Behavioral economics and the impact of message framing on financial planning intentions

by

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B.S., Liberty University, 2008
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

School of Family Studies and Human Services
College of Health and Human Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2019

Abstract

Neoclassical economics asserts that individuals maximize their utility subject to constraints, such as income. Rational choice and expected utility theories are natural outgrowths of utility maximization and posit that, when making decisions, individuals consider all information, weigh the costs and benefits, and then consistently make the best choice to maximize their utility. Behavioral economics, on the other hand, advances that these constant-rationality assumptions are dubious and unrealistic. Among other things, behavioral economics recognizes that individuals use heuristics and that decision making can be subject to cognitive biases, which cause divergences from neoclassical rational choice expectations. A popular (and growing) use of applied behavioral economics is in “choice architecture” and “nudges”—that is, increasing desirable outcomes by strategically structuring information and choices (i.e., the framing of information and choices).

In financial planning, there are many financially healthy behaviors, such as planning for retirement, engaging in monthly budgeting, and ensuring that various risks are covered by insurance. Despite these tasks being objectively useful, positive, and valuable behaviors, many individuals do not engage in these behaviors (or other behaviors that are regularly recommended by financial advisors and planners).

Therefore, this dissertation investigated whether applying a behavioral economics-based approach—namely narrative message framing through a prospect theory lens—affected the intentions to engage in retirement planning, monthly budgeting, and analyzing the need for insurance. In short, whether narrative message framing can be used as a “nudge” to increase financial planning intentions. This study also incorporated regulatory focus theory, which

regards how individuals self-regulate. Under this theory, framing effects may be stronger when the frame matches the individual's regulatory focus—this is known as regulatory fit.

Using primary data from randomized experiments, this dissertation explored three financial planning domains and investigated four research questions in each domain: (a) the effect of narratives on financial-planning intentions; (b) whether the valence of the narrative (positive or negative framing in the story) mattered (and if this varied by domain); (c) whether the framing effect, if any, depended on the individual-level characteristic of regulatory focus; and (d) whether regulatory fit enhanced framing effects. The three financial planning domains explored were retirement planning (a behavior with future consequences), cash-flow and budget planning (a behavior with present consequences), and insurance-needs planning (a behavior that involved risk analysis).

Results indicated that narrative message framing was effective to increase financial planning intentions. Moreover, the framing effect depended on the underlying financial behavior. The framing effect also varied based on the individual's regulatory focus. Stated simply, stories were powerful, framing mattered, and people responded differently to those frames. These findings are relevant to financial planners, financial services companies, financial-related non-profits and professional organizations, and policymakers, among others, all of whom can use these results to increase (nudge) the intentions to engage in various positive financial behaviors.

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Acknowledgements

Thank you to Kansas State University, the Personal Financial Planning Faculty, my Committee, and, in particular, Dr. Martin Seay, for their help, thoughts, and encouragement along this journey. Also, to my Ph.D. cohort—thank you all for becoming lifelong friends.

Dedication

To my amazing wife, Regan, and our incredible children, Noah and Zoe (and other after-born children). You all are my everything.

Chapter 1 - Introduction

This dissertation revolved around several core premises. First, financial planning can be complicated, challenging, and scary—to many people, money matters are foreign to them and often stressful and induce anxiety (O'Neill et al., 2005; Sages, Britt, & Cumbie, 2013). Second, stories are powerful (indeed, many of our timeless truths have been communicated by stories, fables, or parables) (Green & Brock, 2002). Third, the way information is presented matters (more technically, that framing influences decision making) (Tversky & Kahneman, 1981). Fourth, people can respond differently to the same information (Cesario, Grant, & Higgins, 2004). These premises set the background, inform the research questions, influence the experiments, and impact the implications that this dissertation advances.

Financial planning can be complicated, challenging, and scary; there are a lot of decisions, which are made over the course of a lifetime, that affect one's financial arc. Emblematic of these decisions are to save for retirement, abide by a monthly budget, and have sufficient insurance in place. Not only do these decisions affect the decision maker, but they often have collateral consequences as well, such as on spouses, children, and even extended family members.

Despite the importance of these decisions—and the gravity of the consequences of not engaging in those behaviors (e.g., not having saved for retirement)—research demonstrates that many people lack the financial knowledge or competence to make impactful savings and investment decisions (Lusardi & Mitchell, 2007, 2011). Regrettably, this is compounded by an ever-changing tax law, ongoing health insurance reform, and the proliferation of financial products, among other factors (Lei & Yao, 2016; Marsden, Zick, & Mayer, 2011).

This is borne out empirically as well. For example, in the 2012 Household Financial Planning Survey, commissioned by the Certified Financial Planner Board of Standards, Inc., and the Consumer Federation of America, more than half of the respondents indicated that "it's hard for me to know who to trust for financial advice" (Princeton Research, 2012, p. 4). Similarly, more than half of respondents noted that "to me investing seems complicated" (Princeton Research, 2012, p. 4). And, again, more than half indicated that they are worried about losing money if they invest it (Princeton Research, 2012).

To help with this complexity, financial planning has developed into a robust field across various domains such as investment management, cash-flow and budget planning, insurance planning, tax planning, and estate planning. Through applied practice from practitioners and scholarly research from academicians, the field has developed core behaviors that clients are often advised to implement, such as goal-based retirement savings planning, monthly cash-flow monitoring and budgeting, and performing an insurance-needs analysis; these three behaviors, in particular, were investigated in this dissertation.

Not only can financial planning help with decisions in these discrete domains, it offers other benefits as well. Those with a personal financial plan tend to feel more confident about managing their money, saving, and investment behaviors (Princeton Research, 2012). They also tend to feel more likely to meet their financial goals (such as saving for retirement). Those with financial plans are also more likely to describe themselves as "living comfortably"—that is, more optimistic about their financial status (Princeton Research, 2012, p. 6). Similarly, the 2008 FPA and Ameriprise Value of Financial Planning Study found that those in a financial planning relationship were nearly twice as likely to report being confident about their financial futures compared to those without financial professional support (Harris Interactive, 2008). It also found that those with a comprehensive financial plan report feeling that they are on track for various financial goals, such as retirement or education saving (Harris Interactive, 2008). Those with a comprehensive financial plan also feel more prepared for unexpected life events due to having an emergency fund (Harris Interactive, 2008). Importantly, financial planning is not just for the affluent. In the CFP Board and CFA Study, although families with fewer resources were more susceptible to uncontrollable credit card debt, those with a financial plan generally handled credit cards to minimize this risk (Princeton Research, 2012).

In short, financial planning can be hard and complicated—there is a lot involved across the various financial planning domains that require technical knowledge, skill, and application. There are some basic and universally prescribed behaviors: (a) saving for retirement, (b) abiding by a monthly budget, and (c) having sufficient insurance in place; these are standard healthy financial best practices that should be adopted by the public at large. Yet, as more fully explained below, that is not the case; investigating how to increase financial planning behavior adoption and implementation rates, then, is a valuable (and very much needed) area of research.

Theoretical Framework

This study incorporated two main theoretical lenses. First (and primarily), was behavioral economics. Behavioral economics posits that the way information is presented matters. This premise is rooted in prospect theory. Prospect theory posits that losses and gains are not necessarily equivalent, and that, generally, people tend to avoid losses; stated otherwise, losses hurt more than equivalent gains—this is known as loss aversion. Based on prospect theory and loss aversion, then, negatively framed information may influence people to avoid those consequences (so that they, too, do not suffer the same consequences). One approach to increase financial planning implementation, then, is to critically evaluate the way financial planning information is presented.

Indeed, behavioral economics has been used in similar contexts to incentivize (or "nudge") individuals to engage in healthy or positive behaviors (e.g., Thaler & Sunstein, 2009). In the financial context, one of the most famous examples is Thaler and Benartzi's (2004) "Save More Tomorrow" (SMarT) savings program. In a nutshell, to increase savings rates, they created a prescriptive savings program that exploited the now-mainstays of behavioral economics—decisional inertia (status quo bias) and loss aversion—which resulted in a threefold increase in average savings rates in retirement plans among participants (Thaler & Benartzi, 2004). Similarly, behavioral economics can be used in other financial planning contexts, like those explored in this dissertation.

The second main theoretical lens applied here was regulatory focus theory. Regulatory focus theory is a psychological theory that regards how people approach pleasure and pain. The integration of psychological theory to financial planning research has become more common (e.g., Asebedo et al., 2019). Under regulatory focus theory, there are two styles of self-regulation, promotion focus and prevention focus. Prior research and theory indicate that regulatory focus affects the influence of message framing. Stated simply, some people may be more sensitive to avoid losses (prevention focused) and others may be more prone to pursue gains (promotion focused).

When applied to framing, then, a particular frame (i.e., a gain or loss frame) can fit one's underlying regulatory focus state. That is, those that are promotion focused may respond more favorably to a gain frame, and those that are prevention focus may respond more favorably to a loss frame. This phenomenon is known as regulatory fit. Stated more simply, people can respond differently to the same information; that is, there can be individualized differences to processing, evaluating, and acting upon information and message framing.

Research Purpose and Questions

Although there are objectively beneficial and rational financial behaviors and practices—such as regularly saving for retirement (Asebedo et al., 2019), monthly budgeting, and having sufficient insurance—many Americans do not adequately implement these behaviors (Munnell, Hou, & Webb, 2014; Princeton Research, 2012). Indeed, even though financial planning and using a financial advisor have myriad benefits to provide (e.g., Blanchett, 2019; Blanchett & Kaplan, 2013; Grable & Chatterjee, 2014), implementation and usage rates are low—and this is exacerbated in minority communities (White & Heckman, 2016). For example, the 2012 Household Financial Planning Survey found that only 31% of respondents reported having ever prepared a comprehensive financial plan, which is a cornerstone to comprehensive financial planning (Princeton Research, 2012). Furthermore, this report noted that this trend had not changed much over 15 years (Princeton Research, 2012). This lack of planning potentially creates primary and collateral consequences that can largely be avoided. In sum, having a solution to a problem is only as good as its implementation.

This lack of implementation is similar to the problem addressed by Thaler and Benartzi (2004). This dissertation, therefore, examined ways to use aspects of behavioral economics, namely prospect theory and message framing—as influenced by one's regulatory focus—to increase intentions (which may lead to later adoption) of these financial behaviors. Consequently, one potential way to bridge the implementation problem is to enhance the way we communicate the benefits of financial planning. For example, do we tout the benefits and upsides of engaging in a behavior—such as saving regularly for retirement—or do we highlight and emphasis the consequences of not doing so? Does this depend on the specific underlying behavior? Does this depend on underlying characteristics of the client, like regulatory focus?

Relatedly, because stories are powerful, should advisors communicate these ideas in a sterile, fact-based manner, or should they integrate a story to communicate these ideas? Our common human experience tells us that a colorful and vivid anecdote often makes more of an indelible impression than a litany of statistics. Indeed, both the deepest religious truths (e.g., Christ's parables) and timeless secular wisdom (e.g., Aesop's Fables) were often communicated by stories. Moreover, if in narrative form, does the "valence" (that is, is the narrative told in a gain-based outcome or a loss-based outcome) matter, too? This question is a natural implication of prospect theory (and loss aversion).

Therefore, the main focus of this dissertation was to perform primary research using survey-based experiments to investigate the impact of narrative message framing on financial planning intentions. Based on behavioral economics, prospect theory, and regulatory focus theory, this dissertation investigated the effect of narrative (story) message framing on financial planning intentions—in particular, intentions to engage in the financial behavior in the next six months—across three financial planning domains: (a) retirement planning, (b) cash-flow planning and budgeting, and (c) insurance.

