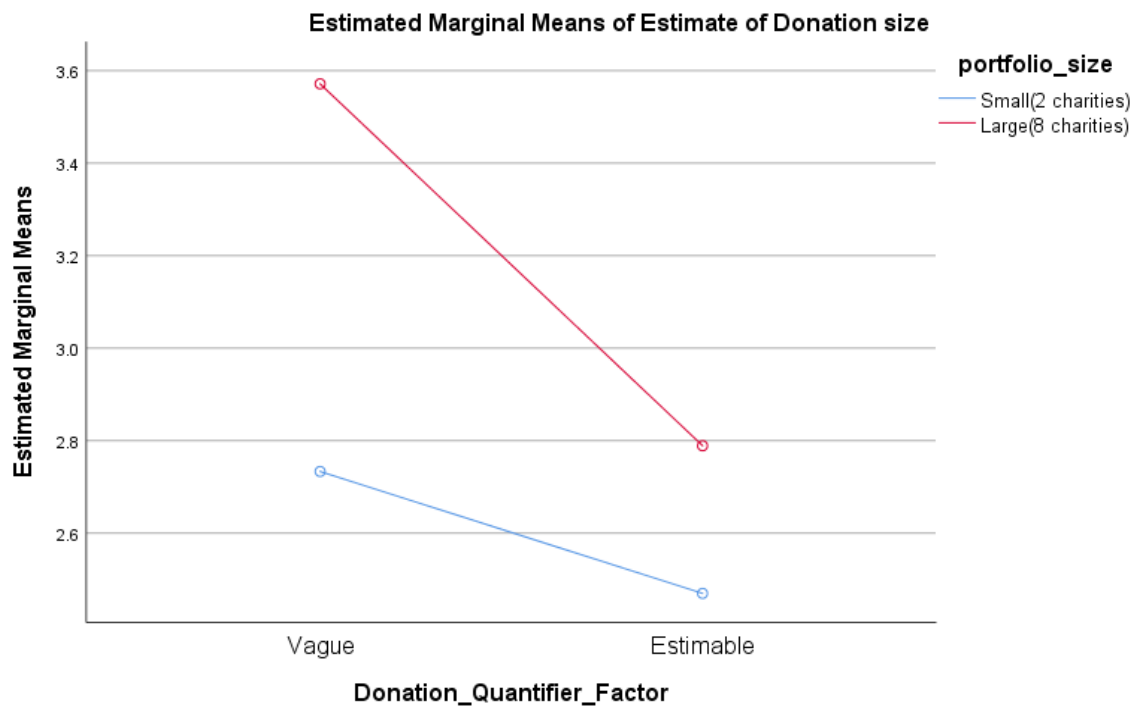
Figure 33

Plot of Estimated Marginal Means– Hypotheses 3 & 4 (Evaluation Frame vs. Quantifier)
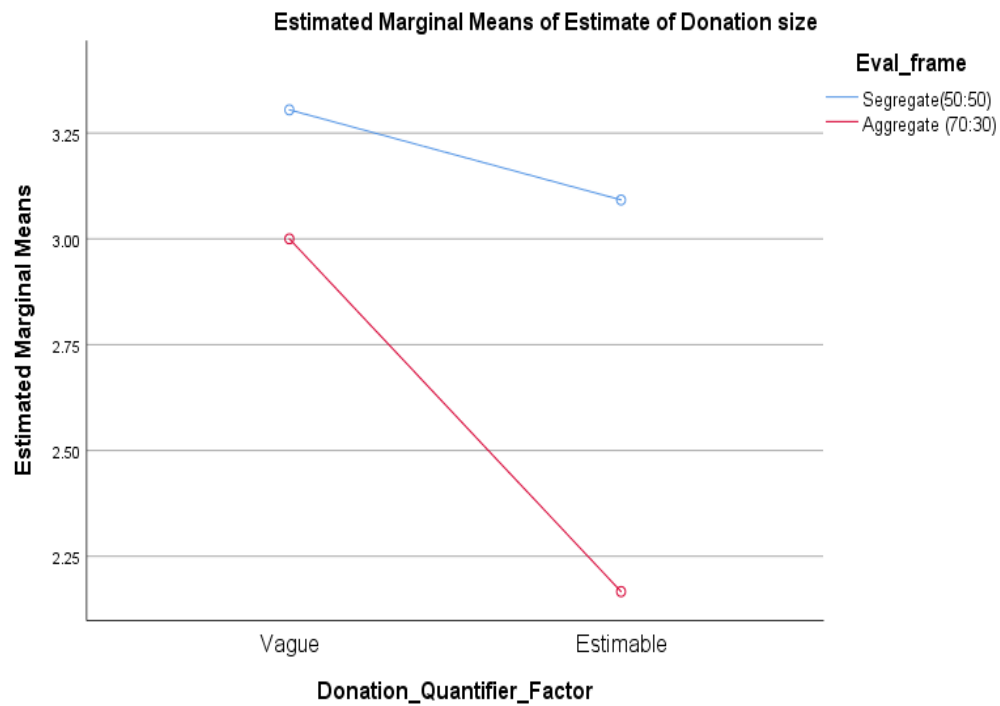
Figure 34

Plot of Estimated Marginal Means – Hypotheses 3 & 4 (Evaluation Frame vs. Portfolio Size)
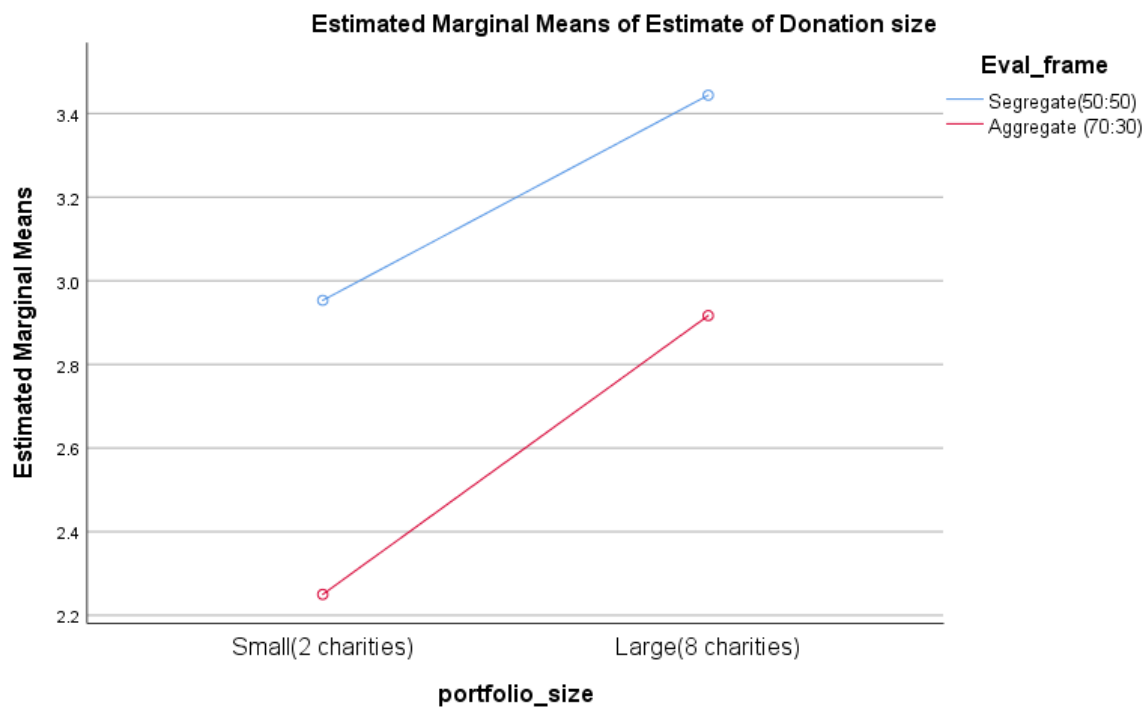
Studies have shown that a t-test may be feasible for comparing means of the aggregate portfolio evaluation frame variable to other variables in this case as long as the effect size is large and also bears risk to credibility of the findings due to high false positive rate that could occur for unequal sample sizes combined with unequal variances (de Winter, 2013; Janušonis, 2009). Therefore, an independent sample t-test has been carried out to test H3 (hypothesis 3) which was most impacted by the small cell size of the aggregate portfolio evaluation frame variable, but it needs to be treated with caution because of the small cell sizes for the aggregate frame variable.

Results of the independent sample t-test are as follows: The Mean values of each of these coded categories are used in the independent sample t-test and are listed in Figure 35 below.

Figure 35

T-Test Means and Standard Deviations – Evaluation Frame

Segregate Frame	Aggregate Frame
3.19 (1.21) n= 136	2.56 (1.01) n= 9

Equal variances assumed as the p value for the F test is equal to 0.722, hence greater than 0.5. T-test value = 1.541, p (two tailed) = 0.125 (shown in Figure 36), indicating no significant difference in overestimation between segregate (M = 3.19, SD = 1.21) and aggregate (2.56, SD = 1.01) collapsed across donation quantifier factor and charity size (hypothesis 3).

Figure 36

T-Test Results – Evaluation Frame

		F	Sig	t	df	Sig (2 tailed)
Donation Size Overestimation	Equal variances assumed	0.127	0.722	1.541	143	0.125
	Equal variances not assumed			1.798	9.5869	0.104

These results mean that responses received did not provide sufficient evidence to support H3 which states that when evaluating a portfolio of multiple causes with ambiguous donation information (i.e., expressed in vague or estimable quantifier formats), segregated framing of the portfolio evaluation leads to lower overall consumer overestimation of the donation amount, compared to aggregated framing of the same portfolio.

Chapter 5. Discussion

The literature review sends a clear message that cognitive distortion results in consumer overestimation of donation amount to cause-related marketing campaigns. Confusion associated with expressing CRM donation information, either as a percentage of profit or a percentage of proceeds, leads many consumers to engage in inappropriate estimation strategy selection while attempting to take computational short cuts, which results in near universal overestimation of the donation amount (Pracejus, Olsen & Brown, 2004; Olsen, Pracejus & Brown, 2003; Vardarajan & Menon, 1988). The ethical literature on CRM further sends the message that this cognitive distortion resulting from confusion associated with expressing CRM donation information can effectively be used in CRM strategies to manipulate consumer perception of underlying motivations for corporate sponsorship of CRM, and thus consumer choice of a brand (Hamby & Brinberg, 2018; Vlakos et al., 2016; Müller, Fries & Gedenk, 2014; Moosmayer & Fuljahn, 2010; Subrahmanyan, 2004; Hajjat, 2003; Barone, Miyazaki & Taylor, 2000; Strahilevitz, 1999; Dahl & Lavack, 1995).

This possibility to manipulate consumers using CRM strategies raises an ethical concern for marketing and public policy from a consumer protection perspective (Pracejus et al., 2020; Olsen, Pracejus & Brown, 2003). Such concerns arise from the fact that the parties involved, for-profits and charities, have essentially different goals and unequal leverage in the alliance (Andreasen, 1996). Hence, when charities enter into partnership with a financially stronger partner, they may be powerless to set clear rules of conduct. Thus, charities' reputations, consumer affinity to their causes could be exposed to the risk of being exploited by the corporation to influence consumers participation in CRM campaigns (Farache et al., 2007). Further, it should be noted that Federal Trade Commission (FTC) enforcement policy against deceptive acts and practices (1983) defined three conditions to satisfy the deceptive practices definition: (1) The practice must be likely to mislead consumers; (2) the ability to

mislead consumers is examined from the perspective of consumer reasonableness in the group targeted; and (3) the practice must be material, thereby influencing consumers' decisions. Therefore, when a corporation's efforts to more effectively manipulate the CRM donation message for greater audience effect leads to consumer confusion and overestimation of donation amount due to use of ambiguous donation information format, it could be perceived as ethically walking a fine line with respect to violation of the FTC policy.

One of the goals of this research is to further contribute to the fast-growing body of knowledge on CRM, by providing an understanding of the determinants of consumer overestimation of the donation amount in the unexplored context of multiple cause portfolio CRM campaigns. This will help to expose policy makers to an additional area of focus in CRM practice, where regulation or a code of conduct is urgently needed from a public policy perspective.

The goal of this study was to investigate effects of cause portfolio size and framing of donation information on how consumer overestimate amount to be donated by a cause-related marketing (CRM) campaign. Current research points to cognitive bias as the underlying reason for people overestimating the effectiveness of their own contribution to public good. This overestimation can be exacerbated in the context of cause related marketing (CRM) campaigns. Unlike previous studies that focus on CRM campaigns with ties to a single cause, this study aimed to further explore the cognitive bias involved in overestimation via factors of campaign framing and as well as size. This study also took into account personality factors related to positive and negative affect. We discuss the implications of our findings below. This section is structured in order of the research hypotheses posed in the study.

The first hypothesis (H1) sought to identify the extremity of consumer overestimation when donation information is ambiguous (vague, estimable) as function of size cause portfolio

size (small, medium, large). Results showed that while donation quantifier (vague vs. estimable vs calculable) was predictive of overestimation extremity, with calculable as the driving factor, neither cause portfolio size on its own, nor donation quantifier as a function of cause portfolio were predictive of overestimation extremity. This is a surprising finding in that, the main effect of donation quantifier is driven by the higher mean in the calculable category. This indicates that when tangible information is available, individuals overestimate their donation amounts even more. This speaks to the logical flaw inherent in cognitive biases. It means that under certain conditions, cognitive biases are consonant with logical fallacies (misconception that results from faulty reasoning or information processing) resulting in overestimation of donation amount. In other words, even when tangible information is available, individuals may still perceive this as if the cognitive resources available for donation estimate calculation are less than the cognitive resources required (RA < RR), subjects will resort to heuristic processing which could lead to overestimation (Anand & Sternthal, 1989).

Next, in H2a and H2b we investigated the influence that positive and negative affect have on the cause portfolio size determinant of overestimation. Results showed that there were no interaction effects of positive or negative affect with regards to overestimation. While a main effect of negative affect on overestimation was encountered, there no main effect of positive affect with regards to overestimation. It is possible that although positive mood is associated with higher life satisfaction ratings, this same effect does not translate to financial overestimation. While studies do show that people who have more money are in fact happier (an empirical negation of the maxim "money can't buy happiness") it is possible that this does not translate to their estimation of charitable impact. In fact, it could perhaps be argued that someone with a negative affect would be more likely to overestimate a donation in a way of seeking hope. This, however, would require that negative affect has not translated to hopelessness and pessimism. At any rate, some interactions with regards to overestimation may

exist between small and large portfolio sizes under medium negative affect conditions. Our sample showed a reasonable distribution across low, medium and high positive and negative affect. This indicates a sample of individuals whereby those primed for positivity were pretty well matched with those primed for negativity across high, medium and low levels. Therefore, it was not the case that we failed to capture a reasonably extreme high/low level of affect. One possibility is simply that the PANAS is not the best tool to use when connecting mood to monetary investment. Future studies should look into mood scales more closely tied to investment, charity and monetary factors.

Lastly, in H3 and H4 we investigated the framing effects: segregated vs. aggregated, on consumer overestimation. In H3 we first looked at whether segregated framing led to lower overestimation in portfolios of multiple causes when donation information was ambiguous (vague or estimable). Results revealed no significant difference in overestimation between segregated and aggregated framing. In H4 we then looked at the potential moderating impact of segregated framing on the effect cause portfolio size has on donation overestimation. Results revealed no such interaction. Given our previous null results, the lack of findings related to framing was not terribly surprising. What becomes clear from our analyses is that individuals are relatively insusceptible to nuances regarding CRM. This suggests that overestimation appears to be a thought process that does not necessarily take into consideration the many variables we have presented here, including framing. Framing involves a consideration about calculations and ratios, and we know from our first hypothesis that individuals overestimate in the presence of calculable evidence. Therefore, it should perhaps come as no surprise that overestimation is not moderated by calculable framing effects.

The consistently nonsignificant null results of our study indicate a resiliency of overestimation that is not moderated by nuanced factors such as charity size, framing effects or mood. All but 6 respondents indicated donation estimation categories that are higher than

the actual $29,982 donation made the popular Canadian retailer as result of advertisement and sale price for notebook computer comparable to the study. Our results show that individuals make their overestimations based on concrete, calculable information and little else seems to come into play in the assessment. With regard to our failure to reject the null for our hypotheses investigating interactions, the variability of overestimation across various levels of one independent variable within the same level of another independent variable was the primary reason for null findings.

Nonsignificant Findings

A statistical power analysis was performed for sample sizes in order to explore issues behind the non-significant results (Figure 17). Analysis of the mean of each coded category used to test H1, H2 indicates that existence of the predicted relationships cannot be ascertained. However, this is not due to low statistical power as the effect sizes in this study was considered to be large using Cohen's (1988) criteria with alpha = .05 and power = 0.7 – 0.93. On the other hand, effect size for coded categories used to test H3 and H4 indicates low to medium, which suggests that statistical power was enough to detect the predicted relationships if it exists.

Figure 37

Effect Sizes

Variable	Effect Size	Description
Donation Quantifier	0.782	Large
Portfolio Size	0.665	Large
Positive affect level	0.699	Large
Negative affect level	0.609	Large
Aggregate/Segregate evaluation frames	0.454	Medium

Figure 38

Correlation Matrix that Shows Degree of Association between Variables

	Overestimation of Donation Amount	Portfolio Size	Donation Quantifier	Negative Affect	Positive Affect	Donation Frame
Overestimation of Donation Amount	1	0.065	0.177** (p=.001)	-0.113* (p=0.040)	0.058	-0.020
Portfolio Size	0.065	1	-0.018	-0.054	0.177** (p=0.001)	0.045
Donation Quantifier	0.177** (p=.001)	-0.018	1	-0.682** (p=0.000)	0.102	-0.187** (p=0.000)
Negative Affect	-0.113* (p=.040)	-0.054	-0.682** (p=.000)	1	-0.179** (p=0.001)	0.142** (p=0.008)
Positive Affect	0.058	0.177** (p=0.001)	0.102	-0.179** (p=0.001)	1	0.088
Donation Frame	-0.020	0.045	-0.187** (p=0.000)	0.142** (p=0.008)	0.088	1.000

**Correlation is significant at the 0.01 level (2-tailed)

*Correlation is significant at the 0.05 level (2-tailed)

Further, a correlation matrix was developed to evaluate the degree of association between the variables (Figure 38). Results further validated findings from the study indicating significant correlation between negative affect and overestimation of donation amount. In fact, it could perhaps be argued that someone with a negative affect would be more likely to overestimate a donation in a way of seeking hope. On the other hand, an interesting observation is that negative affect level has some degree of correlation with all variables except portfolio size which speaks to strength of impact of negative affect priming to reinforces a greater degree

of pessimism and avoidance behavior in everyday life of individuals, (Robinson & Kirkeby, 2005; Robinson & Von Hippel, 2006).

The correlation matrix also demonstrates resiliency of overestimation that is not moderated by nuanced factors such as charity size, framing effects or positive mood.

Limitations of Study

The present study provides a framework for studying the concepts of interest in a nuanced and novel way. The methodology, however, does have limitations, and all results should be viewed in the context of these limitations. A list of 2, 5 and 8 charities were provided in each advertisement depending on the test conditions. However, it has been observed that confining the list of charities to those specified could influence responses depending on how they align with respondents' personal charity preferences. The actual list of charities chosen could influence responses. It is also possible that results may have been more statistically significant had only single charity versus a large portfolio been compared, rather than trying to compare small, medium, and large portfolios.

Another potential limitation of the study is our use of a 6-point scale to approximate the continuous variable of donation estimate. This use of categories was intended to make it easier for respondents to estimate the donation size without having to resort to using a calculator. Previous research has proven that ordinal variables with 5 or more categories can be used as continuous without any significant harm to the analysis (Arieli-Attali, Ou & Simmering, 2019; Sullivan & Artino, 2013; Norman, 2010; Zumbo & Zimmerman, 1993). The premise is that although the donation estimate is an ordinal variable in our study, we treated it as continuous because we assumed the 6 donation estimate levels as a continuum representing respondents' preferences for donation estimate and also assumed that intervals between any two point are essentially equal. However, by constraining the continuous variable into

categories, the variability of the actual values is lost. Furthermore, this can be viewed as one step removed from indicating actual donation values, as the values themselves are not shown. This has the potential to be confusing to some readers. However, the benefit of using the 6-point scale is in the simplicity for respondents. Respondents did not need to make a difficult calculation but could instead simply choose one of the 6 categories that best matched their quick estimation of the donation amount.

Gender imbalance could also be a limitation of this study given the fact that 67% of the 350 respondents were female versus 33% male. Research suggests women are more likely to respond more positively to CRM campaigns than men (Anuar & Mohamad, 2011; Chéron, Kohlbacher & Tan Shen Hui, 2018; Witeck, 2016) due to stronger predisposition to empathic feelings among women, which drives prosocial behaviors (Moosmayer & Fuljahn, 2010). Further, Moosmayer and Fuljahn, (2010) elaborated that this predisposition to empathy drives higher sensitivity towards benefit of CRM campaigns to the charity and ensures that impact of donation size on consumer goodwill towards a CRM campaign is particularly relevant for women than for men. Therefore, men are more likely to provide lower estimate of donation amount than women, resulting in larger variance from the mean estimate than women. It could be argued that a sample gender imbalance could further exacerbate this variance. Future research will have to measure empathy as a variable such that it could be used to normalize estimate for donation amount provided by men versus women.

We also observed a vastly uneven distribution in aggregated vs. segregated groups, with a much higher self-selection into the segregated group. The reasoning for this is like due to a perception of equity in a 50:50 split, without much other information being known. This is a limitation in two ways. First, it limits the interpretations we can make about main effects and interactions of the framing variable. Second, it potentially conflates equity with equality regarding the splitting of donations. Without knowing the financial needs/size of the individual

charities, assuming a 50:50 split, while equal, may not be an equitable choice. This also created substantial difficulty for carrying out the ANOVA, since it resulted in numerous cells which did not meet the required minimum of 30 participants within the cell. The issue with high self-selection into the aggregate group could have been fixed by partitioned presentation of the conditions in the portfolio frame variable in the experimental design which allows random assignment only one condition to one questionnaire at any time.

Future Directions

The variation we saw across our sample on the factors of interest indicates a broad snapshot of the issue at hand. Future studies would benefit from looking at the factors addressed in this study within certain charity types or specific donor types. For example, unlike the current study that focused on CRM campaigns related to children's health, recreation and social service, perhaps future studies should focus on the impact of donation framing (segregate versus aggregate) on consumer overestimation in CRM campaigns related to a single issue only (e.g., children's health issues).

Some of these scales that could be considered are:

- Big-Five Inventory - BFI (John & Srivastava, 1999). It uses a 44-item measure to examine extent to which the 5 broad traits generally found in many prominent personality models applies to the participant. The traits include neuroticism-N (high scorers on this trait are prone to feeling sad, worried, anxious, and dissatisfied with themselves), extraversion-E (high scores denotes friendly, assertive, outgoing, cheerful, and energetic traits), openness to experience -O (high scores denotes tolerant, intellectually curious, imaginative, and artistic traits), agreeableness-A (high scores denotes polite, considerate, cooperative, honest, and trusting traits), and conscientiousness-C (high scores denote

responsible, cautious, organized, disciplined, and achievement-oriented traits). Responses use 5-point Likert scale to determine where the five dimensions of personality lies along a continuum of opposing poles.