As explored more in Chapter 2, these behaviors were selected because they represent behaviors with a future consequence (retirement planning), with a current consequence (monthly budgeting), and risk assessment and analysis (insurance needs analysis). In short, due to framing, different behaviors can be interpreted as risk-seeking or risk-averse, which can affect the expected reaction under prospect theory. Intentions to engage in the behaviors were examined because, as examined more in Chapter 2, various behavioral theories consider intentions as a precedent (and necessary) step to actual behavioral action and implementation. To be clear, although this dissertation examined three behaviors, the research purpose and questions were not about the behaviors per se, but rather the impact of framing and narrative messaging on financial planning intentions; multiple behaviors were examined because the underlying nature of a behavior could affect its perceived riskiness.

This dissertation used three experiments, one for each domain:

Experiment 1 & Research Question (RQ) 1 (Retirement Savings Planning):

A. Does narrative message framing influence intentions to engage in retirement planning?
B. Does the valence of the narrative (positive or negative) influence intentions to engage in retirement planning?
C. Does the individual-level characteristic of regulatory focus affect the narrative effect, if any?
D. Does regulatory fit affect the effectiveness of the narrative framing as applied to engage in retirement planning?

Experiment 2 & RQ 2 (Cash-Flow and Budgeting Planning):

A. Does narrative message framing influence intentions to engage in cash-flow and budget planning?
B. Does the valence of the narrative (positive or negative) influence intentions to engage in cash-flow and budget planning?
C. Does the individual-level characteristic of regulatory focus affect the narrative effect, if any?

D. Does regulatory fit affect the effectiveness of the narrative framing as applied to cash-flow and budget planning?

Experiment 3 & RQ 3 (Insurance Needs Analysis):

A. Does narrative message framing influence intentions to engage in insurance needs analysis planning?

B. Does the valence of the narrative (positive or negative) influence intentions to engage in insurance needs analysis planning?

C. Does the individual-level characteristic of regulatory focus affect the narrative effect, if any?

D. Does regulatory fit affect the effectiveness of the narrative framing as applied to insurance needs analysis planning?

Importantly, these questions are relevant on both an individual and public-at-large bases (e.g., in individual client counseling session or in crafting public awareness campaigns). As such, the results of this study are important to several constituencies, chief of whom is financial planners. Getting clients to engage, adopt, and implement financial beneficial behaviors is the entire point of the financial planning profession. If narrative message framing works, it can be used to encourage clients to adopt financially healthy behaviors. Moreover, the results of this study are relevant to policymakers, too, as they work to increase financial literacy and positive financial outcomes at the national levels.

Summary

Financial planning can be powerful and impactful. However, to be effective, it must be implemented. One way to increase that implementation may be with a behavioral-economics-based "nudge." An easy way to do that is by strategically framing and conveying financial planning information. This study therefore sought to examine whether narratives (stories) could be used to increase financial planning intentions and whether that effect, if any, changed based on the underlying behavior, and whether the effect can be increased by framing and regulatory fit. The results should be of interest to an array of audiences ranging from individual advisors to national-level associations and policymakers.

Chapter 2 - Literature Review

This literature review proceeds as follows. First, an overview of neoclassical economic thought and expected utility theory is discussed. Under this view, individuals are rational economic agents, constantly (and consistently!) seeking to optimize their utility. Consequently, message and narrative framing should have no impact on the decision choice.

Second, behavioral economics—a modern development in economics and finance—is explored. Under this school of thought (and its precursors), people are *not* always rational and are not always utility-maximizing actors. The quintessential example of this is prospect theory, which is explored in detail. From this approach, therefore, framing matters and can be outcome determinative.

Next, because this study explores the effect of framing, regulatory focus theory is examined. Under regulatory focus theory, people have chronic regulatory states, which can either be promotion-focused or prevention-focused. An implication of this theory is that a message frame can be consistent with one's regulatory state, which is known as "regulatory fit." Past research has shown that regulatory fit can enhance the effect of the framing.

Past empirical investigations of framing and narratives are explored. Of particular relevance here is the medical literature, which has a robust framing literature (e.g., in the public and individual health context). Indeed, this literature indicates that framing effects can be behavior-specific, depending on the underlying nature of the behavior; this is the approach taken by this dissertation.

Because this dissertation explored intentions (as compared to actual behavioral changes over time), past literature and theory exploring intentions, in particular, are examined. Finally, the hypotheses are set forth based on theory and existing literature.

Neoclassical Economic Thought—Expected Utility Theory

Neoclassical economics asserts that individuals maximize their utility subject to constraints, such as income (Nicholson & Snyder, 2017). This is known as constrained optimization (Thaler, 2015). This is implied by the assumption of no satiation—that is, extra goods always provide extra utility (Nicholson & Snyder, 2017). Under constrained optimization, the consumer will select a bundle of goods (an indifference curve) that lies tangent to their budget constraint, thereby maximizing the utility as constrained by their income (Nicholson & Snyder, 2017). Mathematically, this tangency is the point at which the slope of the budget constraint is equivalent to the slope of the indifference curve (Nicholson & Snyder, 2017).[1]

Rational choice and expected utility theories are natural outgrowths of utility maximization, which posits that, when making decisions, individuals consider all information, weigh costs and benefits, and then consistently make the best choice to maximize their utility (Burton & Shah, 2013). This is known as the "economic man" or *homo economicus* (Thaler & Sunstein, 2009). As summarized by Thaler (2015), "Optimization + Equilibrium = Economics" (p. 6). Indeed, it is this rationality coupled with utility maximization that leads to the prospect of predictable behavior (Burton & Shah, 2013). In short, how people will make various decisions.

Formal decision-making research and theory, in particular, traces back to French mathematicians Blaise Pascal and Pierre de Fermat, who discussed gambling scenarios (Harman & Gonzalez, 2015). Relatedly, Bernoulli (1954) used expected utility to address the St.

[1] To be more precise, the tangency requirement is only a necessary (but not sufficient) condition. If indifference curves are assumed to be convex (due to diminishing marginal rates of substitution (MRS) between goods), however, the tangency condition will be both a necessary and sufficient condition for a maximum point. Equivalently, the utility function is assumed to be quasi-concave (Nicholson & Snyder, 2017). Moreover, to rule out the possibility of linear segments, sometimes strict quasi-concavity is often assumed (Nicholson & Snyder, 2017). Mathematically, the tangency point is typically calculated by the Lagrange multiplier method (Dixit, 1990; Nicholson & Snyder, 2017). In addition to its tractability, the Lagrange multiplier also provides economic insight (i.e., it represents the common benefit-cost ratio for all the inputs) (Nicholson & Snyder, 2017).

Petersburg paradox, which presented the issue of a coin flip gamble with an expected value of infinity; Bernoulli postulated that it was not necessarily the direct dollar prize of gamble (its expected value), but rather the utility (its expected utility) derived from the gamble, and that marginal utility decreased as wealth increased (Nicholson & Snyder, 2017). Later, in the mid-twentieth century, expected utility theory blossomed due to the work of, among others, von Newmann and Morgenstern (1947).

As relevant here, expected utility theory (EUT) and rational choice theory posit similar choice behavior for rational consumers regardless of framing (Biswas & Grau, 2008; Maule & Villejoubert, 2007; von Neumann & Morgenstern, 1947). This is known as utility invariance (Maule & Villejoubert, 2007; von Neumann & Morgenstern, 1947). That is, "agents should exhibit consistency across choices" (Hollard, Maafi, & Vergnaud, 2016, p. 624).

Despite the mathematical beauty of EUT, evidence of its violations surfaced, particularly the famous challenge of French economist Maurice Allais (1953), which is now known as the "Allais Paradox" (Burton & Shah, 2013). As explained by Harman and Gonzalez (2015), the Allais Paradox is illustrated by the following gambling pairs:

Gamble Pair 1:

A: 1,000 (p = 1)

B: 1,000 (p = .89), 5,000 (p = .1), 0 (p = .01)

Gamble Pair 2:

A': 1,000 (p = .11), 0 (p =. 89)

B': 5,000 (p = .1), 0 (p = .9)

So, in A (the first pair), there is a 100% chance of winning 1,000, and, in B, an 89% chance to win 1,000, a 10% chance to win 5,000, and a 1% chance to win nothing. In A' (the second pair) there is an 11% chance to win 1,000 and an 89% chance to win nothing; in B', there is a 10% chance to win 5,000 and a 90% chance to win nothing (Harman & Gonzalez, 2015).

According to EUT—in particular, its independence axiom—a rational decision maker, who is optimizing utility, should not base preference on outcomes that are the same in amount and probability (Harman & Gonzalez, 2015). In other words, common outcomes should cancel out. Thus, in Pair 1, gambles A and B result in 1,000 89% of the time, and in Pair 2, they result in 0 for 89% of the time; as such, according to EUT, these common outcomes should cancel, resulting in the following identical gambles (Harman & Gonzalez, 2015):

A(A'): 1,000 (p = .11) B(B'): 0 (p = .01), 5,000 (p = .1)

Thus, if EUT is true, those who prefer A to B must also prefer A' to B'. Empirical evidence, however, shows that most respondents preferred A to B and B' to A' (Harman & Gonzalez, 2015). In short, as noted by Burton and Shah (2013, p. 92), “expected utility theory is a flawed representation of how humans make decisions under uncertainty.”

Despite the mathematical allure of EUT and rational choice, the 20th century was host to the chipping of its veneer. An early naysayer of EUT and rational choice was Simon (1955, 1978, 2000), who advanced the concept of bounded rationality—meaning that individuals have limited capacity to process information. This, in turn, can lead to decision making that is less than mathematically optimal.[2]

Another breakthrough in utility theory was that utility can be “path dependent” (Burton & Shah, 2013). For example, consider a 50/50 gamble to win \$1 million or \$5 million or the certain outcome to win \$2.5 million. Although these have mathematically defined expectancies, the actual choices a consumer makes may depend on their current level of wealth—that is, the utility

[2] Bounded rationality has been used a theoretical framework in explaining suboptimal financial behaviors and choices (e.g., Robb et al., 2015; Seay, Preece, & Le, 2017).

they derive from the gamble is path dependent (from where they start) (Burton & Shah, 2013). Additional explanations for deviations from EUT and rational choice are discussed next.

Behavioral Economics

Although the traditional economic framework was tractable and led to predictable outcomes, as Thaler (2015) argued, “the premises on which economic theory rests are flawed” (p. 6). He advanced three flaws to the traditional framework. First, optimization problems are hard to solve (for example, he advances picking a career or spouse—all of which have demonstrable failures, e.g., divorces; alternatively, consider the optimization difference between a game of tic-tac-toe and chess (Thaler, 2016)). Second, beliefs that form the bases of choices are not unbiased (e.g., overconfidence bias). Third, there are many factors and elements that are left out of the traditional optimization model (Thaler, 2015). Thaler eloquently noted that the core problem of the traditional economic model was that it sought to use one theory (rational utility maximization) to accomplish two goals—first, to model optimal behavior, and second, to predict *actual* behavior (Thaler, 2016).

Behavioral economics is a “mixture of psychology and economics” (Thaler, 2016, p. 1577). Indeed, Thaler argued that a behavioral approach offers better economic models because other social science disciplines can be integrated into the model (Thaler, 2016). For its part, instead of relying on *homo economicus*, behavioral economics relies merely on *homo sapiens*, i.e., ordinary humans. Emblematic of behavioral economics are various effects, biases, and heuristics that have been studied that diverge from traditional economic theory—such as anchoring, availability bias, and the endowment effect, among others (Kahneman, 2011). A foundational theory from behavioral economics is prospect theory, which is described in detail next.

Prospect Theory

Expected utility theory and rationality-based modeling posit that choice framing should have no impact on decision making. However, as studies have shown, that does not empirically hold water. Prospect theory advances a conceptual framework to explain, among other things, how gain and loss framing affects decision making. Under prospect theory, if faced with two choices with various risks involved (low versus high), choice preference will depend on how the choices are framed (Gallagher & Updegraff, 2012).

In their seminal 1979 paper, Kahneman and Tversky critiqued expected utility theory and introduced prospect theory. Prospect theory posits two stages of a decision; first, is the editing phase, and second is the evaluation phase. During the editing phase, there is a preliminary evaluation of the prospects (choices). The purpose of the editing phase is to organize and simplify the options for later evaluation and ultimate choice (Kahneman & Tversky, 1979). This process is accomplished mainly by coding, combination, segregation, or cancelation (Kahneman & Tversky, 1979).

Coding refers to perceiving outcomes as gains or losses relative to some neutral reference point. The reference point—which is a critical element of the process—typically relates to the current position (status quo). Thus, as Kahneman and Tversky explained, “the location of the reference points, and the subsequent coding of outcomes as gains or loss, can be affected by the formulation of the offered prospects, and by the expectations of the decision maker” (1979, p. 274). Combination refers to the operation of “combining the probabilities associated with identical outcomes” (Kahneman & Tversky, 1979, p. 274). Segregation refers to separating a risky component from a riskless component; for example, “the prospect (300, .80; 200, .20) is naturally decomposed into a sure gain of 200 and the risk prospect of (100, .80)” (Kahneman &

Tversky, 1979, p. 274). Finally, cancellation refers to discarding components that are shared by the prospects. They also describe the operators of simplification (rounding probabilities or outcomes) and dominance detection (scanning for dominant alternatives, which are rejected). During the evaluation phase, “the edited prospects are evaluated and the prospect of highest value is chosen” (Kahneman & Tversky, 1979, p. 274). The value of an edited prospect, V, is expressed by two terms, π and v. The first part, π, is combined with a probability decision weight, $\pi(p)$, “which reflects the impact of p on the over-all value of the prospect” (Kahneman & Tversky, 1979, p. 275). To be clear, though, π is not a formal probability measure (as it does not sum to one over possible values). The second part, v, assigns a number to each outcome, v(x), the subjective value of the outcome (which are defined relative to the reference point) (Kahneman & Tversky, 1979).

The key assumptions of the math behind prospect theory is that values do not regard end-state conditions, but rather changes from the reference point. And, second, as noted above, that decision weights are *not* stated probabilities (Kahneman & Tversky, 1979). Summarizing the properties of the value function, then, Kahneman and Tversky posit that the value function is “(i) defined on deviations from the reference point; (ii) generally concave for gains and commonly convex for losses; (iii) steeper for losses than for gains” (1979, p. 279). This results in the oft-described “S-shaped value function.” The S-shaped value function plays a critical role in the framing literature, which is described next.

Framing

From a conceptual perspective, framing has its roots in sociology and psychology (Borah, 2011). Entman (1993) noted that framing revolved around selection and salience; that is, the framing process selects an aspect of perceived reality and then makes it salient. Accentuating certain aspects in a message to influence the focus or impact of a communication is referred to as the "emphasis" approach to framing (Borah, 2011; Druckman, 2001). Applications and principles of framing emanate from prospect theory (e.g., Fatmawati, Dharmmesta, Purwanto, & Nugroho, 2018).

In more simple terms, Kahneman (2011) provided an example about the 2006 World Cup final in which Italy and France played. He noted that, although the statements "Italy won" and "France lost" were logical equivalents (i.e., they both accurately and equivalently described the outcome of the game—the same "truth conditions")—and this is how a *homo economicus* would interpret the statements—they likely do not have the same meaning to a normal reader. Meaning, as described by Kahneman, depends on what happens in associative memory while the statement is being read; here, two equivalent truth conditions can evoke different associations—the taste of victory for Italy fans and the pains of defeat for France fans. Consequently, because statements with equivalent truth conditions can yield different reactions, Kahneman argued that (normal) humans cannot be as rational as *homo economicus*.

More formally, in the decision-making context, Kahneman and Tversky (1979) noted that framing can have a differential impact on choice because individuals usually make decisions based on some reference point rather than in isolation (Biswas & Grau, 2008). When considering a gain or benefit—a positive framed message—people tend to avoid risk; but, when considering a loss or cost—a negative framed message—people tend to take more risks (Fatmawati et al., 2018). In sum, then, framing concerns "the way in which individuals build internal representations of decision problems and how these determine the choices that they make" (Maule & Villejoubert, 2007, p. 25).

In a now infamous article in *Science* in 1981, Amos Tversky and Daniel Kahneman bucked the rational-expectation school of thought and connected the framing of decisions to prospect theory. There, they noted that traditional rational choice theory requires consistency and coherency in choice selection; their article, however, empirically demonstrated systematic violations of those axioms (Tversky & Kahneman, 1981).

They described a decision problem as acts or options the decision-maker must choose from, considering the outcomes, consequences, and even probabilities related to the acts. A decision frame, according to Tversky and Kahneman (1981), is the "decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice" (p. 453). This frame, moreover, was affected by the formulation of the problem and other factors specific to the decision-maker, including his or her norms, habits, and personal characteristics.

In their paper, they described a decision choice experiment consisting of a narrative (vignette) and two options. Famously, the first problem regarded an Asian disease that is about to outbreak in the United States, which would kill 600 people; there were two alternative solutions to the problem, from which to choose (Tversky & Kahneman, 1981). First, "if Program A is adopted, 200 people will be saved"; however, "if Program B is adopted, there is a 1/3 probability that 600 will be saved, and 2/3 probability that no people will be saved" (Tversky & Kahneman, 1981, p. 453). Thus, in both options, the expected value of persons saved was 200. The substantial majority of respondents (72%) selected Problem A, which manifested risk averseness: the certainty of saving 200 was more attractive than the probabilistic chance of an equal expected value (Tversky & Kahneman, 1981).

The second problem was given the same story regarding the looming Asian disease outbreak, but its solutions were posed differently: "If Program C is adopted, 400 people will die"; "if Program D is adopted, there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die" (Tversky & Kahneman, 1981, p. 453). In this problem, the substantial majority of respondents (78%) selected Program D (Tversky & Kahneman, 1981). Under this formulation, the majority of respondents were risk-seeking: they chose the probabilistic outcome rather than the certain option with the same expected value (again, in each Program, the expected value was that 400 people will die) (Tversky & Kahneman, 1981).

This interesting problem demonstrated "reversal"—that is, despite the same expected value (i.e., utility), the inconsistent responses "arise from the conjunction of a framing effect with contradictory attitudes toward risk involving gains and losses" (Tversky & Kahneman, 1981, p. 453). This pattern, as argued by Kahneman and Tversky, violated expected utility theory, but yet can be squared with prospect theory (Tversky & Kahneman, 1981).

In analyzing this phenomenon through prospect theory, they demarcate two phases in the choice process: First, is the "initial phase," referring to the acts, outcomes, and contingencies being framed; and second, is the evaluation phase. Under their formulation, "consider a prospect that yields outcome *x* with probability p, outcome *y* with probability q, and the status quo with probability of $1 - p - q$" (Tversky & Kahneman, 1981, p. 454). Harkening back to prospect theory, the overall value function of the prospect is

$$\pi(p) = v(x) + \pi(q)v(y), \qquad (1)$$

where $v(.)$ is the value associated with outcomes and $\pi(\,.\,)$ is the decision weight (Tversky & Kahneman, 1981, p. 454).

Under prospect theory, the outcomes are thus expressed as positive or negative deviations—i.e., gains or losses—from the neutral outcome (value of zero) (Tversky & Kahneman, 1981). A key aspect is the S-shaped value function, which is "concave above the reference point and convex below it," and that the curve is steeper in the loss region than the gain region, indicating that losses generate a more extreme displeasure than an equal magnitude gain (Tversky & Kahneman, 1981, p. 454). In other words, "the displeasure associated with losing a sum of money is generally greater than the pleasure associated with winning the same amount" (Tversky & Kahneman, 1981, p. 454).

Prospect theory also differed from the traditional expected utility model in the treatment of probabilities (Tversky & Kahneman, 1981). Under an expected utility paradigm, uncertain outcomes were weighted by their probability; however, in prospect theory, they were multiplied by a decision weight—a monotonic probability function regarding probability (but not the probability itself) (Tversky & Kahneman, 1981). Here, low probabilities were over-weighted and more likely outcomes were under-weighted (Tversky & Kahneman, 1981).

If persons acted and thought linearly (consistently), then preferences would be independent of framing (Tversky & Kahneman, 1981); nonlinearities, however, preclude this result in reality. Tversky and Kahneman (1981) demonstrated this in the following thought experiment involving two decisions to choose from; in decision 1, choosing between (a) "a sure gain of $240" or (b) a "25% chance to gain $1,000" and a "75% to gain nothing" (p. 454); in decision 2, choosing between (a) "a sure loss of $750" or (b) "a 75% chance to lose $1,000 and a 25% chance to lose nothing" (p. 454).

In these thought experiments, the majority of respondents chose the sure gain—which was a risk-averse choice, i.e., a risk-free prospect was preferred to a risky prospect. However, in decision 2, the majority chose the gamble, which was a risk-seeking option (relative to the risk-free option). Here, then, respondents were risk-averse in choices with gains but yet risk-seeking in choices facing losses—this is a key conclusion of prospect theory due to the value function (Tversky & Kahneman, 1981).

Tversky and Kahneman (1981) also showed the effect of framing on contingent outcomes. They found what they dubbed the "certainty effect," described as "a reduction of the probability of an outcome by a constant factor has more impact when the outcome was initially certain than when it was merely probable" (p. 455). Another key takeaway in the contingency context was that the ability to reduce the probability of a harm from, say, one percent to zero (uncertain to certain) was valued more highly than the same one percent change from two percent to one percent (Tversky & Kahneman, 1981).

In sum, based on the shape of the value function, prospect theory has three characteristics relevant to the framing effect. First, gains and losses are reference dependent—one's feelings about the gain and loss are relative, based on a reference point (i.e., not purely on absolute terms) (Peng et al., 2017). Second, due to the slope of the value function, losses have larger psychological impacts than equivalent gains (Peng et al., 2017). And, third, sensitivity to gains and losses diminish as you move away from the reference point (Peng et al., 2017).

Even though pure prospect theory is often applied to rationalize framing effects, other rationales have been advanced, too. For example, fuzzy-trace theory posits that decision-makers do not necessarily pay attention to details or exact calculations, but rather make decisions based on simple and vague distinctions (Peng et al., 2017; Reyna & Brainerd, 1991). Another advanced reason for framing effects is affective theory (Peng et al., 2017). This theory holds that framing results from emotional responses; those in a loss frame, for example, minimize negative emotions by compensating with positive emotions (Peng et al., 2017).

Other related developments in the framing space regard the underlying brain activity involved during decision making—known as neuroeconomics (Kahneman, 2011). As applied to framing, the amygdala tends to be active when choices conform to a frame; the anterior cingulate tends to be active when choosing the unnatural choice; and those who are least susceptible to framing effects tend to have active frontal areas of the brain (Kahneman, 2011).

Regulatory Focus Theory

In addition to prospect theory's examination of message framing, another key related theoretical framework is regulatory focus theory (Higgins, 1998; Yi & Baumgartner, 2009). Higgins (1997) noted that, "people are motivated to approach pleasure and avoid pain" (p. 1280). This simple principle—known also as the hedonic principle—undergirds many psychological theories about human motivation and behavior (Higgins, 1997).

Self-regulatory theory posits that the hedonic principle operates differently when serving different needs, such as nurturance and security (Higgins, 1997). In other words, other than the hedonic nature of the outcome, decisions can be made based on whether "the imagined prospective outcome sustains [the individual's] current regulatory state" (Idson, Liberman, & Higgins, 2004, pp. 926-927). Regulatory focus theory, then, "delineates how people engage in self-regulation, the process of bringing oneself into alignment with one's standards and goals" (Brockner, Higgins, & Low, 2004, pp. 203-204).