- Neo Five-Factor Inventory - Neo FFI (Costa & McCrae, 1992). It uses a 60-item measure to examine extent to which the 5 broad personality traits mentioned above are applicable to the participant. Responses also use 5-point Likert scale ranging from strongly agree to strongly disagree.

- Rosenberg Self-Esteem Scale – RSES (Rosenberg, 1979). It uses a 10-item unidimensional scale to measure participants' global self-esteem. measure of global self-esteem using statements related to overall feelings of self-worth or self-acceptance. A 4-point scale, ranging from strongly agree to strongly disagree, is used to examine the extent to which the statements apply to the participant.

Future studies would also do well to constrain the framing effects grouping in such a way that ensures a balance between framing types. Because individuals are susceptible to framing effects, it is likely not sufficient to leave this up to self-selection in order to achieve a balance between framing groups. Such a balance is ultimately necessary to be able to determine the main and interaction effects of framing. For example, our study observed a vastly uneven distribution in aggregated vs. segregated groups, with a much higher self-selection into the segregated group. The reasoning for this is likely due to a perception of equity in a 50:50 split, given a situation where there was only limited information provided to respondents. This limited the interpretations we can make about main effects and interactions of the framing variable and potentially conflated equity with equality regarding the splitting of donations, thus creating substantial difficulty for carrying out the ANOVA, since it resulted in numerous cells which did not meet the required minimum of 30 participants within the cell.

Further, future studies would do well to expand upon the potential demographic effects related to charitable donation activity/consumer overestimation. While the present study considered age and sex, other factors have potential impact. For example, it may be important to include socioeconomic status or geographic location.

Research on consumer attitude towards Cause Related Marketing (CRM) campaigns suggests that demographic characteristics (age, gender, education, geographical location and socioeconomic status) are key drivers of consumer attitudes towards Cause Related Marketing (CRM) campaigns. Witek (2016) even suggested that young, educated women who live in large cities have the most favorable attitudes toward CRM campaigns and the higher the level of education and socioeconomic status, the more favorable the attitude. Therefore, demographic characteristics are critical considerations in shaping the form of message, as well as the type, specific character and content of CRM campaigns (Witek, 2016). Campaigns may need to be tailored to each particular demographic group of customers (Hall & Witek, 2016). Moosmayer and Fuljahn, (2010) further elaborated on the impact of donation amount in differentiating the CRM message to particular demographic groups, pointing out that due to the fact women are more sensitive to CRM than men, programs targeting women will be more effective if the messaging promises substantially higher donation levels to causes. However, Olsen, Pracejus & Brown (2003), while supporting the consensus that perceived level of donations tends to drive higher consumer attitude towards co-participation in CRM campaigns, also raises a caution on the possibility of deception related to near universal consumer confusion with the donation messaging leading to overestimation of donation amount and impact on consumer behavior. Exploring impact of demographic characteristics socioeconomic status or geographic location on consumer reaction to the ambiguous donation messaging may be beneficial from a public policy perspective.

Lastly, much of CRM research has been motivated by a desire to frame the elements of a message to consumers to maximize the positive effects for the firm. An examination of more ethical ways to effectively manipulate the CRM donation amount message for greater audience effect is worth considering may be beneficial from a public policy perspective. More specifically, the effective use of clear communication to mitigate the potential for consumer confusion that leads to overestimation of donation amount. Olsen, Pracejus and Brown (2003) explored with a single cause scenario, several potential affirmative disclosures around the term "profit" used in CRM donation amount messaging: (1) a statement defining profit as the sales price minus the cost of each sold product; (2) a percentage statement about the amount of profit; (3) a concrete statement about the amount of profit, and demonstrated that these have been reasonably effective in mitigating the problem of overestimation. Future studies will do well to investigate the extent to which these finding will hold if we compare different single cause CRM campaigns involving products with different price levels (e.g., printers versus automobile vehicles). It will also be good to explore the same for multiple cause CRM campaigns.

Furthermore, Tsiros and Irmak (2020) demonstrated that the use of maximum or minimum donation limits (e.g., "at least $100,000 will be donated" or "maximum of $10 million will be donated") minimizes consumers concerns that the CRM campaign is a thinly veiled marketing scheme. Future studies could explore the degree to which this finding will hold if different wording were used to describe the maximum or minimum limits (e.g., "up to $10 million will be donated" instead of "maximum of $10 million will be donated").

Literature References

Adkins, S. (1999a). *Cause Related Marketing: Who Cares Wins*. Butterworth-Heinemann.

Adkins, S. (1999b). The Wider Benefits of Backing A Good Cause, *Marketing*, September.

Agrawal, U., Mangla, A., & Sagar, M. (2016). Company-Cause-Customer: Interaction Architecture. *Global Journal Of Flexible Systems Management*, *17*(3*)*, 307-319. https://doi.org/10.1007/s40171-016-0128-2

Anand, P., & Sternthal, B. (1989). Strategies for Designing Persuasive Messages: Deductions from the Resource Matching Hypothesis, in *Cognitive and Affective Responses to Advertising*, ed. Patricia Cafferata and Alice M. Tybout, Lexington, MA: Heath, 135–159.

Anderson, N. H. (1959). Test of a model for opinion change. *Journal of Abnormal and Social Psychology, 59,* 371–381.

Anderson, N. H. (1967). Averaging model analysis of set-size effects in impression formation. *Journal of Experimental Psychology, 75*, 158–165.

Andreasen, A. R. (1996). Profits for nonprofits: find a corporate partner. *Harvard Business Review, 74*(6), 47-59.

Andreasen, A. R. & Drumwright, M. E. (2000). Alliances and ethics in social marketing. In Andreasen, A. R. (Ed.) *Ethical issues in social marketing*. Washington D.C.: Georgetown University Press, 95 – 124.

Andrews, M., Luo, X., Fang, Z., & Aspara, J. (2014). Cause Marketing Effectiveness and the Moderating Role of Price Discounts. *Journal of Marketing, 78* (November), 120-142.

Anghel, L.D., Grigore, G.F., & Roşca, M. (2011). Cause-Related Marketing, Part of Corporate Social Responsibility and its Influence upon Consumers' Attitude. *Amfiteatru Economic, 29*, 72-85.

Arieli-Attali, M., Ou, L. & Simmering, V.R. (2019). Understanding Test Takers' Choices in a Self-Adapted Test: A Hidden Markov Modeling of Process Data. *Front. Psychol.* 10:83. https://doi.org/10.3389/fpsyg.2019.00083

Arkes, H. R. (1991). Costs and benefits of judgment errors: implications for debiasing. *Psychological Bulletin*, *v10*(n3).

Arkes, H. R., Christensen, C., Lai, C., & Blumer, C. (1987). Two Methods of Reducing Overconfidence. *Organizational Behavior & Human Decision Processes, 39*(1), 133. https://doi.org/10.1016/0749-5978(87)90049-5

Arrow, K. J. (1986). Rationality of self and others in an economic system. *Journal of Business, 59* (4), 385-399.

Ashton, R. H. & Kennedy, J. (2002). Eliminating recency with self-review: the case of auditors' 'going concern' judgments. *Journal of Behavioral Decision Making. 15*(3), 221-231.

Athabasca University, AU at a Glance. https://www.athabascau.ca/aboutau/#au-at-a-glance

Bandura, A., & Schunk, D. H. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. *Journal of Personality and Social Psychology*, *41*, 586-598.

Bar-Hillel, M. (1979). The role of sample size in sample evaluation. *Organizational Behavior and Human Performance, 24*, 245-257.

Baron, J. (2002). Value trade-offs and the nature of utility: Bias, inconsistency, protected values, and other problems. Paper for conference on behavioral economics. *American Institute for Economic Research*, Great Barrington, MA, July.

Baylin, G., Cunningham, P., & Cushing, P. (1988). Cause-Related Marketing: Ethical Practice or Exploitive Procedure? *Proceedings of the Conference of the Association of Consumer Psychology*.

Beach, L. R., & Connolly, T. (2005). *The Psychology of Decision Making: People in Organizations*, Sage, Thousand Oaks, CA.

Begling, M., & Nakata, C. (2005). Cause-related marketing: More buck than bang? *Business Horizons, 48*, 443-453.

Blair, E., & Burton, S. (1987). Cognitive Processes Used by Survey Respondents to Answer Behavioral Frequency Questions. *Journal of Consumer Research*, 14 (September), 280–288.

Bolton, L. E., Warlop, L., & Alba, J. W. (2003). Consumer Perceptions of Price (Un)Fairness. *Journal of Consumer Research*, *29* (March), 474–491.

Borque, L. B., & Fielder, E. P., (2003). *How to Conduct Self-administered and Mail Surveys,* 2nd Edition, Sage Publications, Thousand Oaks.

Boven, L. V., & Epley, N. (2003). The unpacking effect in evaluative judgments: When the whole is less than the sum of its parts. *Journal of Experimental Social Psychology, 39*, 263–269.

Brahma, S. (2009). Assessment of Construct Validity in Management Research: A Structured Guideline. *Journal of Management Research, 9*(2), 59-71.

Brannigan, A. (2004). The Rise and Fall of Social Psychology: The Use and Misuse of Experimental Method (Hawthorne, NY:Aldine de Gruyter).

Braun, K. A., Gaeth, G. J., & Levin, I. P. (1997). Framing Effects With Differential Impact: the Role of Attribute Salience. Brucks, M., & MacInnis, D.J. (Eds), *Advances in Consumer Research, 24,* Association for Consumer Research, 405-411.

Brewer, N. T., Chapman, G. B., Schwartz, J. A., & Bergus, G. R. (2007). The influence of irrelevant anchors on the judgments and choices of doctors and patients. *Medical Decision Making*, *27*(2), 203-211.

Brown, N. R. (1995). Estimation strategies and the judgment of event frequency. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21,* 1539-1553.

Brown, N. R. (2002a). Encoding, Representing, and Estimating Event Frequencies: A Multiple Strategy Perspective. in *Frequency Processing and Cognition*, Sedlmeier, P., & Betsch, T. eds. Oxford, UK: Oxford University Press, 37–53.

Brown, N. R. (2002b). Real-World Estimation: Estimation Modes and Seeding Effects. In *Psychology of Learning and Motivation*, Vol. 41, Brian H. Ross, ed. New York: Academic Press, 321–360.

Brown, N. R., & Siegler, R. S. (1993). Metrics and Mappings: A Framework for Understanding Real-World Quantitative Estimation. *Psychological Review*, *100* (3), 511–534.

Budescu, D. V., & Wallsten, T. S. (1985). Consistency in Interpretation of Probabilistic Phrases. *Organizational Behavior and Human Decision Processes, 36*, 391-405.

Burns, K. E., Duffett, M., Kho, M. E., Meade, M. O., Adhikari, N. K., Sinuff, T., Cook, D. J., ACCADEMY Group (2008). A guide for the design and conduct of self-administered surveys of clinicians. *CMAJ : Canadian Medical Association journal = journal de l'Association medicale canadienne*, *179*(3), 245–252. https://doi.org/10.1503/cmaj.080372

Bravo, R., Matute, J., & Pina, J. M. (2012). Corporate social responsibility as a vehicle to reveal the *corporate identity: A study focused on the websites of Spanish financial entities. Journal of Business Ethics, 107*(2), 129–146.

Bryman, A., Teevan, J., & Bell, A. (2009). *Social Research Methods* (Second ed.). Oxford University Press, Canada.

Calgary Herald (2014). RE/MAX, Business October 27, 2014 [online] Available at: https://calgaryherald.com/business/remax

Camerer, C. F. (1987). Do Biases in Probability Judgment Matter in Markets? Experimental Evidence. *American Economic Review, 77*(5), 981-997.