Under regulatory focus theory, there are two styles, promotion focus and prevention focus (Higgins, 1997; Yi & Baumgartner, 2009). Under this theory, "people are motivated to approach desired end-states, which could either be promotion-focus aspirations and accomplishments or prevention-focus responsibilities and safety" (Higgins, 1997, p. 1282). Regulatory focus theory was therefore "concerned with how people approach pleasure and avoid pain in different ways" (Higgins, 1997, p. 1282). In other words, there were different "goal-pursuit strategies" for each orientation (Cesario, Higgins, & Scholer, 2008).

Those that are in a promotion focus are oriented towards satisfying hopes, aspirations, and accomplishment (Idson, Liberman, Higgins, 2004). So, promotion-focus actors tend to prefer "eager strategic means" of goal attainment—meaning that success is the presence of positive outcomes and failure is the absence of positive outcomes (Cesario et al., 2008; Idson et al., 2004). For those in a prevention focus, they aim to meet their duties and responsibilities; the goal is security. So, they tend to use "vigilant strategic means" of goal attainment—meaning that success is the absence of negative outcomes, and failure is the presence of negative outcomes (Cesario et al., 2008; Idson et al., 2004).

Bringing it together, promotion- and prevention-focused self-regulation vary along three dimensions (Brockner et al., 2004). First, the underlying motives being satisfied. Second, the nature of the goals or standards being obtained. And third, the types of outcomes that are most salient (Brockner et al., 2004). For example, those who are promotion-focused, growth and advancement tend to motivate them, so potential gains are more salient; whereas, those that are prevention-focused, their need for security or safety make avoiding potential losses more salient (Brockner et al., 2004).

An outgrowth of regulatory focus theory is regulatory fit. Regulatory fit refers to when an individual pursues a goal that sustains their current regulatory state (Idson et al., 2004). Regulatory fit "places special emphasis on the relation between the motivational orientation of the actor and the manner in which that actor pursues the goal" (Cesario et al., 2008, pp. 444-445). So, when a person uses means that sustain his or her respective orientation, regulatory fit is experienced (Cesario et al., 2008). In short, regulatory fit is the "increased motivational intensity that results when there is a match between the manner in which a person pursues a goal and his or her goal orientation" (Aaker & Lee, 2006, p. 15).

In addition to increased engagement strength, another potential benefit is a sense of "feeling right" about the activity (Cesario et al., 2008). For example, a task that regards advancement would fit a promotion focus, but not a prevention focus; a carefulness task, on the other hand, fits a prevention focus (Idson et al., 2004). Regulatory fit is important because prior literature indicates that it increases motivational intensity (Idson et al., 2004; Shah, Higgins, & Friedman, 1998). Of course, this is relevant to decision making and framing.

Idson et al. (2004) examined the effect of regulatory fit on prospective choice. They hypothesized that regulatory fit "increases the intensity of people's motivation to approach or avoid different alternatives and thereby also influences evaluative responses toward those alternatives" (p. 928). Using regulatory focus theory and regulatory fit, then, those in a promotion focus should have stronger motivation and feel more positive towards a desirable prospective choice; whereas, on the other hand, those in a prevention focus should have a stronger motivation to avoid when anticipating an undesirable choice (Idson et al., 2004).

Relatedly, Cesario et al. (2008) explained that regulatory fit was particularly relevant to motivate behavior change or to increase message effectiveness. Indeed, regulatory fit has been examined in myriad contexts and situations with respect to persuasion (Cesario et al., 2008). In many of these studies, message framing has been examined, too. For example, Cesario, Grant, and Higgins (2004) examined the impact of regulatory fit and message framing on, among other things, the persuasiveness of messages on eating more fruits and vegetables. The message framing concerned "eager" framing (gain/non-gain) and "vigilant" framing (non-loss/loss). They found a significant interaction effect between regulatory focus and type of framing, meaning a regulatory fit effect—those in the promotion-focused condition showing increased intention ratings with the eager framing (compared to vigilant framing), and the opposite in the prevention-focused condition (i.e., showed greater intentions with the vigilant framing) (Cesario et al., 2004).

Similarly, Spiegel, Grant-Pillow, and Higgins (2004) explored the impact of regulatory focus and outcome framing (benefits and costs) on fruit and vegetable consumption; they, too, found a significant interaction effect between regulatory focus and message framing—in particular, promotion-focused messages focusing on benefits were more effective than messages focusing on costs, and prevention-focused messages focusing on costs were more effective than those about benefits (Spiegel, Grant-Pillow, & Higgins, 2004).

Lee and Aaker (2004) applied regulatory fit to message framing and looked at grape juice consumption and attitudes towards sunscreen. They found that promotion-focused appeals were more effective when gain-framed, and prevention-focused concerns were more effective when loss-framed.

As another example, Yi and Baumgartner (2009) examined whether the persuasiveness of a message was improved when it matched chronic regulatory focus. They, too, found that, generally, gain end-state messages were more persuasive than those anchored by loss end-states. Similarly, that positive-valence frames were more persuasive than negative ones; and, that frames emphasizing security were more effective than achievement frames (Yi & Baumgartner, 2009).

In sum, regulatory focus literature demonstrates at least three ways that it and message framing intersect (Yi & Baumgartner, 2009). First, as noted, if a person is promotion focused, then he or she will be extra sensitive to gain end-states (i.e., positive outcomes) (Higgins, 1997).

On the other hand, if the person is prevention focused, he or she will be more sensitive to the presence (or absence) of negative outcomes (Higgins, 1997). Similarly, Idson, Liberman, and Higgins (2000) noted that promotion-focused individuals exhibited more eagerness in working towards gains (compared to non-gains) and prevention-focused individuals exhibited greater vigilance in preventing losses (compared to non-losses). Second, literature suggests that message valences that are congruous with regulatory focus are more persuasive (Yi & Baumgartner, 2009). Third, whether a message concerns achievement or security can interact with their focus (Yi & Baumgartner, 2009).

Framing and Valence Effects

As Hasseldine and Hite (2003) importantly emphasized, "the concept of framing means different things to different people" (p. 519). For example, Druckman (2001) listed at least seven definitions of framing used by scholars, which he classified as either frames-in-communication or frames-in-thought. Frames-in-communication regard what the *speaker* sees as important; whereas, frames-in-thought describes more the *individual's* perception of the situation—i.e., what the receiver of the communication views as important (Druckman, 2001). So, while both frames concern emphasis or salience, they differ on the reference: the speaker or the listener. This dissertation, then, focused on frames-in-thought.

Prior literature often examined valence framing effects, "wherein the frame casts the same critical information in either a positive or a negative light" (Levin, Schneider, & Gaeth, 1998). The literature has identified three different types of commonly used frames (Biswas & Grau, 2008; Levin et al., 1998). First, was risky-choice framing. As explained by Levin et al. (1998), "discrete choices between a risky and a riskless option of equal expected value depended on whether the options were described in positive terms (i.e., lives saved) or in negative terms (i.e., lives lost)" (p. 152). At bottom, these frames present different levels of risks in different ways (Levin et al., 1998). This was the type of framing first introduced by Tversky and Kahneman (1981). Under these frames, individuals are more risk-seeking when avoiding losses than when realizing gains; this, of course, gave rise to the S-shaped value function in prospect theory.

The second type of framing was attribute framing (Biswas & Grau, 2008; Levin et al., 1998). This type of framing may be the "simplest case of framing" (Levin et al., 1998, p. 158). Typically, only a single attribute was framed (Levin et al., 1998). In this context, the relevant measure was the overall evaluation—like an overall degree of favorability—rather than a choice between two discrete options. Under attribute framing, positive framing was more associated with positive evaluations than negative framing (Biswas & Grau, 2008; Levin et al., 1998).

The third type of framing was goal framing (Biswas & Grau, 2008; Levin et al., 1998). Goal framing refers to the individual taking an action or moving towards a goal (Biswas & Grau, 2008). Levin et al. (1998) described a critical difference between goal framing and attribute framing, namely that, in goal framing, the behavior at issue was considered beneficial or good in both frames (Levin et al., 1998). In the positive frame, the benefits of engaging in the behavior were extolled (i.e., the gains that were associated with doing the behavior); whereas, the negative frame described avoiding the losses associated with not doing the behavior (Levin et al., 1998).

As relevant here, Cesario, Corker, and Jelinek (2013) aptly described gain/loss message framing as casting the outcomes of a behavior in terms of "either the benefits afforded by adopting the recommendation or the costs associated with failing to adopt it" (p. 238). The differences in persuasiveness between gain- and loss-framed messages is rooted in the asymmetries between positive and negative information—that is, negative information is more powerful (O'Keefe & Jensen, 2006). There were several posited reasons for this asymmetry. First, "negative information generally has a disproportionate impact on decisions compared with equivalent positive information" (O'Keefe & Jensen, 2006, p. 2). Second, negative stimuli may be detected earlier (at lower levels) than positive stimuli (Dijksterhuis & Aarts, 2003; O'Keefe & Jensen, 2006). Third, negative events may evoke stronger and quicker reactions (O'Keefe & Jensen, 2006; Taylor, 1991). In sum, negative information is more powerful and potent than positive information.

Empirical Examinations of Framing

Framing has been investigated empirically in various contexts and domains, ranging from health care and medical decisions, marketing and consumer product choices, energy saving behavior, and in financial-related contexts. Framing effects in the consumer decision-making context, in particular, have generally been empirically validated (e.g., Biswas & Grau, 2008).

Despite this, in a meta-analysis, Kuhberger (1998) examined over 100 papers about framing effects. He concluded that framing effects, empirically, tended to be of small to moderate size, and that material differences existed between research designs. He further noted that, based on this analysis, the two most important elements were whether the framing was achieved by modifying the reference point or by manipulating outcome salience, and the response mode, i.e., choice versus rating. At bottom, he concluded that, although framing may be a "reliable phenomenon," researchers should distinguish between salience manipulations and reference point manipulations, and care should be given to the experimental design and its effect on framing-effect sizes. Relatedly, in their meta-analysis, O'Keefe and Jensen (2006) argued that "gain-framed and loss-framed appeals do not generally differ in persuasiveness" (p. 16).

Examining framing in different contexts is important because perception of gains and losses—just like perceptions of risk—may vary (Ganzach & Karsahi, 1995; Jacoby & Kaplan, 1972). Consequently, the framing-related literature in several contexts and domains was reviewed.

Marketing and Product Message Framing

Framing has been examined in the marketing and consumer product literature. In the marketing literature, a key concept is consumers' "willingness to pay" (WTP), referring to the maximum amount of money they will pay for a product or service (Ayadi & Lapeyre, 2016). WTP is a function of the perceived trade-offs between the benefits and costs of the product or service (Ayadi & Lapeyre, 2016). Ayadi and Lapeyre (2016), for instance, examined the effect of framing on consumer perceptions as applied to "green" products. They hypothesized a relationship between different frames and the shaping of consumers' WTP; as applied to framing, in particular, they hypothesized that framing the ecological message moderates the influence of WTP on purchase intentions. Positive frames, they noted, stress the ecological contribution of the product; whereas, negative frames highlight the prevention of the negative outcomes. They found a moderating effect of ecological messages on the WTP-intentions relationship, with the relationship stronger for negative framing (Ayadi & Lapeyre, 2016).

Biswas and Grau (2008) explored the intersection of option framing (e.g., added extra options to a base-level car) and cognitive resources (as measured by memorization and recall ability of a number sequence). They found an interaction effect between option framing and cognitive resources; in particular, that under low levels of cognitive ability, respondents were more likely to favor default options (a status quo bias). They also concluded that cognitive constraints serve as a moderator of framing effects, indicating a loss-aversion relationship (Biswas & Grau, 2008).