Camerer, C. F. (1992). The Rationality of Prices and Volume in Experimental Markets. *Organizational Behavior and Human Decision Processes, 51*, 237-272.

Carringer, P. T. (1994). Not just a worthy cause: Cause-related marketing delivers the goods and the good. *American Advertising*, *10*(1), 16-19.

Carroll, A. B. (1979). A three-dimensional conceptual model of corporate performance. *Academy of Management Review, 4*(4), 497-505.

Carroll, A. B. (1991). The pyramid of corporate social responsibility: Toward the moral management of organizational stakeholders. *Business horizons, 34*(4), 39-48.

Carter, C., R., Kaufmann, L., & Michel, A. (2007). Behavioral supply management: A taxonomy of judgment and decision-making biases. *International Journal of Physical Distribution & Logistics Management, 37*(8), 631-669.

Carver, C. S., & Scheier, M. F. (1998). *On the self-regulation of behavior*. New York: Cambridge University Press.

Chakravarti, D., Krish, R., Paul, P., & Srivastava, J. (2002). Partitioned Presentation of Multi-Component Bundle Prices: Evaluation, Choice and Underlying Processing Effects. *Journal of Consumer Psychology*, 12(3), 215-229.

Chang, H. J., Wu, C. H., Ho, J. F., & Chen, P. Y. (2008). On sample size in using central limit theorem for gamma distribution. *Information and Management Sciences, 19*(1), 153-174.

Chun-Tuan Chang, & Yu-Kang Lee. (2008). All Charity Advertisements Are Not Created Equal: Influences of Message Framing, Vividness Valence, and Number Size Framing. *Advances in Consumer Research, 35*, 652–653.

Cohen, L. J. (1981). Can human irrationality be experimentally demonstrated? *Behavioral and Brain Sciences, 4*, 317–370.

Cone, (2010). 2010 Cause Evolution Study [online] Available at: https://www.conecomm.com/2010-cone-communications-cause-evolution-study-pdf

Cone, (2015). 2015 Cone Communications/Ebiquity Global CSR Study [online] Available at: http://www.conecomm.com/research-blog/2015-cone-communications-ebiquity-global-csr-study

Connie, R. B., John, P. F., & Iyer, R. (2002). Framing effects within the ethical decision making process of consumers. *Journal of Business Ethics, 36*(1), 119-140.

Conrad, F. G., & Brown, N. R. (1994). Strategies for estimating category frequency: Effects of abstractness and distinctiveness. *In American Statistical Association, Proceedings of the section on survey methods research* (pp. 1345-1350). Alexandria, VA: American Statistical Association.

Conrad, F. G., Brown, N. R., Cashman, E. R. (1993). How the Memorability of Events Affects Frequency Judgments. *American Statistical Association, Proceedings of the*

Section on Survey Methods Research. Cook, T., & Campbell, D. 1979. *Quasi-Experimentation: Design and Analysis for Field Settings*. Boston, MA: Houghton Mifflin.

Costa, P. T. Jr., & McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO-PI-R) and NEO Five-Factor Inventory (NEO- FFI) Professional Manual*. Odessa, FL: Psychological Assessment Resources.

Crawford, J. R., & Henry, J. D. (2004). The Positive and Negative Affect Schedule (PANAS): Construct validity, measurement properties and normative data in a large non-clinical sample. *British journal of clinical psychology*, 43(3), 245-265

Dadush, S. (2010). Profiting in (Red): The Need for Enhanced Transparency in Cause-Related Marketing. *New York University Journal of International Law & Politics, 42*(4), 1269.

Dahl, W. D., & Lavack, A. M. (1995). Cause-related marketing: Impact of size of corporate donation and size of cause-related promotion on consumer perceptions and participation. In Stewart, D.W. and Vilcassim, N.J. (Eds), *1995 AMA Winter Educators' Conference*, American Marketing Association, Chicago, IL, 477-481.

Darley, W. K., & Smith, R. E. (1993). Advertising claim objectivity: Antecedents and effects. *Journal of Marketing*, *57*(4), 100–113.

Das, N. & Kerr, A. H. (2009). Improving the Impact of Cause-Related Donation Exchanges Through Message Framing: A Conceptual Perspective. *Journal of Applied Business Research, 25*(2)*,* 69-78.

DeLong, J. B., Shleifer, A., Summers, L. H., & Waldman, R. J. (1991). The Survival of Noise Traders in Financial Markets. *Journal of Business, 64,* 1-19.

Deshpande, R., & Webster, Jr., F. E. (1989). Organizational Culture and Marketing: Defining the Research Agenda. *Journal of Marketing*, *53* (January): 3-15.

De Visscher, A., Vogel, S. E., Reishofer, G., Hassler, E., Koschutnig, K., De Smedt, B., & Grabner, R. H. (2018). Interference and problem size effect in multiplication fact solving: Individual differences in brain activations and arithmetic performance. *NeuroImage, 172*, 718–727. https://doi.org/10.1016/j.neuroimage.2018.01.060

De Winter, J. C. (2013). Using the Student's t-test with extremely small sample sizes. *Practical Assessment, Research, and Evaluation, 18*(1), 10.

Díaz-García, A., González-Robles, A., Mor, S., Mira, A., Quero, S., García-Palacios, A., Banos, R. & Botella, C. (2020). Positive and Negative Affect Schedule (PANAS): psychometric properties of the online Spanish version in a clinical sample with emotional disorders. *BMC psychiatry, 20*(1), 56.

Dillman, A. D., Smyth, J. D., & Christian, L. M. (2008). *Internet, Mail, and Mixed-Mode Surveys: The Tailored Design Method* (Third ed.). John Wiley & Sons.

Dotson, M., Clark, J. D. Davé, D. S., & Morris, K. J. (2012). Effects of the framing of product information on consumer preferences: An experimental comparison of wines from different regions in the united states. *International Journal of Management, 29*(3), 64-74.

Drumwright, M. (1996). Company advertising with a social dimension: The role of noneconomic criteria. *Journal of Marketing*, *60* (October), 71-87.

Easterby-Smith, M., Thorpe, R., & Jackson, P. (2008). *Management Research: Theory and Research*, Sage, London.

Easwaramoorthy, M., Barr, C., Gumulka, G., & Hartford, L. (2006). Business Support for Charities and Nonprofits, *Research Bulletin*, *13*(2). Toronto: Imagine Canada.

Eddy, D. M. (1982). Probabilistic Reasoning in Clinical Medicine: Problems and Opportunities in *Judgment and Decision Making*, Kahneman, D., Slovic, P. & Tversky, A. eds. Cambridge, UK: Cambridge University Press.

Edell, J. A., & Staelin, R. (1983). The information processing of pictures in print advertisements. *Journal of Consumer Research*, *10*(1), 45–60.

Eilert, M., & Robinson, S. (2020). The Impact of Cause Portfolio Focus and Contribution Amount on Stakeholder Evaluations. *Business & Society, 59*(7), 1483–1514. https://doi.org/10.1177/0007650318761858

Einhorn, H. J., & Hogarth, R. M. (1981). Behavioural decision theory: processes of judgment and choice. *Annual Review of Psychology, 32*, 53-88.

Epley, N. & Gilovich, T. (2005). When effortful thinking influences judgmental anchoring: differential effects of forewarning and incentives on self-generated and externally provided anchors. *Journal of Behavioral Decision Making, 18*(3), 199-212.

Evans, J. St. B. T., & Bradshaw, H. (1986). Estimating Sample-Size Requirements in Research Design: A Study of Intuitive Statistical Judgment. *Current Psychological Research & Reviews, Spring, 5(1), 10–19.*

Evans, J. St. B. T., & Pollard, P. (1985). Intuitive statistical inferences about normally distributed data. *Acta Psychologica*, *60*, 57–71.

Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance, 25*(2), 383-417.

Farache, F., et al. (2007). Ethics and cause related marketing: five major ethical conflicts. In *X SEMEAD.*

Faro, D. & Rottenstreich, Y. (2006). Affect, empathy, and regressive mispredictions of others' preferences under risk. *Management Science, 52*(4), 529-541.

Federal Trade Commission (1983), "FTC Deception Policy Statement," Letter from James C. Miller III (Former) FTC Chairman to the Honorable John D. Dingell, Chairman, Committee on Energy and Commerce, U.S. House of Representatives, (October 14), 1–15. https://www.ftc.gov/system/files/documents/public_statements/410531/831014deceptionstmt.pdf

Fehr, E., & Tyran, J-R. (2005). Individual Irrationality and Aggregate Outcomes. *Journal of Economic Perspectives*, *19*(4), 43-66.

Fiedler, K., & Juslin, P. (2006). *Information sampling and adaptive cognition.* Cambridge University Press.

File, K. M., & Prince, R. A. (1998). Cause related marketing and corporate philanthropy in the privately held enterprise. *Journal of Business Ethics, 17*, 1529–1539.

Fischhoff, B. (1982). Debiasing, in Kahneman, D., Slovic, P. and Tversky, A. (Eds), *Judgment Under Uncertainty: Heuristics and Biases*, Kahneman, Cambridge University Press, New York, NY, 422-444.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1978). Fault trees: Sensitivity of estimated failure probabilities to problem representation. *Journal of Experimental Psychology: Human Perception and Performance*, *4*(2), 330-334.

Frisch, D. (1993). Reasons for framing effects. *Organizational Behavior and Human Decision Processes, 54*, 399-429.

Ganguly, A., Kagel, J. H., & Moser, D. (2000). Do asset market prices reflect traders' judgment biases? *Journal of Risk and Uncertainty 20*(3), 219-245.

Gamliel, E., & Herstein, R. (2007). The effect of framing on willingness to buy private brands. *The Journal of Consumer Marketing, 24*(6), 334-334.

Gamliel, E., & Herstein, R. (2012). Effects of message framing and involvement on price deal effectiveness. *European Journal of Marketing, 46*(9), 1215-1232.

Garthoff, R. L. (1990). Estimating Soviet military force levels: Some light from the past. *International Security 14*(4), 93–116.

Gigerenzer, G. (1991). How to make cognitive illusions disappear: Beyond "heuristics and biases," *European Review of Social Psychology*, *2*, 83–115.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky, *Psychological Review*, *103*, 592–596.

Gigerenzer, G. (2004). Fast and frugal heuristics: The tools of bounded rationality in *Blackwell Handbook of Judgment and Decision Making,* Koehler & Harvey, Blackwell Publishing, UK.

Gilbride, T. J., Guiltinan, J. P., & Urbany, J. E. (2008). Framing effects in mixed price bundling. Marketing Letters, *19*(2), 125-139.

Grau, S. L., Garretson, J.A., & Folse, J. A. (2007). Cause-related marketing (CRM): The influence of donation proximity and message-framing cues on the less-involved consumer," *Journal of Advertising, 36*(4), 19-33.

Grau, S. L., Garretson, J. A., & Pirsch, J. (2007). Cause-related marketing: An exploratory study of campaign donation structures issues. *Journal of Nonprofit & Public Sector Marketing, 18*(2), 69-91.

Griffin, D., & Varey, C. (1996). Towards a consensus on overconfidence. *Organizational Behavior and Human Decision Processes*, *65*(3), 227-31.

Groebner, D.F., et al. (2005). *Business Statistics. A Decision-making Approach*. Pearson Education, Inc., Upper Saddle River, New Jersey, 07458.

Groen, G. J., & Parkman, J. M. (1972). A chronometric analysis of simple addition. *Psychological Review, 79*, 329–343.

Guerreiro, J., Rita, P., & Trigueiros, D. (2016). A text mining-based review of cause-related marketing literature. *Journal of Business Ethics, 139*(1), 111-128.

Gurin, M. G. (1987). Cause-related marketing in question. *Advertising Age,* Special Report, (July 27), S-16.