A classic consumer product framing example was Levin (1987) (Donovan & Jalleh, 1999). Levin investigated the role of information on the evaluation of a single stimuli (Levin, 1987); the simple task was for respondents to indicate their associations to a purchase of meat that was described as either 75% lean or 25% fat (with "lean" being a positively associated frame and "fat" being a negatively associated frame). He found that responses were evaluated more favorably—across several criteria, such as taste and quality—for the positive-framed description. Based on these results, he explained that "the stimulus label elicits associations which, in turn, affect the evaluation of the stimulus object" (1987, p. 86). In other words, describing the stimuli in more positive terms (e.g., lean meat) leads to more favorable associations.

Gamliel and Herstein (2007) examined the effect of framing on a consumer's willingness to buy private brands (those owned and sold by the retailer itself). In particular, they explored the negative and positive framing of the price differential between the private brand and the national brand. The negative frame was couched as "losing" the spread between the national brand and the private brand; the positive frame was couched as an equal savings. They found that the negative framing was related to more decisions to buy the private brand (Gamliel & Herstein, 2007). Squaring their results with prospect theory, they explained that the subjective value of the gain was less than the subjective value of the loss (Gamliel & Herstein, 2007).

Another related empirical example was price discounting. A price discount can be expressed different ways—i.e., as a percent reduction, dollars off, or volume discount (buy one, get one free) (Gendall et al., 2006). Gendall et al. (2006), for example, argued that, generally, price discounts expressed as dollars-off or cents-off were better than percent-off for high-priced products and that the opposite was likely true for low-price products.

Health Message Framing

Message framing has been extensively studied in the medical literature, in particular in framing health communication (e.g., to encourage a particular behavior, such as engaging in regular exercise) (Gallagher & Updegraff, 2012). Much of the health behavior framing literature focuses on intentions or attitudes towards the behavior, which is of particular importance to this dissertation (as it focused on intentions, too) (Gallagher & Updegraff, 2012). Admittedly, this was a practical limitation, as intentions and actual behaviors may diverge (Gallagher & Updegraff, 2012; Webb & Sheeran, 2006).

In the health domain, message framing has been examined in two general contexts—public health decisions and personal health decisions (Rothman & Salovey, 1997). Indeed, scholars have noted increased efforts to integrate psychological theories into health campaigns to improve effectiveness (Jasper, Woolf, & Chrisman, 2014).

In the public health context, the disease problem—as originally advanced by Tversky and Kahneman (1981)—demonstrated that framing alters decision preferences (Rothman & Salovey, 1997). The disease problem has been replicated in other related contexts, such as in nuclear accidents, gas explosions, and cancer (Rothman & Salovey, 1997). Shifting to personal health decisions, Rothman and Salovey (1997) noted that, in addition to framing, context matters, too. In other words, the framing was not the only information available; prior perceptions—such as family history of a specific disease—facilitated the impact of the framed message. Cho and Boster (2008), for example, found that antidrug ads that focused on the negatives of drug use were more persuasive (relative to ads focusing on the positives of drug abstinence) but only for those that had friends who used drugs.

Detweiler et al. (1999) aptly synthesized the application of prospect theory and framing to health choices. Under prospect theory, one would expect that people were risk averse when gains were emphasized (i.e., made salient); but they were risk-seeking when losses were emphasized. In addition to this general framework, Rothman and Salovey (1997) argued that the function of the health behavior affects the framing effect. There are three general functions of health behaviors: (a) to prevent, (b) to detect, and (c) to treat. The function of the behavior can affect the perceived risk of the behavior (e.g., a detection behavior can be seen as risky due to the prospect of identifying illness) and thereby influence the framing effect.

Loss-framed information may be best served to promote detection behaviors due to their ability to detect illnesses (Rothman & Salovey, 1997). For example, loss framing increased participants' positive attitudes about breast self-examinations (Meyerowitz & Chaiken, 1987), mammography screenings (Banks et al., 1995), blood-cholesterol screenings (Maheswaran & Meyers-Levy, 1990), skin cancer exams (Block & Keller, 1995), and even HIV testing (Kalichman & Coley, 1995). Because the loss framing effect depends on the assessment of the underlying risk, the individual's understanding of the detection behavior potentially affects their loss sensitivity (Rothman & Salovey, 1997). In the breast exam context, for example, Rothman and Salovey (1997) noted that a woman who actually worried about finding a lump would be particularly sensitive to loss framing—but those with a lesser perceived risk of finding a lump may be less affected by loss framing.

Unlike detection behaviors, prevention behaviors allow people the ability to maintain current health and reduce risk of future health maladies (Rothman & Salovey, 1997). One critical difference between detection and prevention behaviors was the perceived degree of proximal risk (Detweiler at al., 1999). In other words, detection behaviors—such as a Pap smear or mammography—are considered risky at the time of the test as the test can uncover the loss (the disease or health malady) (Detweiler at al., 1999).

A classic example of a prevention behavior was sunscreen use; applying sunscreen is a relatively risk-free behavior—it is the lack of the behavior (applying the sunscreen) that carries the risk. As Rothman and Salovey (1997) noted, because loss framing encourages risky preferences, loss framing may actually be counter-productive for preventative behaviors. Therefore, gain framing should be used to promote preventative health behaviors. This has been borne out empirically; for instance, Christopherson and Gyulay (1981) demonstrated that focusing on positive consequences increased usage of car seats, and Linville, Fischer, and Fischhoff (1993) regarding condom use. Similarly, Rothman et al. (1993) showed that women exposed to a gain-framed message (compared to a loss-framed message) were significantly more likely to request a higher level of SPF sunscreen. Detweiler et al. (1999) showed that positive framing was successful in persuading beachgoers to use sunscreen.

Treatment, or recuperative, behaviors ameliorate an existing health or medical problem (Rothman & Salovey, 1997). Rothman and Salovey (1997) argued that treatment behaviors should be similar to prevention behaviors in terms of framing; that is, to undergo the treatment is normally seen as a risk-averse (safer) option relative to no treatment (and succumbing to the malady). For surgical decisions, for example, gain-framed information (as to the likelihood of survival) has resulted in greater participation (Rothman & Salovey, 1997). In addition to choosing simply treatment or non-treatment, choice can also be structured between two different treatments. Consider, for example, the decision to undergo radiation or surgery for cancer treatments. McNeil et al. (1982) showed that loss framing the likelihood of dying led to decreased preferences for surgery—in these cases the framing was based on the short- and long-term consequences (e.g., better long-term survival but greater risk of surgical-based death in the short-term).

It is important to emphasize and provide a theoretical justification for the divergence in these framing results (Rothman et al., 1999). The predominant view, as advanced by Rothman and Salovey (1997), was the behavioral function, as explained above, provided a theoretical justification for different frames having different results on behaviors. Because detection behaviors informed people that they were sick, detection behaviors could be considered risky decisions (exposing people to bad news) despite their long-term benefits (Rothman et al., 1999). On the other hand, prevention behaviors merely reduce or mitigate a potential future illness—and, in the short-run, maintain the health status quo; as such, they are not risky decisions (in fact, the only risk involved is *not* engaging in the behavior) (Rothman et al., 1999).

Empirically, this framework was demonstrated by Rothman, Martino, Bedel, Detweiler, and Salovey (1999) that examined mouth rinse that was designed to be either a detection behavior (detecting plaque) or prevention behavior (preventing plaque); thus, there was a single health behavior that could serve either function. There, after the loss-framed message, participants were more likely to request samples of a plaque-detecting rinse; but, after the gain-framed message, were more likely to request the plaque-preventing rinse (Rothman et al., 1999). This phenomenon was similarly replicated in the Pap test context by Rivers et al. (2005), as a Pap test can be framed in either a prevention frame (e.g., preventing cervical cancer from developing) and a detection frame (detecting early cervical cancer).

Another view, advanced by Mann, Sherman, and Updegraff (2004), on the other hand, emphasized a person's dispositional sensitivity to favorable or unfavorable outcomes and this moderated the effect of message framing. That is, individual differences interact with the framing effect. In particular, Mann et al. (2004) focused on the approach and avoidance motivations. These were related to behavior regulation, similar to the prevention/promotion focus advanced by Higgins (1997). The approach system (e.g., the behavioral activation system, "BAS") controls appetitive motivation and the avoidance system (the behavior inhibition system, "BIS") controls aversive motivation. Accordingly, those with BAS sensitivity respond to reward and incentive cues, and those with BIS sensitivity respond to punishment and threat cues (Carver, Sutton, & Scheier, 2000; Mann, Sherman, & Updegraff, 2004). Consequently, under this view, individual dispositional motivation needs to be examined along with message framing to understand and predict behavioral effects.

Rothman and Salovey (1997) also hypothesized that, in addition to the nature of the behavioral function, frequency may also matter—for example, a single vaccine with lifetime protection is different than sunscreen that must be applied repeatedly. Robbertson (1975), for instance, suggested that loss framing may not be effective for those behaviors that require continued effort (like sunscreen application), but may be effective to promote a one-time behavior (like a vaccine).

Another potential moderator of framing effect is the risk (or perceived risk) of the behavior. This has been demonstrated in several contexts. Apanovitch, McCarthy, and Salovey (2003) considered this in the context of HIV testing. Although HIV testing is a detection behavior—such that loss-framing should be particularly effective—those with lower-perceived risks of testing positive responded favorably to gain framing; whereas, those with higher perceived risks responded to loss framing, as expected (Apanovitch et al., 2003). Explaining this, they noted that for those with a lower perceived risk (based on known past physical practices), HIV testing was a psychologically safe behavior with basically a certain outcome and therefore persuaded by gain framing. On the other hand, those with a higher perceived risk of testing positive faced a more uncertain test outcome and therefore were more susceptible to loss framing.

Similarly, Abhyankar, O’Connor, and Lawton (2008) considered risk as a moderator on the effect of framing and the MMR vaccine. Although vaccines are prototypical prevention behaviors (by definition), some vaccines may have perceived health risks, like the MMR vaccine. Here, they found that loss-framing (rather than gain-framing) was more effective in increasing MMR intentions. They attributed this finding to the degree of perceived risk in obtaining the vaccine (i.e., the MMR vaccine is potentially risky) (Abhyankar, O’Connor, & Lawton, 2008).

Rothman and Salovey (1997) further proposed that the decision-making process is influenced by framing in three stages of the decision process. First, the attention given to the message affects the degree to which a mental representation is formed. Second, subjective experience and context can affect individual receptivity to the framing. Third, the influence of the framing depends on the perceived function of the behavior (as described above).

Rothman and Salovey (1997) argued that framing can only be influential if the framed information becomes a part of the cognitive representation of the issue. Thus, considering how the information is processed is of paramount importance. In terms of persuasive appeals, there are two modes of processing; systematically, referring to focusing on the details of the message, and heuristically, referring to the surface level of the message (Petty & Cacioppo, 1986;

Rothman & Salovey, 1997). Systematic processing is more associated with persuasiveness of gain- and loss-framed information (Takemura, 1992, 1993; Wegener, Petty, & Klein, 1994). Systematic processing can be affected by contextual variables, such as being involved or interested in the particular issue (Rothman & Salovey, 1997). Maheswaran and Meyers-Levey (1990) also argued that personal involvement with an issue affects the effectiveness of framing. According to their argument, negatively charged (valence) information has more effect when systematically processed. Thus, if there is a high degree of personal involvement, there is an advantage to use loss framing. Though, Rothman and Salovey (1997) noted that this argument cannot account for certain preference reversals or some gain-framed effectiveness for highly involved persons.

Financial Context Framing

Framing effects have been studied in the financial context, too. An early example in financial domains—although not expressly invoking the concept of framing—is Dickson (1981). Dickson demonstrated that a difference in risk attitudes between professional risk-managers and professional non-risk managers, all of whom were business managers with years of work experience. In loss-framed scenarios (in which there was a prospect of loss), the risk managers were more risk averse; but the groups were not different in profit (gain) scenarios.