Haigh, M. S., & List, J. (2005). Do professional traders exhibit myopic loss aversion? An experimental analysis. *Journal of Finance, 90*, 523-34.

Hajjat, M. M. (2003). Effects of cause-related marketing on attitudes and purchase intentions: The moderating role of cause involvement and donation size. *Journal of Nonprofit & Public Sector Marketing*, *11*(1), 93.

Hamby, A., & Brinberg, D. (2018). Cause-Related Marketing Persuasion Knowledge: Measuring Consumers' Knowledge and Ability to Interpret CrM Promotions. *Journal of Consumer Affairs, 52*(2). https://doi.org/10.1111/joca.12167

Hartmann, M., Klink, J., & Simons, J. (2015). Cause related marketing in the German retail sector: Exploring the role of consumers' trust. *Food Policy, 52*, 108–114. https://doi.org/10.1016/j.foodpol.2014.06.012

Harvey, N. & Bolger, F. (1996). Graphs versus tables: Effects of data presentation format on judgmental forecasting. *International Journal of Forecasting*, *12* (March), 119–137.

Hays, W. L. (1981). *Statistics* (3rd ed.). Holt, Rinehart and Winston: New York.

Hodgkinson, G. P., Maule, A. J., Brown, N. J., Pearman, A. D. & Glaister, K. W. (2002). Further reflections on the elimination of framing bias in strategic decision making. *Strategic Management Journal, 23*(11), 1069-1076.

Hogarth, R. M. (1987). *Judgment and Choice: The Psychology of Decision*, 2nd ed., Wiley, Chichester.

Holbrook, M. B. (1978). Beyond attitude structure. *Journal of Marketing Research*, *15*(4), 546–556.

Hsee, C. K., & Leclerc, F. (1998). Will products look more attractive when presented separately or together? *Journal of Consumer Research*, *25*(2), 175-186.

Hsee, C. K., Loewenstein, G. F., Blount, S., & Bazerman, M. H. (1999). Preference reversals between joint and separate evaluations of options: A review and theoretical analysis. *Psychological Bulletin*, *125*(5), 576.

IEG Sponsorship Reports (2013). *IEG sponsorship reports 2013*, [online] Available at: https://www.sponsorship.com/iegsr/2013/01/07/2013-Sponsorship-Outlook--Spending-Increase-Is-Dou.aspx

IEG Sponsorship Reports (2018). *IEG sponsorship reports 2018*, [online] Available at: https://www.sponsorship.com/Report/2018/01/08/Signs-Point-To-Healthy-Sponsorship-Spending-In-201.aspx

IEG Sponsorship Reports (2019). *IEG sponsorship reports 2019*, [online] Available at: https://www.sponsorship.com/Latest_Thinking/Sponsorship_Infographics/Sponsorship_Spending_of_Causes_to_Grow_4.6%_in_201.aspx

Janušonis, S. (2009). Comparing two small samples with an unstable, treatment-independent baseline. *Journal of Neuroscience Methods, 179*, 173–178.

Jefferies, N. O. (2009). Ranking bias in association studies. *Human Heredity, 67*, 267–275

John, O. P., & Srivastava, S. (1999). "The Big-Five trait taxonomy: history, measurement, and theoretical perspectives," *in Handbook of Personality: Theory and Research*, 2nd Edn, eds L. A. Pervin and O. P. John (New York, NY: Guilford Press), 102–138.

Kabongo, J. D., Chang, K., & Li, Y. (2013). The impact of operational diversity on corporate philanthropy: An empirical study of U.S. companies. *Journal of Business Ethics, 116*, 49-65.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review,* 93 1449–1475.

Kahneman, D., & Fredrick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgments. In T. Gilovich, T. D. Griffin, and D. Kahneman (eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment* (pp. 49–81). Cambridge: Cambridge University Press.

Kahneman, D., & Lovallo, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science, 39*(1), 17-31.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgment under Uncertainty – Heuristics and Biases*. New York: Cambridge University Press.

Kahneman, D., & Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology*, *3*, 430-454.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review*, *80*(4), 237-251.

Kahneman, D., & Tversky, A. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124-1131.

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, *47*(2), 263-291.

Kahneman, D., & Tversky, A. (1996). On the reality of cognitive illusions. *Psychological Review, 103*(3), 582-591.

Kaplan, M. F. (1981). Amount of information and polarity of attraction. *Bulletin of the Psychonomic Society, 18*, 23–26.

Kaufmann, M., & Betsch, T. (2009). Origins of the sample-size effect in explicit evaluative judgment. *Experimental Psychology, 56*(5), 344-353.

Kaufmann, L., Carter, C. R., & Buhrmann, C., (2010). Debiasing the supplier selection decision: a taxonomy and conceptualization. *International Journal of Physical Distribution & Logistics Management, 40*(10), 792–821. https://doi.org/10.1108/09600031011093214

Keren, G., & Lewis, C. (2000). Even Bernoulli might have been wrong: A comment on intuitions about sample size', *Journal of Behavioral Decision Making*, *13*, 125-132.

Kerr, N. L. (1989). Illusions of efficacy: The effect of group size on perceived efficacy in social dilemmas. *Journal of Experimental Social Psychology, 25*, 287-313.

Khalili, O. (2010). Mobile giving meets mobile marketing, but are Americans ready? *Cause Capitalism (Blog)*, November. http://causecapitalism.com/mobile giving meets mobile marketing but are americans-ready/

Kim, H. J., Kim, J-I., & Han, W. H. (2005). The effects of cause related marketing on company and brand attitude. *Seoul Journal of Business, 11*(2), 83-117.

Kim, Y. J., & Lee, W. (2009). Overcoming consumer skepticism in cause-related marketing: The effects of corporate social responsibility and donation size claim objectivity. *Journal of Promotion Management*, *15*(4), 465–483.

Klemz, B. R., & Gruca, T. S. (2003). Dueling or the battle royale? The impact of task complexity on the evaluation of entry threat. *Psychology & Marketing, 20*(11), 999-1015.

Koschate-Fischer, N., Huber, née S. I. V., & Hoyer, W. D. (2016). When will price increases associated with company donations to charity be perceived as fair? *Journal of the Academy of Marketing Science: Official Publication of the Academy of Marketing Science, 44*(5), 608. https://doi.org/10.1007/s11747-015-0454-5

Koschate-Fischer, N., Stefan, I. V., & Hoyer, W. D. (2012). Willingness to pay for cause-related marketing : the impact of donation amount and moderating effects. *Journal Of Marketing Research : JMR, 49*(6), 910-927

Kotler, P., & Lee, N. (2011). *Corporate Social Responsibility; doing the most good for your company and your cause*. New Jersey: John Wiley & Sons.

Koundouri, P., & Kourogenis, N. (2011). On the Distribution of Crop Yields: Does the Central Limit Theorem Apply? *American Journal of Agricultural Economics, 93*(5), 1341–1357. https://doi.org/10.1093/ajae/aar055

Krell, C., & Grant, H. (2010). Naive learning algorithms utilized for the prediction of stock prices to compare economic models of decision making. *IEEE, Proceedings of the 2010 Winter Simulation Conference B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, & E. Yücesan, eds.*

Kroll, C. (1996). Consumers note marketers' good causes: Roper? *Advertising Age,* November *11*, p.51.

Kropp, F., Holden, S. J. S., & Lavack, A. M. (1999). Cause-related marketing and values in Australia. *International Journal of Nonprofit & Voluntary Sector Marketing, 4*(1), 69.

Kruger, J. (1999). Lake Wobegon be gone! The "below-average effect" and the egocentric nature of comparative ability judgments. *Journal of Personality and Social Psychology, 77*(2), 221–232.

Kruglanski, A. W., Friedland, N., & Farkash, E. (1984). Lay person's sensitivity to statistical information: The case of high perceived applicability. *Journal of Personality and Social Psychology*, 46, 503–518.

Ku H., & Hung, Y., (2019). Framing effects of per-person versus aggregate prices in group meals. *Journal of Consumer Behaviour, 18*(1), 43–52. https://doi.org/10.1002/cb.1743

Kuesten, C., Chopra, P., Bi, J., & Meiselman, H. L. (2014). A global study using PANAS (PA and NA) scales to measure consumer emotions associated with aromas of phytonutrient supplements. *Food Quality And Preference, 33*, 86-97. doi:10.1016/j.foodqual.2013.11.004

Kumar, A., & Lim, S. S. (2008). How Do Decision Frames Influence the Stock Investment Choices of Individual Investors? *Management Science, 54*(6), 1052. https://doi.org/10.1287/mnsc.1070.0845

Kuncel, N. R., Credé, M., & Thomas, L. L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. *Review of Educational Research, 75*(1), 63–82.

Lafferty, B. A., Lueth, A. K. & McCafferty, R. (2016). An Evolutionary Process Model of Cause-Related Marketing and Systematic Review of the Empirical Literature. *Psychology & Marketing*, *33*(11), 951-970.

Landreth,S., Pirsch, J., & Garretson, J. A. (2004). Cause-related marketing campaign donation structures: Maximizing firm benefit and minimizing consumer mistrust, in *Marketing and Public Policy Proceedings,* Debbie Scammons and Marlys Mason and Rob Mayer (Eds.). Salt Lake City, Utah.

Langen, N., Grebitus, C., & Hartmann, M. (2011). Is there need for more transparency and efficiency in cause-related marketing? *International Journal on Food System Dynamics*, *1*(4), 366-381.

Langer, T., & Weber, M. (2001). Prospect theory, mental accounting and differences in aggregated and segregated evaluation of lottery portfolios. *Management Science, 47*(5), 716-733.

Larrick, R.P. (2004), "Debiasing", in Koehler, D.J. and Harvey, N. (Eds), *Blackwell Handbooks of Experimental Psychology*, Blackwell, Malden, MA, pp. 317-37.

Lavrakas, P. (2008). Favorability ratings. In P. J. Lavrakas (Ed.), *Encyclopedia of survey research methods* (pp. 272-272). Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781412963947.n180

LeBoeuf, R. A., & Shafir, E. (2006). The long and short of it: Physical anchoring effects. *Journal of Behavioral Decision Making, 19*(4), 393–406.

LeFevre, J., Greenham, S. L, & Waheed, N. (1993). The development of procedural and conceptual knowledge in computational estimation. *Cognition and Instruction, 11*, 95-132.

LeFevre, J. A., Sadesky, G. S., & Bisanz, J. (1996). Selection of procedures in mental addition: Reassessing the problem size effect in adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*(1), 216.

Lemaire, P., Lecacheur, M., & Farioli, F. (2000). Children's Strategy Use in Computational Estimation. Canadian Journal of Experimental Psychology, 54(2), 141-148.

Levin, D. M. (1988). *The opening of vision: Nihilism and the postmodern situation*. London: Routledge.

Levin, I. P., & Gaeth, G. J. (1988). How consumers are affected by the framing of attribute info. *Journal of Consumer Research, 15*(3), 374-374.

Light, R. J., & Margolin, B. H. (1971). An Analysis of Variance for Categorical Data. *Journal of the American Statistical Association, 66*(335), 534. https://doi.org/10.1080/01621459.1971.10482297

Lim, S. S. (2006). Do investors integrate losses and segregate gains? Mental accounting and investor trading decisions. *Journal of Business*. 79(5), 2539–2573.

List, J. A. (2004). Neoclassical Theory versus Prospect Theory: Evidence from the marketplace. *Econometrica*, *72*(2), 615-625.

Liu, H., & Chiu, Y. (2015). Sales framing, mental accounting, and discount assignments. *Asia Pacific Management Review, 20,* 201-209. https://doi.org/10.1016/j.apmrv.2015.01.002

Lucas, R., & Prescott, E. (1971). Investment under uncertainty, *Econometrica, 39*(5), 659-81.