Another early empirical example was Ganzach and Karsahi (1995), who examined the influence of framing in credit card usage. The loss-framed message explained the disadvantages of using cash or checks (compared to the credit card), and the gain-framed message discussed the mirror-image issue set in a positive light. They concluded that loss framing had a stronger effect on credit card behavior—with those subjected to the loss-framed message more than doubling usage (Ganzach & Karsahi, 1995).

Roszkowski and Snelbecker (1990) explored framing effects on the risk tolerances of financial planners (who are routinely dealing with risk and financial management). They used the classic Kahneman and Tversky human-life based choices and substituted dollars for lives and constructed the scenario around stock market investments; in addition to the gain and loss framing, they also introduced an ownership element, i.e., "your" money as compared to "client's" money. Roszkowski and Snelbecker (1990) found, among other things, a significant main effect for frame and a significant three-way interaction between age, ownership, and frame. In particular, that gain framing led to avoiding risks and loss framing led to taking risks. Thus, they concluded that even professional financial planners are subject to the same framing biases.

Framing has also been examined in other financial planning-related domains. Hasseldine and Hite (2003) examined the effect of framing (in particular, goal framing) in the tax compliance setting. They found a lack of a main effect for framing manipulation but did find a significant interaction effect between framing and gender (Hasseldine & Hite, 2003). Specifically, their results suggested that men were more persuaded by the negative message, but women were more persuaded by the positive message.

Pincus, Hopewood, and Mills (2017) examined the distinction between statistical and narrative evidence framing in the context of buying long-term care insurance. They argued that insurers have traditionally framed the insurance purchasing decision in a suboptimal manner by couching it in terms of a high probability loss frame.

Other Empirically Examined Influencers of Framing

Feelings, mood, and disposition can also affect the influence and receptivity to message framing (Rothman & Salovey, 1997). At the simplest level, current mood may affect whether a situation is interpreted in terms of gains or losses (Rothman & Salovey, 1997). There is some theoretical examination in the literature about mood congruency—that is, a specific mood may influence how a situation is perceived—but little direct empirical examination (Rothman & Salovey, 1997). An example of the intersection of mood congruency and framing would be that loss-framed arguments are more effective (persuasive) if the respondent is in a sad mood. Although current mood may play a role, chronic disposition (optimistic or pessimistic) might also shape the influence of framing (Scheier & Carver, 1985).

The literature also explored the effect of other individual-level characteristics on the framing effect. In the health messaging literature, for instance, Updegraff et al. (2007) found that tailored messages—those in which the message matches the recipient's motivational orientation (as determined by the BIS/BAS scale (Carver & White, 1994))—can be more effective than untailored messages. Another example of individual-level characteristic is that of health locus of control. Health locus of control refers to a person's perception of control over their health outcomes—that is, is their health status determined by their own behavior or external forces (Williams-Piehota et al., 2004). Williams-Piehota et al. (2004) found that, with respect to mammography utilization, messages matched with health locus of control were more likely to motivate behavior, and that this effect was particularly strong for internally focused subjects. This resonated with prior work done by Quadrel and Lau (1989), which found that health locus matched messages were more likely to motive breast self-exams (with the benefit primarily demonstrated by internally focused subjects).

Narratives

Not only can the positive or negative valence of information (as explored above) affect decision making, other research has also explored the presentation of that information (agnostic as to its valence charge). Although not framing per se, one example is the use of jargon versus simple description. James (2018), for example, found that using technical jargon instead of simple descriptions of financial planning techniques resulted in decreased understanding and decreased interest in learning about those techniques. Similarly, James (2016) found that different phrases related to requests to leave charitable bequest resulted in different interest levels.

Another presentation-related approach is narrative framing—that is, in effect, presenting information in a story-like format instead of a strictly fact-based (or even statistical-based) presentation. Under this approach, the presentation of the information—in a story like manner—elicits a different emotional response in the decision-maker. This phenomenon is akin to framing because it hypothesizes that choice is not a function of strictly mathematic utility under uncertainty, but rather the choice is affected by how the information is presented (like the thought experiments in the prospect theory literature) (Carlsson Hauff et al., 2014).

This approach exploits what has been dubbed the "affect heuristic," in which emotions play important roles in decision making (Carlsson Hauff et al., 2014). Relatedly, under the affect heuristic, the risks and benefits of an activity may be judged by the associated negative and positive feelings associated with it (Finucane, Alhakami, Slovic, & Johnson, 2000). Indeed, Alhakami and Slovic (1994) noted that, if an activity was "liked," people tend to judge the risk as low and the benefits as high; whereas, on the other hand, if the activity was "disliked," the opposite was true.

In the literature, a "narrative" refers mainly to "stories, accounts, tales, or descriptions" (Carlsson Hauff et al., 2014, p. 497; Shankar et al., 2001). They are normally chronologically weaved together by causal events to portray a particular plot or meaning (Hauff et al., 2014). Bennett and Royle (2016) defined narrative as "a series of events or actions which are connected in time" (p. 55). Stories and narratives are pervasive in our existence, starting as soon as early childhood (Shankar et al. 2001). Moreover, most of the information that we actually obtain in our daily lives is conveyed by narrative (Wentzel et al. 2010). Relatedly, others have argued that the human memory system uses narratives to store knowledge (Schank & Abelson, 1955); and that narrative and story structure helps us store and retrieve ideas (Myrsiades, 1987). Shankar, Elliot and Goulding (2001) aptly noted that, "It is inconceivable to think of our lives without stories: whether listening, watching or reading them, or telling them" (p. 431).

Scholars and researchers have described narratives as a "source of sense-making," which affect our emotions and help us find meaning (Carlsson Hauff et al., 2016, p. 153; Mossberg, 2008). Indeed, narratives are an important way that experiences are made meaningful (Polkinghorne, 1988; Shankar et al., 2001). Scholars trace the origins and use of narrative to at least back to Aristotle, namely his work *Poetics* (Shankar et al., 2001). In western culture, Gergen and Gergen (1988) synthesized the following key features of narratives: (a) the valued end point; (b) events relevant to the goal estate (that help make the point); (c) a particular order of the events; (d) causal sequencing; and (e) demarcations (i.e., beginning, middle, and end). Relatedly, there tends to be four basic plot structures—comedy, romance, tragedy, and satire (Frye, 1957; Shankar et al., 2001).

Narrative processing refers to how individuals process and make decisions related to stories (Carlsson Hauff et al., 2014). Narrative processing may encourage the individual to think of themselves in the narrative or evoke autobiographical memories (Carlsson Hauff et al., 2014; Sujan et al., 1993). Narrative processing also encourages the establishing of meaningful relationships between the narrative elements (Wentzel, 2010). Narrative processing helps individuals make meaning of the information; this aspect is known as "transportation," which refers to the individual transporting themselves into the narrative (Carlsson Hauff et al. 2014, 2016; Gerrig, 1993; Green & Brock, 2000; Woodside et al., 2008). Formally, Green and Brock (2000, 2002) dubbed this the "Transportation-Imagery Model" of narrative persuasion.

Due to the transportation, the reader may be given a taste of the consequences described by the narrative (Padgett & Allen, 1997; Wentzel, 2010). During transportation, the reader gives exclusive focus to the story; this can lead to a sense of a more "real" experience, which can create affect and feeling (Carlsson Hauff et al., 2014). It is the concept of transportation that advances that emotive response is increased (Carlsson Hauff et al., 2014; Escalas, 2004; Mar & Oatley, 2008). In sum, it is this emotional response (affective aspect) that makes narratives effective forms of persuasion (Oatley, 2002). Wentzel et al. (2010), however, showed this may not always be the case; they demonstrated that, when manipulative intent is made salient—i.e., the reader feels he or she is being manipulated (e.g., being flattered before a purchase)—the advantage of narrative ads over fact ads disappears.

The express use of narratives in the consumer space is probably most obvious in the advertising context—like a commercial that tells a short story; for example, Escalas (1998) performed a content analysis study and found that over 20% of ads used well-developed stories. Past literature in this space has generally found that narrative ads receive more favorable evaluations than fact-based ads (Wentzel et al., 2010). In the advertising space, researchers posit that the narrative structure triggers narrative processing (Adaval & Wyer, 1998; Escalas, 2004; Polyorat, Alden, & Kim, 2007; Wentzel et al., 2010). As noted above, the narrative processing enhances persuasion by increasing emotional (affective) reactions (Deighton, Romer, & McQueen, 1989; Green & Brock, 2000; Wentzel et al., 2010). As argued by Wentzel et al.

(2010), "to the extent that the ad conveys a positively valenced experience, narrative processing and transportation are likely to elicit affect that is also positive in nature" (p. 512).

Fact-based ads, on the other hand, trigger more analytical processing, which does not necessarily trigger an emotional response (Wentzel et al., 2010). These types of ads trigger analytical processing that "attempts to fulfill the ideal of a formal, mathematical system of description and explanation" (Bruner, 1986, p. 12).

Narratives have been used in other contexts, too, such as in healthcare decision making (Winterbottom et al., 2008). In this setting, narratives are a type of decision aid, designed to help patients make treatment choices (O'Connor et al., 2003; Winterbottom et al., 2008). Although decision aids have been historically up-to-date fact-based information about the treatment, a more recent development is to present them as patient narratives (instead of factual information) (Elwyn et al., 2006; Winterbottom et al., 2008). In a systematic review of the medical literature, Winterbottom et al. (2008) found that narrative information affected decision making in about of a third of reviewed studies (17 studies met the inclusion criteria), and that first-person narratives tended to have increased likelihood for having an effect.

The power of narratives has even morphed into what some scholars have dubbed the "narrative bias" (Betsch, Haase, Renkewitz, & Schmid, 2015). The narrative bias refers to the phenomenon of the "excessive influence of narrative information, exemplars, and testimonies" (Betsch et al., 2015, p. 241). The classic example of narrative bias is demonstrated by Borgida and Nisbett (1977). In that study, they found that brief, face-to-face comments about college courses had a greater effect on course selection than average course evaluation scores. As Betsch et al. (2015) explained, "such reasoning is considered to be biased, i.e., formally incorrect, because it fails to weigh different samples of data according to the respective sample size" (p. 241).

Negativity Bias

Related to the narrative bias generally, is that of a potential "negativity bias" (Betsch et al., 2015). Baumeister et al. (2001) poignantly commented that "bad is stronger than good." In short, negative-valenced events are stronger than their positive counterparts (e.g., losing money as compared to winning money). More specifically, negativity bias refers to the phenomenon of weighing information about the *presence* of a risk more strongly than information about the *absence* of the risk. As relevant to narrative framing, negativity bias implies that narratives may have an asymmetric effect by portraying or implying a higher risk than that borne by factual, statistical information (Betsch et al., 2015).

Rozin and Royzman (2001) developed a four-type taxonomy of negativity bias. First, was negativity potency, which refers to the negative event being more potent and more salient than its positive counterpart (Rozin & Royzman, 2001). Negativity potency is, in effect, derived from the prospect function and loss aversion, as described earlier regarding prospect theory. Second, greater steepness of negative gradients refers to the notion that "negative events grow more rapidly in negativity as they are approached in space or time than do positive events" (Rozin & Royzman, 2001, p. 298). Third, was negativity dominance, which refers to the phenomenon that holistic perceptions of positive and negative events are more negative than just their mathematical or algebraic sums (Rozin & Royzman, 2001). Fourth, was negative differentiation, which refers to the notion that "negative stimuli are generally construed as more elaborate and differentiated than the corresponding positive stimuli" (Rozin & Royzman, 2001, p. 299). A typical example of negative differentiation are the words used to describe negative phenomenon is richer and more varied than positive stimuli (Peeters, 1971; Rozin & Royzman, 2001).

Financial Narratives

Researchers have examined narratives in financial-related domains. Carlsson Hauff et al. (2014) examined the effect of narrative versus fact framing on consumers for retirement savings decisions. They hypothesized that narrative-format information, compared to strictly fact-based information, in the financial context would result in a stronger positive affect, which, in turn, leads to a stronger emotive response, culminating in stronger intention (e.g., to purchase a financial product like a mutual fund). They found that, indeed, narrative formats evoked stronger positive affect and emotive responses.

In another experiment, Carlsson Hauff et al. (2016) examined whether the level of trust in the sender of a narrative versus fact-related information influenced intentions to save in a mutual fund. Like the prior study, they hypothesized that the narrative format increases positive affect, which in turn increases interest, and this increased interest leads to increased intentions to save; and, specific to this study, that trust in the sender increases intention to save. Again, they largely confirmed their hypotheses.

Herzenstein, Sonenshein, and Dholakia (2011) examined the role of narratives in peer-to-peer lending. They hypothesized that narrative information allows potential borrowers to manage the communication of their identity and facilitate impression formation and management (e.g., trustworthiness, successfulness, morality, religiosity, etc.)—in short, how a stranger (the creditor) will view the borrower. They found that those with poorer credit scores generated more identities (perhaps trying to overcompensate for lower objective credit information), and lenders favored seeing more aspects of identity; indeed, this was true for identities related to being trustworthy and successful.

James and Routley (2016) examined the impact of donor stories on charitable bequest giving intentions. There, they asked respondents to review a vignette that was about a deceased donor or a living donor (images of the donor were also present). In accord with an avoidance response to mortality salience, they found that stories about living donors generated more interest than stories relating to deceased donors. As such, they suggested that stories can increase bequest intentions (James & Routley, 2016).

Examining Behavioral Intentions

This study examined financial planning intentions and not actual behavior. Therefore, the theoretical justification for examining intentions specifically and the related empirical work on intentions are discussed next.

Theoretical Importance of Intentions

Gordon Allport, the famed American psychologist and considered a father to personality psychology, wrote that the attitude concept is "the primary building stone in the edifice of social psychology" (1954, p. 45). Despite this apparent psychological consensus in the mid-20th century, Wicker (1969) famously argued in a meta-analysis that "little evidence" supports the existence of "stable, underlying attitudes within the individual which influence both his verbal expressions and his actions" (p. 75). In the wake of Wicker's critique, newer, more tailored models of the attitudinal-behavioral relationship were developed (Webb & Sheeran, 2006).

In modern psychological literature, intentions have been defined as "self-instructions to perform particular behaviors or to obtain certain outcomes" (Webb & Sheeran, 2006, p. 249). Forming an intention typically ends the deliberative process and indicates the effort to be exerted to effectuate the desired outcome (Webb & Sheeran, 2006). Intentions, then, are a key determinant of actual behavior (Webb & Sheeran, 2006).

Models of attitude-behavior relations—such as the theory of reasoned action, the theory of planned behavior, and the model of interpersonal behavior—all use intentions as a key predictor of behavior (Webb & Sheeran, 2006). The role of intentions in each of these models will be briefly discussed in turn.

The theory of reasoned action (TRA), as elucidated by Fishbein and Ajzen (1975), was created to predict volitional behavior. It holds that attitudes and subjective norms impact and affect behavior by their influence on the creation of intentions to engage in that behavior (Webb & Sheeran, 2006). Thus, behavior intention is the "proximal determinant" of actual behavior (Webb & Sheeran, 2006, p. 249). Moreover, under the TRA, intention also mediates attitudes and subjective norms, thereby making intention "the most immediate and important predictor of behavior" (Webb & Sheeran, 2006, p. 249).

Later, Ajzen (1985, 1991) added additional concepts to the TRA, creating the theory of planned behavior (TPB). The theory of planned behavior recognized that behaviors also require perceived and actual control over the behavior (Ajzen, 1991). In other words, whether the person believes the behavior to be easy or difficult also predicts actual behavior. Relatedly, the person must have actual control over the behavior. Thus, while the TPB also viewed intentions as the most important driver of behavior—indeed, Ajzen (1991) noted that, generally, "the stronger the intention to engage in a behavior, the more likely should be its performance" (p. 181)—it realized the role—and potential moderating effect—of behavioral control. A common theme, then, between the TRA and TPB was that intentions were a central focus, and "intentions are assumed to capture the motivational factors that influence a behavior and to indicate how hard people are willing to try or how much effort they would exert to perform the behavior" (Ajzen, 1991, p. 181; Armitage & Conner, 2001, p. 477).

Another commonly used behavioral-change model is the transtheoretical model (TTM) as elucidated by Prochaska and DiClemente (1984). As originally used, this model posited that there were five distinct stages through which people pursue and attain health goals—and the model has been now used outside the health context. The five stages are precontemplation, contemplation, preparation, action, and maintenance (Prochaska & DiClemente, 1984; Webb & Sheeran, 2006). Behavioral intention is not an express aspect of the model, but researchers and scholars have averred that, at a minimum, intention increases linearly across the first three stages of change (Godin, Lambert, Owen, Nolin, & Prud'homme, 2004; Sutton, 2000; Webb & Sheeran, 2006). Thus, progress through the stages can be viewed through the lens of increasing behavior intention (moving towards actual behavior and behavior modifications).

Intention is also a construct central to related areas, such as goal striving and self-regulation (Webb & Sheeran, 2006). In the goal striving context, under Locke and Latham's (1990) theory of goal setting, intention formation for a task is critical to promote goal achievement (Webb & Sheeran, 2006). Under control theory (Carver & Scheier, 1982), which regards self-regulation and comparing one's current state to an aspirational future state, intentions are a determinant of behavior change (Webb & Sheeran, 2006).

In sum, intention is an important aspect of contemporary behavioral models and related domains, such as goal setting and self-regulation.

Moderators of Intentions

Literature indicates that several variables may moderate (influence) the impact of intention on behavior (Webb & Sheeran, 2006). Webb and Sheeran (2006) synthesized the literature and delineated three classes of intention-moderating variables: (a) conceptual factors, which were "theoretically specified variables that are predicted to affect how well intentions are realized in behavior" (p. 252); (b) measurement factors, such as time intervals and method of measurement (e.g., objective versus self-reporting), which can influence the intention-behavior relationship; and (c) study characteristic factors, such as the type of sample (e.g., students versus non-student sample, in which students may have higher test-taking abilities or greater innate desire to answer consistently and congruently) (Webb & Sheeran, 2006).

Empirical Examinations of Intentions

In addition to the theoretical importance of behavioral intentions, intentions have been examined empirically as well. Webb and Sheeran (2006) synthesized the literature and noted that correlational studies demonstrated that intentions were associated with behavior, even across different theoretical frameworks (e.g., TPB versus TRA). Armitage and Connor (2001), for example, found in a meta-analysis of studies using the TPB that the average correlation between intention and behavior of .47. In applying the TRA and TPB to exercise behavior, the average correlation between intention and behavior was .47 (Hagger, Chatzisarantis, & Biddle, 2002; Hausenblas, Caron, & Mack, 1997; Webb & Sheeran, 2006). Sheeran (2002) performed a meta-analysis of 10 meta-analyses and found that intentions accounted for 28% of the variance in behavior on average. In sum, then, empirical data suggests that intentions have a big impact on actual behavior (Webb & Sheeran, 2006).

Nevertheless, there are some cautions in the literature about drawing conclusions on intentions from correlational studies. Many of these studies are cross-sectional and use self-reporting, meaning that there could be consistency and self-presentational biases (Webb & Sheeran, 2006). Even more acute is that, due to the inherent nature of cross-sectional analysis, it is impossible to rule out that it is actually behavior that causes the intention. Also, there is the ever-present concern of spurious association, in which an unmeasured variable is actually driving the relationship (Kenny, 1979; Webb & Sheeran, 2006).

A better way to measure the causal impact of intention on behavior is through experimentation; that is, changing intention and then observing whether a change in behavior results (Webb & Sheeran, 2006). Some studies have used this approach. Brubaker and Fowler (1990), for example, examined persuasive messaging to increase testicular self-examinations (TSE). Those that received the persuasive messaging reported stronger intentions to perform TSE compared to those who only received factual information; one month later, rates of TSE performance were also higher among those who received the persuasive messaging (Brubaker & Fowler, 1990). Gratton et al. (2007) also used a TPB-based intervention to increase intentions and ultimately consumption of fruits and vegetables by children.

Measuring Intentions

Researchers have used inconsistent measures to examine the intention construct (Armitage & Conner, 2001). Some researchers have proposed to consider both intention and self-prediction (Armitage & Conner, 2001; Sheppard, Hartwick, & Warshaw, 1988). For example, "I intend to perform behavior X," measures behavioral intentions; whereas, "How likely is it you will perform behavior X?" measures self-predictions (Armitage & Conner, 2001; Warshaw & Davis, 1985). Sheppard et al. (1988) argued that self-predictions measures are preferred, as they likely include contemplation of other factors that may affect the performance of the behavior and competition behaviors (Armitage & Conner, 2001). Notably, in a meta-analysis, Sheppard et al. (1988) concluded similarly, noting that self-predictions had a stronger relationship with behavior (mean r = .57) than behavioral intentions (mean r = .49).

Hypotheses

Based on prospect theory, narrative literature, the robust medical framing literature, and regulatory focus theory, several hypotheses were examined. Similar to the medical framing literature, financial behaviors were selected based on their similarities to prevention, treatment, and detection behaviors, distinctions of which are rooted in behavioral economics' prospect theory.

First, retirement-income planning was selected as a prevention behavior because the behavior prevents future harm (that is, by planning today, future financial harm is forestalled).

H1a: Narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement savings.

H1b: Positive-valence (gain) narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement savings.

H1c: Negative-valence (loss) narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement savings.

H1d: Positive-valence (gain) narrative message framing will be more effective than negative-valence narrative message framing for intentions to actively plan for having sufficient retirement savings.

H1e: For promotion-focused respondents, positive-valence (gain) narrative message framing will be more effective than negative-valence (loss) framing for intentions to actively plan for having sufficient retirement savings.

H1f: For prevention-focused respondents, negative-valence (loss) narrative message framing will be more effective than positive-valence (gain) narrative for intentions to actively plan for having sufficient retirement savings.

H1g: For promotion-focused respondents, as the strength of promotion focus increases, positive-valence (gain) narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement savings.

H1h: For prevention-focused respondents, as the strength of prevention focus increases, negative-valence (loss) narrative framing will be positively associated with intentions to actively plan for having sufficient retirement savings.

Second, cash-flow and budget planning was selected as a treatment behavior because current budgeting can "treat" current cash shortages and allow current savings.

H2a: Narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting.

H2b: Positive-valence (gain) narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting.

H2c: Negative-valence (loss) narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting.

H2d: Positive-valence (gain) narrative message framing will be more effective than negative-valence narrative message framing for intentions to engage in monthly cash-flow budgeting.

H2e: For promotion-focused respondents, positive-valence (gain) narrative message framing will be more effective than negative-valence (loss) framing for intentions to engage in monthly cash-flow budgeting.

H2f: For prevention-focused respondents, negative-valence (loss) narrative message framing will be more effective than positive-valence (gain) narrative for intentions to engage in monthly cash-flow budgeting.

H2g: For promotion-focused respondents, as the strength of promotion focus increases, positive-valence (gain) narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting.

H2h: For prevention-focused respondents, as the strength of prevention focus increases, negative-valence (loss) narrative framing will be positively associated with intentions to engage in monthly cash-flow budgeting.

Third, insurance-needs analysis was selected as detection behavior because it identifies whether there is a current financial malady (insufficient insurance protection).

H3a: Narrative message framing will be positively associated with intentions to engage in an insurance needs analysis.

H3b: Positive-valence (gain) narrative message framing will be positively associated with intentions to engage in an insurance needs analysis.

H3c: Negative-valence (loss) narrative message framing will be positively associated with intentions to engage in an insurance needs analysis.