Marketing News. (1987). Charge-card consumers choose charities for their contributions. 21(21, October 9), 10.

Marshall, G. N., Wortman, C. B., Kusulas, J. W., Hervig, L. K., & Vickers Jr., R. R. (1992). Distinguishing optimism from pessimism: Relations to fundamental dimensions of mood and personality. *Journal of Personality and Social Psychology, 62*(6), 1067-1074.

Mayer, E. R. Stull, A. T., Campbell, J., Almeroth, K., Bimber, B., Chun, D., & Knight, A. (2007). Overestimation bias in self-reported SAT scores. *Education Psychological Review, 19*(4), 443–454.

Meissner, P., & Wulf, T. (2017). The effect of cognitive diversity on the illusion of control bias in strategic decisions: *An experimental investigation. European Management Journal, 35*(4), 430–439. https://doi.org/10.1016/j.emj.2016.12.004

Meyer, H. (1999). When the cause is just. *Journal of Business Strategy, 20*(6), 27-31.

Merz, E. L., Malcarne, V. L., Roesch, S. C., Ko, C. M., Emerson, M., Roma, V. G., & Sadler, G. R. (2013). Psychometric properties of Positive and Negative Affect Schedule (PANAS) original and short forms in an African American community sample. *Journal of affective disorders*, 151(3), 942–949. https://doi.org/10.1016/j.jad.2013.08.011

Meyers-Levy, J., & Maheswaran, D. (1990). Message framing effects on product judgments. In Goldberg, E., Gorn, G., & Pollay, R.W. (Eds)*, Advances in Consumer Research, 17,* Association for Consumer Research, 531-534.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*, 81-97.

Minton, E. A., & Cornwell, T. B. (2016), The Cause Cue Effect: Cause-Related Marketing and Consumer Health Perceptions. *Journal of Consumer Affairs, 50,* 372–402. https://doi.org/10.1111/joca.12091

Moen, D. H., & Powell, J. E. (2005). Illustrating the central limit theorem through Microsoft excel simulations. *College Teaching Methods & Styles Journal (CTMS), 1*(2), 35-46.

Montibeller, G., & Winterfeldt, D. (2015). Cognitive and Motivational Biases in Decision and Risk Analysis. Risk Analysis: *An International Journal, 35*(7), 1230-1251. https://doi.org/10.1111/risa.12360

Moosmayer, D. C., & Fuljahn, A. (2010). Consumer perceptions of cause related marketing campaigns. *Journal of Consumer Marketing*, *27*(6), 543–549.

Müller, S. S., Fries, A. J., & Gedenk, K. (2014). Full Length Article: How much to give? — The effect of donation size on tactical and strategic success in cause-related marketing. *International Journal of Research in Marketing*, *31*, 178-191. https://doi.org/10.1016/j.ijresmar.2013.09.005

Murphy, I. P. (1997). Pillsbury Proves Charity, Marketing Begins at Home? *Marketing News,* February 17, 16.

Mussweiler, T., & Englich, B. (2003). Adapting to the Euro: Evidence from bias reduction. *Journal of Economic Psychology*, *24*(3), 285-292.

Muth, J. (1961). Rational expectations and the theory of price movements, *Econometrica, 29*, 315-335.

Newell, A., & Simon, H. A. (1972). *Human problem solving*, *14*, Englewood Cliffs, NJ: Prentice-Hall.

Nisbett, R. E., Krantz, D. H., Jepson, C., & Kunda, Z. (1983). The use of statistical heuristics in everyday inductive reasoning. *Psychological Review, 90*, 339–363.

Nisbett, R. E., & Ross, L. (1980). *Human inference: Strategies and shortcomings of social judgment*. Englewood Cliffs, NJ: Prentice Hall.

Nordstrom, C. R., Williams, K. B., & LeBreton, J. M. (1996). The effect of cognitive load on the processing of employment selection information. *Basic and Applied Social Psychology, 18*, 305-318.

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education, 15*(5), pp. 625-632. Retrieved from: https://link.springer.com/article/10.1007%2Fs10459-010-9222-y#citeas.

Olsen, G. D., Pracejus, J. W., & Brown, N. R. (2003). When profit equals price: Consumer confusion about donation amounts in cause related marketing. *Journal of Public Policy and Marketing, 22,* 170-180.

Oppenheimer, D. M., LeBoeuf, R. A., & Brewer, N. T. (2008). Anchors aweigh: A demonstration of cross-modality anchoring and magnitude priming. *Cognition*, *106*, 13-26.

Pavot, W., & Diener, E. (1993). Review of the satisfaction with life scale. *Psychological assessment, 5*(2), 164.

Peng, J., Li, H., Miao, D., Feng, X., & Xiao, W. (2013). Five different types of framing effects in medical situation: a preliminary exploration. *Iranian Red Crescent medical journal*, *15*(2), 161–165. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3652505/

Peracchio, L., & Meyers-Levey, J. (1997). Evaluating Persuasion-Enhancing Techniques from a Resource-Matching Perspective. *Journal of Consumer Research*, *24* (September), 178–191.

Perry, P. R. (1985). Portfolio Serial Correlation and Non-Synchronous Trading. *Journal of Financial and Quantitative Analysis*, *20*(4), 517.

Perry, V. G. (2008). Is Ignorance Bliss? Consumer Accuracy in Judgments about Credit Ratings. *The Journal of Consumer Affairs, 42*(2), 189-205.

Piaget, J., & Inhelder, B. (1975). *The origin of the idea of chance*. New York: Norton. (Original work published 1951).

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies, *Journal of Applied Psychology*, *88*: 879-903.

Polonsky, M. J., & Wood, G. (2001). Can the overcommercialization of cause-related marketing harm society? *Journal of Macromarkerting, 21*(1), 8-22.

Pracejus, J. W., Deng, Q. (Claire), Olsen, G. D., & Messinger, P. R. (2020). Fit in cause-related marketing: An integrative retrospective. *Journal of Global Scholars of Marketing Science, 30*(2), 105–114. https://doi.org/10.1080/21639159.2018.1509365

Pracejus, J. W., Olsen, G. D., & Brown, N. R. (2004). On the Prevalence and Impact of Vague Quantifiers in the Advertising of Cause Related Marketing (CRM). *Journal of Advertising, 32,* 19-28.

Proctor, J (2015). CBC News Analysis. Starbucks 'Race Together' campaign stirs controversy and coffee to court cash [online]. Available at : http://www.cbc.ca/news/canada/british-columbia/starbucks-race-together-campaign-stirs-controversy-and-coffee-to-court-cash-1.3000491

Read, D., Loewenstein, G., & Rabin, M. (1999). Choice bracketing. *Journal of Risk and Uncertainty, 19*, 171–197.

Redelmeier, D. A., & Tversky, A. (1990). Occasional Notes: Discrepancy between Medical Decisions for Individual Patients and for Groups. *The New England Journal of Medicine*, *322*(16), 1162-1164. Retrieved May 17, 2011, from ProQuest Nursing & Allied Health Source. (Document ID: 2835022).

Redelmeier, D. A., & Tversky, A. (1992). On the Framing of Multiple Prospects. *Psychological Science, 3*(3), 191.

Reeves, T., & Lockhart, R. S. (1993). Distributional Versus Singular Approaches to Probability and Errors in Probabilistic Reasoning. *Journal of Experimental Psychology: General 122*(2), 207-226.

Renshon, J. (2009). Assessing Capabilities in International Politics: Biased Overestimation and the Case of the Imaginary 'Missile Gap'. *The Journal of Strategic Studies, 32*(1), 115-147.

Rickard, S. (2012). Electoral Systems, Voters' Interests and Geographic D*ispersion. British Journal of Political Science, 42*(4), 855-877. Retrieved September 17, 2020, from http://www.jstor.org/stable/23274170

Robinson, M. D., & Kirkeby, B. S. (2005). Happiness as a belief system: Individual differences and priming in emotion judgments. *Personality and Social Psychology Bulletin*, *31*, 1134–1144.

Robinson, M. D., & Von Hippel, W. (2006). Rose-colored priming effects: Life satisfaction and affective priming. *The Journal of Positive Psychology*, *1*(4), 187-197.

Rosenberg, M. (1979). *Conceiving the Self*. New York, NY: Basic Books.

Ross III, J. K., Patterson, L. T., & Stutts, M. A. (1992). Consumer perceptions of organizations that use cause-related marketing. *Journal of the Academy of Marketing Science*, *20*(1), 93-97.

Ross, J. K., Stutts, M. A., & Patterson, L. T. (1991). Tactical considerations for the effective use of cause-related marketing. *Journal of Applied Business Research*, *7*(2), 58-65.

Samuelson, P. A. (1947). *Foundations of Economic Analysis*, Harvard University Press, Boston, MA.

Sang Gyu Kwak, & Jong Hae Kim. (2017). Central limit theorem: the cornerstone of modern statistics. *Korean Journal of Anesthesiology, 70*(2), 144–156. https://doi.org/10.4097/kjae.2017.70.2.144

Sanna, L. J., Schwarz, N., & Stocker, S. L. (2002). When debiasing backfires: accessible content and accessibility experiences in debiasing hindsight. *Journal of Experimental Psychology: Learning, Memory and Cognition, 3*, 497.

Savage, L. J. (1954). *The Foundations of Statistics*, Wiley, New York, NY.

Schiller, Z. (1988). Doing Well by Doing Good. *Business Week, 3082*, 53-57.

Schulz-Hardt, S., Jochims, M. & Frey, D. (2002). Productive conflict in group decision making: genuine and contrived dissent as strategies to counteract biased information seeking. *Organizational Behavior and Human Decision Processes, 88*(2), 563-586.

Schwarz, N., & Clore, G. L. (1983). Mood, misattribution and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology, 45*, 513–523.

Sedlmeier, P., & Gigerenzer, G. (1997). Intuitions about sample size: The empirical law of large numbers. *Journal of Behavioral Decision Making, 10,* 33–51.

Seidlitz, L., & Diener, E. (1993). Memory for positive and negative life events: Theories for the differences between happy and unhappy persons. *Journal of Personality and Social Psychology, 64*, 654–663.

Shaban, R. Z. (2005). Theories of clinical judgment and decision-making: A review of the theoretical literature. *Journal of Emergency Primary Health Care, 3(*1-2).

Shavitt, S., Sanbonmatsu, D., Smittipatana, S., & Posavac, S. (1999). Broadening the conditions for illusory correlation formation: Implications for judging of minority groups. *Basic and Applied Social Psychology, 21*, 263–279.

Shirota, Y., & Suzuki, S. (2014). Visualization of the central limit theorem and 95 percent confidence intervals. *Gakushuin Economics Papers, 50*(4), 125-136.

Siegler, R. S. (1987). The perils of averaging over strategies: An example from children's addition. *Journal of Experimental Psychology: General*, *116*, 250-264.

Simon, H. A. (1955). A behavioural model of rational choice. *Quarterly Journal of Economics*, *69*(1), 99-118.

Slovic, P., & Lichtenstein, S. (1971). Comparison of Bayesian and regression approaches to the study of information processing in judgment. *Organizational Behavior and Human Performance, 6* (6), 649-744.

Smith, S. M., & Alcorn, D. S. (1991). Cause Marketing: A New Direction in the Marketing of Corporate Responsibility. *Journal of Consumer Marketing*, *8*(Summer), 19-35.

Smith, A. R., & Price, C. P. (2010). Sample size bias in the estimation of means. *Psychonomic Bulletin & Review, 17* (4), 499-503.

Soman, D. (2004). Framing, loss aversion, and mental accounting. *Blackwell handbook of judgment and decision making*, 379-398.

Stanforth, N., & Hauck, W. (2010). The effects of ethical framing on consumer price perceptions. *Journal of Fashion Marketing and Management, 14*(4), 615-623.

Steul, M. (2006). Does the framing of investment portfolios influence risk-taking behavior? Some experimental results. *Journal of Economic Psychology. 27(4)*, 557-570.

Stewart, D. (2010a). DDBA-804: Research Methodologies & Techniques, Study Guide – Experimental Design, *Athabasca University*, Week 5.

Stewart, D. (2010b). DDBA-804: Research Methodologies & Techniques Seminar Discussions – Experimental Design, *Athabasca University*, Week 5.

Strahilevitz, M. (1999). The effects of product type and donation magnitude on willingness to pay more for a charity-linked brand. *Journal of Consumer Psychology*, *8*(3), 215-241.

Strahilevitz, M., & Myers, J. (1998). Donations to charity as purchase incentives: How well they work may depend on what you are trying to sell. *Journal of Consumer* Research*, 24*(4), 434–446.

Suh, E., Diener, E., & Fujita, F. (1996). Events and subjective well-being: Only recent events matter. *Journal of Personality and Social Psychology*, *70*, 1091–1102.

Sullivan, G. & Artino Jr., A. R. (2013). Analyzing and Interpreting Data from Likert-Type Scales. *Journal of Graduate Medical Education. 5*(4), pp. 541-542.

Tal, G. (2011). *Overestimations in forecasting new transportation demand management policies: Chronicle of an error foretold*. Ph.D. dissertation, University of California, Davis, United States -- California. Retrieved July 4, 2011, from Dissertations & Theses: Full Text. (Publication No. AAT 3336345).

Tan, C., Teo, H., & Benbasat, I. (2010). Assessing Screening and Evaluation Decision Support System: A Resource-Matching Approach. *Information Systems Research, Linthicum, 21*(2), 305-330.

Thaler, R. H. (1993). *Advances in Behavioral Finance*, Russel Sage Foundations, New York, NY.

Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral Decision Making, 12, 183-206.

Thaler, R. H. (2000). From homo economicus to homo sapiens. *Journal of Economic Perspectives, 14*(1), 133-41.

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science. 36* 643–660.

Tiberghien, K., De Smedt, B., Fias, W., & Lyons, I. M. (2019). Distinguishing between cognitive explanations of the problem size effect in mental arithmetic via representational similarity analysis of fMRI data. *Neuropsychologia, 132*. https://doi.org/10.1016/j.neuropsychologia.2019.107120

Treen, E., Atanasova, C., Pitt, L., & Johnson, M. (2016). Evidence from a Large Sample on the Effects of Group Size and Decision-Making Time on Performance in a Marketing Simulation Game. *Journal of Marketing Education, 38*(2), 130-137.

Tsiros, M., & Irmak, C. (2020). Lowering the Minimum Donation Amount Increases Consumer Purchase Likelihood of Products Associated with Cause-Related Marketing Campaigns. *Journal of Marketing Research (JMR), 57*(4), 755–770. https://doi.org/10.1177/0022243720916463

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science, New Series, 185*(4157), 1124-113.

Tversky, A., & Kahneman, D. (1980). *Causal schemas in judgments under uncertainty*. *In Progress in Social Psychology*, ed. M. Fishbein, 1:49-72. Hillsdale, NJ: Erlbaum. 240 pp.

Tversky, A., & Kahneman, D. (1986). Rational choice and the framing of decisions. *Journal of Business, 59*(4), 251-78.

Varadarajan, R. P., & Menon, A. (1988). Cause-related marketing: a coalignment of marketing strategy and corporate philanthropy. *Journal of Marketing*, *52*(3), 58-74.

Venkatraman, S., Aloysius, J. A., & Davis, F. D. (2006). Multiple prospect framing and decision behavior: The mediational roles of perceived riskiness and perceived ambiguity. *Organizational Behavior and Human Decision Processes, 101*(1), 59–73. https://doi.org/10.1016/j.obhdp.2006.04.006

Vlachos, P. A., Koritos, C. D., Krepapa, A., Tasoulis, K., & Theodorakis, I. G. (2016). Containing cause-related marketing skepticism: A comparison across donation frame types. *Corporate Reputation Review, 19*(1), 4-21.

von Neumann, J., & Morgenstern, O. (1947). *Theory of Games and Economic Behavior*, 2nd ed., Princeton University Press, Princeton, NJ.

Watson, D., & Clark, L. A. (1984). Negative Affectivity: The disposition to experience aversive emotional states. *Psychological Bulletin, 96*, 465-490.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*(6), 1063-1070.

Watson, D., & Tellegen, A. (1985). Toward a consensual structure of mood. *Psychological Bulletin, 98*, 219-235.

Webb, D. J., & Mohr, L. A. (1998). A Typology of Consumer Responses to Cause-Related Marketing: From Skeptics to Socially Concerned. *Journal of Public Policy & Marketing*, *17*(2), 226-238.

Wei, S., Ang, T., & Liou, R.-S. (2020). Does the global vs. local scope matter? Contingencies of cause-related marketing in a developed market. *Journal of Business Research, 108*, 201–212. https://doi.org/10.1016/j.jbusres.2019.11.018

Weick, K. E. (1984). Small wins: Redefining the scale of social problems. *American Psychologist, 39*, 40-49.

Winterich, K. P., & Barone, M. J. (2011). Warm Glow or Cold, Hard Cash? Social Identity Effects on Consumer Choice for Donation Versus Discount Promotions. *Journal of Marketing Research, 48* (February), 855–868.

Witek, L. (2016). Influence of Socio-Demographic Characteristics of Consumers on Attitudes Towards Cause Related Marketing. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 64(6),* 2173–2182. https://doi.org/10.11118/actaun201664062173

Witek, L. & Hall, H. (2016). Prosumption use in creation of cause related marketing programs through crowdsourcing. *Procedia Economics and Finance, 39*: 212 – 218.

Wong, K. F. E., & Kwong, J. Y. Y. (2005). Comparing two tiny giants or two huge dwarfs? Preference reversals owing to number size framing. *Organizational Behavior and Human Decision Processes, 98*(1), 54–65. https://doi.org/10.1016/j.obhdp.2005.04.002

Wu, S., & Hung, J. (2008). A performance evaluation model of CRM on non-profit organizations. *Total Quality Management & Business Excellence*, *19*(4), 321. Retrieved February 20, 2011, from ABI/INFORM Global. (Document ID: 1460438051)

Yauch, C., & Steudel, H. (2003). Complementary Use of Qualitative and Quantitative Cultural Assessment Methods. *Organizational Research Methods*, 6(4), 465-481.

Zheng, L., Zhu, Y., & Jiang, R. (2019). The Mediating Role of Moral Elevation in Cause-Related Marketing: A Moral Psychological Perspective. *Journal of Business Ethics, 156*(2), 439–454. https://doi.org/10.1007/s10551-017-3614-3

Zolner, K., Compeau, L., Jones, J., & Munger, J. (2010). Consumers' Perceptions of Nonprofit Solicitations: Some Preliminary Evidence on Framing and Price Effects. *Journal of Nonprofit & Public Sector Marketing*, *22*, 1-13

Zumbo, B. D., & Zimmerman, D. W. (1993). Is the selection of statistical methods governed by level of measurement? *Canadian Psychology, 34*, 390-400.

Appendix 1: Pre-Test Questionnaire

Consumer Estimation of Donation Amount in Cause-Related Marketing _PRE TEST
Introduction

Thank you for agreeing to complete this survey. Your participation is appreciated and it will help to shape the outcome of the research. The research study is titled "Consumer Overestimation of Donation Amount in Cause-Related Marketing. The study is being conducted by Ken Atere from Athabasca University, Alberta.

Purpose of this research study is to gauge the extent of respondents' familiarity and disposition towards business corporations whose charities support children's health, recreational and social service issues in Canada. This survey will take approximately 8 minutes to complete. Your participation in this survey is absolutely voluntary and you can withdraw at any time. You are at liberty to omit any question. Responses will be anonymous and will be used in confidence.

At the end of the survey, you will be entered in a draw where you can win $100. If you have questions about the survey, please email: e_atte@yahoo.com

Consumer Estimation of Donation Amount in Cause-Related Marketing   PRE TEST

1. For each of the following charitable organizations, indicate how favourable you feel toward the organization. If you are not familiar with the organization, then simply check the box on the right-hand side:

	Favourable	Mostly Favourable	No Opinion	Mostly Unfavourable	Unfavourable	Not familiar with this charity
Children's Miracle Network	☐	☐	☐	☐	☐	☐
Make a Wish Foundation	☐	☐	☐	☐	☐	☐
Ronald McDonald House Charities	☐	☐	☐	☐	☐	☐
Sick Kids Foundation	☐	☐	☐	☐	☐	☐
Canadian Tire Jump Start	☐	☐	☐	☐	☐	☐
CIBC Children's Foundation	☐	☐	☐	☐	☐	☐
SOS Children's Villages Canada	☐	☐	☐	☐	☐	☐
Tim Horton Children's Foundation	☐	☐	☐	☐	☐	☐
Juvenile Diabetes Research Foundation Canada	☐	☐	☐	☐	☐	☐
World Vision Canada	☐	☐	☐	☐	☐	☐
Council on Drug Abuse (CODA)	☐	☐	☐	☐	☐	☐
Big Brothers Big Sisters of Canada	☐	☐	☐	☐	☐	☐
Boys and Girls Clubs of Canada	☐	☐	☐	☐	☐	☐
The Canadian Red Cross Society	☐	☐	☐	☐	☐	☐
CARE Canada, Bethany Care Society	☐	☐	☐	☐	☐	☐
Canadian Breast Cancer Foundation	☐	☐	☐	☐	☐	☐
Multiple Sclerosis Society of Canada	☐	☐	☐	☐	☐	☐
Canadian Cancer Society	☐	☐	☐	☐	☐	☐
Heart and Stroke Foundation of Canada	☐	☐	☐	☐	☐	☐

CONSUMER OVERESTIMATION OF DONATION AMOUNT

	Favourable	Mostly Favourable	No Opinion	Mostly Unfavourable	Unfavourable	Not familiar with this charity
Canadian Wildlife Federation	☐	☐	☐	☐	☐	☐
The David Suzuki Foundation	☐	☐	☐	☐	☐	☐
World Wildlife Fund Canada	☐	☐	☐	☐	☐	☐
Tides Canada Foundation	☐	☐	☐	☐	☐	☐
The Nature Conservancy of Canada	☐	☐	☐	☐	☐	☐
MADD Canada	☐	☐	☐	☐	☐	☐
United Way of Canada	☐	☐	☐	☐	☐	☐

Consumer Estimation of Donation Amount in Cause-Related Marketing _PRE TEST

2. Approximately how much do you donate to charitable organizations each year?

◯ $0

◯ $1-$100

◯ $101-$500

◯ $501-$1000

◯ $1001-$5000

◯ $5001 or more

Consumer Estimation of Donation Amount in Cause-Related Marketing _PRE TEST		

3. Please indicate which of the following charities you have donated to, and whether this was recently or in the past:

	I have donated to this charity recently (within the last year)	I have donated to this charity in the past (but not in the last year)	I have never donated to this charity.
Children's Miracle Network	☐	☐	☐
Make a Wish Foundation	☐	☐	☐
Ronald McDonald House Charities	☐	☐	☐
Sick Kids Foundation	☐	☐	☐
Canadian Tire Jump Start	☐	☐	☐
CIBC Children's Foundation	☐	☐	☐
SOS Children's Villages Canada	☐	☐	☐
Tim Horton Children's Foundation	☐	☐	☐
Alberta Children's Hospital Foundation	☐	☐	☐
Juvenile Diabetes Research Foundation Canada	☐	☐	☐
World Vision Canada	☐	☐	☐
Council on Drug Abuse (CODA)	☐	☐	☐
Big Brothers Big Sisters of Canada	☐	☐	☐
Boys and Girls Clubs of Canada	☐	☐	☐
The Canadian Red Cross Society	☐	☐	☐
CARE Canada, Bethany Care Society	☐	☐	☐
Canadian Breast Cancer Foundation	☐	☐	☐
Multiple Sclerosis Society of Canada	☐	☐	☐
Canadian Cancer Society	☐	☐	☐

	I have donated to this charity recently (within the last year)	I have donated to this charity in the past (but not in the last year)	I have never donated to this charity.
Heart and Stroke Foundation of Canada	☐	☐	☐
Calgary Humane Society for Prevention of Cruelty to Animals	☐	☐	☐
Canadian Wildlife Federation	☐	☐	☐
The David Suzuki Foundation	☐	☐	☐
World Wildlife Fund Canada	☐	☐	☐
Tides Canada Foundation	☐	☐	☐
The Nature Conservancy of Canada	☐	☐	☐
Alcoholics Anonymous MADD Canada, United Way of Canada	☐	☐	☐
Toronto Intergroup	☐	☐	☐

Consumer Estimation of Donation Amount in Cause-Related Marketing _PRE TEST

4. What is your age?

◯ 18 to 24

◯ 25 to 34

◯ 35 to 44

◯ 45 to 54

◯ 55 to 64

◯ 65 to 74

◯ 75 or older

Consumer Estimation of Donation Amount in Cause-Related Marketing _PRE TEST

5. What gender do you identify with?

○ Female

○ Male

○ Transgender

Consumer Estimation of Donation Amount in Cause-Related Marketing _PRE TEST

6. Please provide your email to be entered in the draw to win $100 gift card:

Appendix 2: Example of Main Experiment Questionnaire

Consumer Estimation of Donation Amount in Cause-Related Marketing (Vague Quantifier & 2 Causes Portfolio Conditions)
Welcome to My Survey

Thank you for agreeing to complete this survey. Your participation is appreciated and it will help to shape the outcome of the research. The research study is titled "Consumer Estimation of Donation Amount in Cause-Related Marketing". The study is being conducted by Ken Atere from Athabasca University, Alberta.

Purpose of this research study is to gauge the extent of respondents' familiarity and disposition towards business corporations whose charities support children's health, recreational and social service issues in Canada. This survey will take approximately 8 minutes to complete. Your participation in this survey is absolutely voluntary and you can withdraw at any time. You are at liberty to omit any question. Responses will be anonymous and will be used in confidence.

At the end of the survey, you will be entered in a draw where you can win $100.
If you have questions about the survey, please email: e_atte@yahoo.com

	Consumer Estimation of Donation Amount in Cause-Related Marketing (Vague Quantifier & 2 Causes Portfolio Conditions)
PANAS QUESTIONNAIRE	

This scale consists of a number of words that describe different feelings and emotions. Read each item and then list the number from the scale below next to each word. Indicate to what extent you feel this way right now, that is, at the present moment OR indicate the extent you have felt this way over the past week (circle the instructions you followed when taking this measure).

1. Please indicate:

	Very Slightly or Not at All	A Little	Moderately	Quite a Bit	Extremely
Interested	○	○	○	○	○
Distressed	○	○	○	○	○
Excited	○	○	○	○	○
Upset	○	○	○	○	○
Strong	○	○	○	○	○
Guilty	○	○	○	○	○
Scared	○	○	○	○	○
Hostile	○	○	○	○	○
Enthusiastic	○	○	○	○	○
Proud	○	○	○	○	○
Irritable	○	○	○	○	○
Alert	○	○	○	○	○
Ashamed	○	○	○	○	○
Inspired	○	○	○	○	○
Nervous	○	○	○	○	○
Determined	○	○	○	○	○
Attentive	○	○	○	○	○
Jittery	○	○	○	○	○
Active	○	○	○	○	○
Afraid	○	○	○	○	○

Consumer Estimation of Donation Amount in Cause-Related Marketing (Vague Quantifier & 2 Causes Portfolio Conditions)				

2. Please indicate your level of agreement or disagreement with the following items:

	Disagree completely	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Agree completely
I like buying products which donate part of their profits to a charitable cause	○	○	○	○	○
I am willing to pay more for a product if the manufacturer is donating part of the profits to charity	○	○	○	○	○
If a company is donating part of its profits to a charity, then I am more likely to buy its products	○	○	○	○	○
Companies who advertise that they are donating part of their profits to charity are good corporate citizens	○	○	○	○	○
The more charities a company chooses to donate to, the better it is	○	○	○	○	○
If a company has a limited sum to donate, it is better for the company to donate to a single charity rather than multiple charities	○	○	○	○	○

3. When was the last time you purchased each of the following for your personal or family use?

	Never	Within the last year	1-2 years ago	3-5 years ago	More than 5 years ago
Desktop computer	○	○	○	○	○
Laptop computer or notebook computer	○	○	○	○	○
Tablet or iPad	○	○	○	○	○

4. Last year, a company called Gig-a-Byte Computers had a cause-related marketing promotion. During this one-month promotion, they donated funds to a charity for each computer they sold. The company sold a total of 1,000 computers during that month for $999.99 each. From the sale of each computer, the company donated 10% of profits to the charity.

Based on your knowledge of last year's donation from Gig-a-Byte as described above, please indicate your level of agreement or disagreement with the following statements:

	Disagree completely	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Agree completely
Gig-a-Byte benefited from the relationship with the charity	◯	◯	◯	◯	◯
The charity benefited from the relationship with Gig-a-Byte.	◯	◯	◯	◯	◯
There was a good fit between Gig-a-Byte and the charity	◯	◯	◯	◯	◯
Gig-a-Byte's donation made a real difference to society.	◯	◯	◯	◯	◯

5. Gig-a-Byte Computers is planning a new cause-related marketing promotion for the current year. It will differ from their cause-related marketing promotion last year because this year they plan to split the donation between 2 different charities.

Please review the ad carefully. You will be asked questions about this ad, but you will not be able to return to this page.

2019 ANNUAL MAKE-A-DIFFERENCE EVENT

This Week's Special

$999 ⁹⁹

FREE SHIPPING

- Windows 10,
- 2-in-1 13.3" Touch-Screen Laptop
- 7ᵗʰ Gen Intel Core i7 - 12GB Memory
- 512GB Solid State Drive
- Bluetooth; touch screen; backlit keyboard; HDMI output

GigaByte

As part of our ongoing commitment to support programs related to children's health, recreation and social service issues in the communities where we do business, generous donation from the sale of this item will be made to the following portfolio of 2 charities listed below

Computer Products Inc.

1. Make a Wish Foundation
2. Ronald McDonald House Charities

Click 'OK' when you are finished reviewing the ad.

◯ OK

6. Thinking about the **ad** you just viewed, for each question below please circle a number to rate your **impression of the ad**:

	1 Very Slightly or Not at All	2 A Little	3 Moderately	4 Quite a Bit	5 Extremely
Positive	☐	☐	☐	☐	☐
Favorable	☐	☐	☐	☐	☐
Interesting	☐	☐	☐	☐	☐

7. Thinking about the **product** you saw in the ad, for each question below please circle a number to rate your **impression of the product**:

	1 Very Slightly or Not at All	2 A Little	3 Moderately	4 Quite a Bit	5 Extremely
Like	☐	☐	☐	☐	☐
Favorable	☐	☐	☐	☐	☐
Good	☐	☐	☐	☐	☐

8. Thinking about the **product** you saw in the ad, for each question below please circle a number to indicate how likely you would be to **purchase this product**:

	1 Very Slightly or Not at All	2 A Little	3 Moderately	4 Quite a Bit	5 Extremely
Like	☐	☐	☐	☐	☐
Probable	☐	☐	☐	☐	☐

9. As you saw in the ad, Gig-a-Byte Computers is donating funds to {2} different charities for each computer they sell during the month. The company hopes to sell 1,000 computers during the month for $999.99 each. From the sale of each computer, the company will make a generous donation to the charities.

Based on this sales estimate, approximately how much is the combined amount that Gig-a-Byte will donate to the charities from this cause-related marketing promotion?

- Less than $30,000

- $30,000 - $59,999

- $60,000 - $89,000

- $90,000 - $119,999

- $120,000 - $149,99

- $150,000 or more

Consumer Estimation of Donation Amount in Cause-Related Marketing (Vague Quantifier & 2 Causes Portfolio Conditions)

10. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 2 charities

○ A laptop for $975 from a competitor where there is no charitable donation

11. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation to be split equally between {2} charities

○ A laptop for $900 from a competitor where there is no charitable donation

12. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation to a single charity

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between {2} charities

13. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation to a single charity

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 5 charities.

14. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to a single charity

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 8 charities

15. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 2 charities

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 5 charities

16. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 2 charities

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 8 charities

17. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 5 charities

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split equally between 8 charities

18. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split 50:50 between 2 charities

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation, to be split 70:30 between 2 charities

19. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will a generous donation, to be split equally between 5 charities

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make make a generous donation, splitting the donation unequally between 5 charities so that the 1st charity receives about twice as much as the 5th charity.

20. Imagine that you are in the market for a laptop computer this year. For each of the following pairs of choices, indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will a generous donation, to be split equally between 8 charities

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make make a generous donation, splitting the donation unequally between 8 charities so that the 1st charity receives about twice as much as the 8th charity

21. Imagine that you are in the market for a laptop computer this year. Please indicate which you would prefer:

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a generous donation to a charity

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a donation of 10% of profits to a charity

○ A laptop for $999.99 from Gig-a-Byte, knowing that they will make a donation of 10% of the selling price to a charity

Consumer Estimation of Donation Amount in Cause-Related Marketing (Vague Quantifier & 2 Causes Portfolio Conditions)

22. What is your age?

 ⬭ 18 to 24

 ⬭ 25 to 44

 ⬭ 45 to 64

 ⬭ 65+

23. What gender do you identify with?

 ⬭ Female

 ⬭ Male

 ⬭ Transgender

Consumer Estimation of Donation Amount in Cause-Related Marketing (Vague Quantifier & 2 Causes Portfolio Conditions)

24. Please indicate your highest level of education:

( ) Less than high school

( ) Completed high school

( ) Some college or university

( ) Graduated with Bachelor's degree

( ) Graduated with Master's degree or Ph.D.

25. Approximately how much did you donate to charitable organizations last year?

( ) $0

( ) $1-$100

( ) $101-$500

( ) $501-$1000

( ) $1001-$5000

( ) $5001 or more

Appendix 3: Research Ethics Board (REB) Approval

Athabasca University
RESEARCH CENTRE

CERTIFICATION OF ETHICAL APPROVAL

The Athabasca University Research Ethics Board (AUREB) has reviewed and approved the research project noted below. The AUREB is constituted and operates in accordance with the current version of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS) and Athabasca University Policy and Procedures.

Ethics File No.: **23544**

Principal Investigator:
Mr. Ken Atere, Graduate Student
Faculty of Business\Doctorate in Business Administration

Supervisor:
Dr. Shaun McQuitty (Supervisor)

Project Title:
Consumer Overestimation of Donation Amount in Cause-Related Marketing Campaigns: Effect of Multiple Cause Portfolio Size and Framing

Effective Date: August 01, 2019   **Expiry Date**: July 31, 2020

Restrictions:

Any modification or amendment to the approved research must be submitted to the AUREB for approval.

Ethical approval is valid *for a period of one year*. An annual request for renewal must be submitted and approved by the above expiry date if a project is ongoing beyond one year.

A Project Completion (Final) Report must be submitted when the research is complete *(i.e. all participant contact and data collection is concluded, no follow-up with participants is anticipated and findings have been made available/provided to participants (if applicable))* or the research is terminated.

Approved by: **Date:** August 1, 2019

Saud Taj, Chair
Faculty of Business, Departmental Ethics Review Committee

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Athabasca University Research Ethics Board
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