H3d: Negative-valence (loss) narrative message framing will be more effective than positive-valence narrative message framing for intentions to engage in an insurance needs analysis.

H3e: For promotion-focused respondents, positive-valence (gain) narrative message framing will be more effective than negative-valence (loss) framing for engaging in an insurance needs analysis.

H3f: For prevention-focused respondents, negative-valence (loss) narrative message framing will be more effective than positive-valence (gain) narrative for engaging in an insurance needs analysis.

H3g: For promotion-focused respondents, as the strength of promotion focus increases, positive-valence (gain) narrative message framing will be positively associated with intentions to engage in an insurance needs analysis.

H3h: For prevention-focused respondents, as the strength of prevention focus increases, negative-valence (loss) narrative framing will be positively associated with intentions to engage in an insurance needs analysis.

Chapter 3 - Methods

Data and Sample

The population of interest in this study was adults in the United States that did not currently engage in one of the three examined financial behaviors. This study used a convenience sample recruited through Amazon's Mechanical Turk platform (MTurk) with a Qualtrics-based survey (e.g., Hunt & Scheetz, 2019). MTurk has been used in financial planning-related primary research (e.g., Hoffmann & McNair, 2018; James & Routley, 2016) The goal number of respondents was approximately 1,200, which would result in approximately 400 per experiment and about 100 respondents per treatment (including control groups). Respondents were paid fifty cents for satisfactorily completing the survey.

MTurk samples have been used in an array of fields, such as psychology, behavioral economics, and consumer behavior (Goodman, Cryder, & Cheema, 2013). A benefit of MTurk is that data collection can be done quickly and cost effectively. Naturally, then, a legitimate concern is that MTurk participants are unlike those found in traditional sample pools. Goodman et al. (2013) surveyed the literature and noted, however, that prior studies indicated that MTurk responses were demographically accurate (Rand, 2011); the psychometric properties of responses validated (Buhrmester, Kwang, & Gosling, 2011); and MTurk samples can even be used for replicating classic experiments (e.g., Suri & Watts, 2011) and decision making research (Paolacci, Chandler, & Ipeirotis, 2010). Despite these showings, other valid concerns may be the effect of language or cultural barriers (for international participants)[3] and the amount of time

[3] Though this is minimized—if not eliminated—in this study due to the requirement of being based in the United States and to be English speaking.

commitment invested by MTurkers (e.g., not paying sufficient attention to the study materials) (Goodman et al., 2013).

Nevertheless, recent literature and studies indicate that MTurk samples are comparable to those from traditional sample pools (Hoffmann & McNair, 2018). Generally, MTurkers learn about MTurk from news articles, friends, and Internet searches (Goodman et al., 2013). Compared to the US population generally, MTurkers are not outliers in terms of demographics; though they tend to have slightly lower average income, are slightly younger, and tend to have fewer than average children (Goodman et al., 2013). But, compared to standard Internet samples generally, Buhrmester et al. (2011) found that a greater percentage of MTurkers were non-White and older than typical Internet samples. Mason and Suri (2012), moreover, found that MTurkers tend to be more diverse socio-demographically than traditional student sample pools—and commentators have consistently critiqued the reliance on college student samples (Buhrmester, Kwang, & Gosling, 2011; Sears, 1986).

Another valid concern for any MTurk-based survey was reliability (i.e., truthful and consistent responses). As applied at least to demographic responses, Rand (2011) found that more than 95% of MTurkers accurately reported their country location (as verified by IP address matching). Buhrmester, Kwang, and Gosling (2011) conducted a study investigating compensation and time completion levels. They found that compensation levels did not affect data quality, but could affect participation rates (i.e., data collection times). They also concluded that MTurk data met acceptable psychometric standards by comparing MTurk mean alpha reliability scores to traditional sample alphas and using test-retest reliabilities. Other researches have concluded similarly; for example, Goodman et al. (2013) concluded that "MTurk generally provides an excellent opportunity for inexpensive and efficient behavioral data collection with reliable results" (p. 214).

In this study, to ameliorate some of the potential reliability concerns, MTurkers could only see and respond to the survey if they had completed 1,000 prior human intelligence tasks (HITs), had an approval rate of 99% or greater (Peer, Vosgerau, & Acquisti, 2014), and reported being based in the United States. Limiting the sample pool to those MTurkers with a solid history of successful HIT completions, reduced, at least in part, the overall data quality risk.[4] Indeed, Peer et al. (2014) found that MTurkers with high reputations (in that study, above a 95% approval rating) rarely failed attention check questions, and that more productive high-reputation workers (those who completed more than 500 HITs) produced higher data quality (compared to those with fewer than 100 HITs). This current study, therefore, had even higher entrance limits.

Another potential concern was that MTurkers would just click-through the survey without sufficiently reading the prompts. Some studies have used attention or comprehension checks to allay this concern; however, the literature is mixed (e.g., Vannette, 2017). In this survey, several strategies were employed to reduce this risk. First, the survey contained several timers in various question blocks (e.g., for the demographic portion and the regulatory focus block). If a respondent answered too quickly (indicating they did not fully read the questions), they were screened out of the survey (e.g., Hunt & Scheetz, 2019).[5] Second, after the completion of the survey, surveys with a duration of less than 60 seconds (again, indicating a failure to earnestly read the questions and prompts), were listwise deleted.[6]

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[4] In particular, this reduces potential "bot risk," in which the respondents are really automated processes. There were six survey durations of less than 60 seconds that would have otherwise been included.
[5] In particular, the demographic block was set to seven seconds or less and the RFQ block was set to eight seconds or less; of course, a concern, in retrospect, was that these timers were too low.
[6] These respondents, however, were still paid as they completed the survey and submitted a code to MTurk.

Another potential risk was "gaming" the survey eligibility screeners. That is, the survey population of interest was those people not presently engaging in one of the financial behaviors; these behaviors were screened early in the survey. If a respondent indicated they currently engaged in the behavior, they were screened out. To minimize the screener-gaming concern, screener questions were not indicated as such (so the respondents did not know which questions were acting as screeners) (Buchheit et al., 2018).[7] Additionally, to prevent retakes (and to answer differently to the screeners), the "ballot box" feature was implemented in Qualtrics, which is designed to prevent survey retakes by the same respondent.[8]

Data was collected in two batches, both of which took less than one week. The first batch consisted of about 10% of the total respondent count; the data was then reviewed to ensure that the survey worked correctly;[9] the second batch consisted of the balance of the total respondent count.[10] There were over 2,000 starts of the survey. Due to the different proportions of respondents that did not engage in one of the behaviors—that is, the proportion of those who did not budget was different than those who did not have a retirement plan—the data was reviewed periodically to ensure that the experiment blocks had roughly the same number of eligible respondents; to increase experiment block counts, the respective screener was showed to more respondents as needed (Hunt & Scheetz, 2019).

Some respondents may have completed the survey but not properly submitted for payment; those responses were removed from the survey (as they could not be paid, their data

[7] The informed consent statement did expressly note that screener and eligibility questions were present early in the survey (e.g., Hunt & Scheetz, 2019).
[8] However, there may be ways to circumvent this function. That notwithstanding, the other quality measures also implicitly help here, too, namely requiring high quality MTurkers. Nevertheless, in future studies, using a two-stage survey process may reduce this risk further (e.g., Hunt & Scheetz, 2019).
[9] The survey was also tested before launching by the author, other PhD students, and simulated data.
[10] A custom qualification was created to ensure first batch respondents did not participate in the second batch.

was not used).[11] Similarly, some respondents may have completed the survey, but entered the code wrong in MTurk (e.g., adding a hyphen, leaving off a digit, or pasting the code twice in the same space) (Hunt & Scheetz, 2019); those respondents were paid, and their data included if the responses could reasonably be matched with a submission. Some respondents may have completed the survey, though not clicked the last button on the survey completion screen, yet they submitted the generated code for payment in MTurk; these respondents were paid, and their data included. The final analytical sample survey consisted of 1,156 completed responses;[12] the final respondent count by experiment block and treatment are found in Figure 1.

Experimental Design

The experimental design is shown in Figure 1 with actual experiment and treatment numbers.

[11] This was only about seven responses.
[12] This count is net of other data cleaning measures discussed later (namely regarding regulatory focus score).

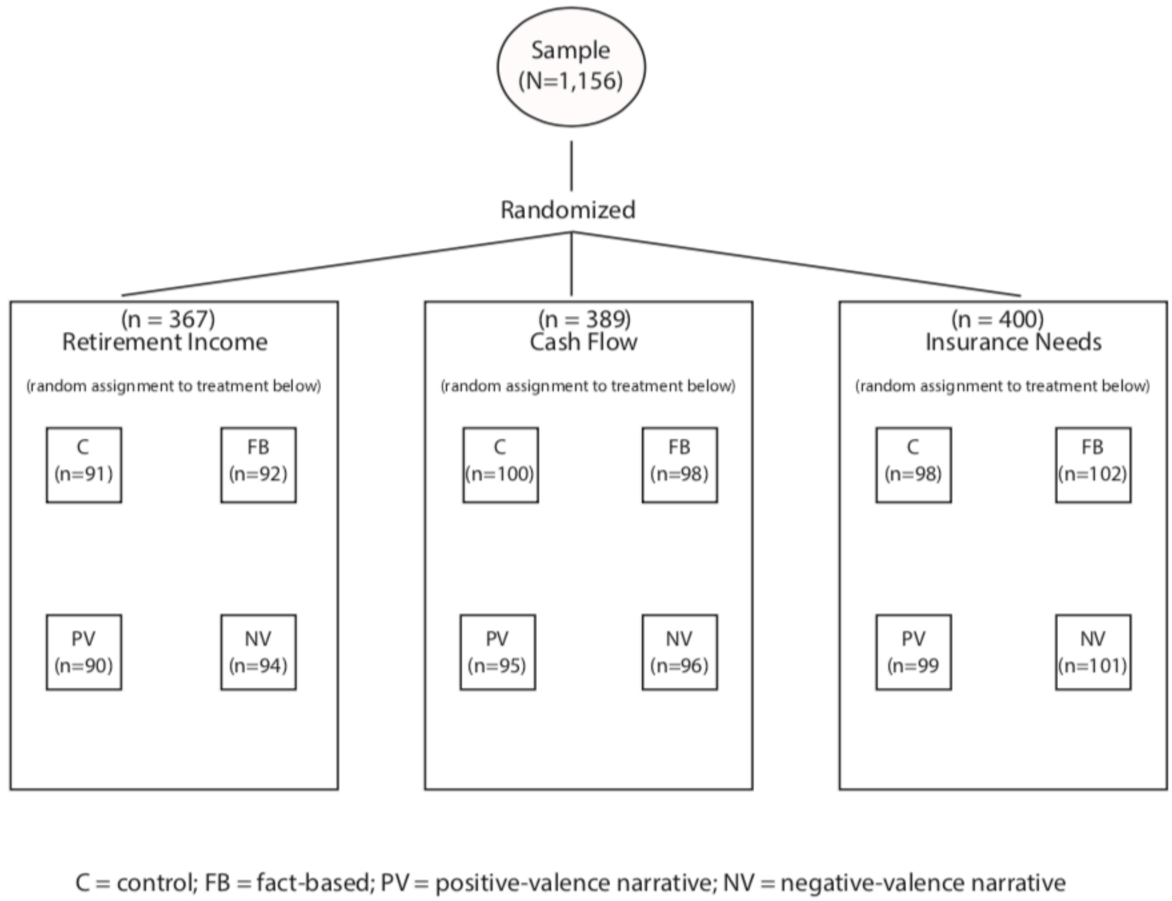

Figure 1. Experimental Design

Early in the survey, respondents were randomly given a screener question about engaging in one of the three behaviors; if they answered in the negative (i.e., did not currently engage in the behavior) and otherwise met eligibility questions, the survey continued. After answering demographic and regulatory state questions, respondents were then assigned to one of the three experiments, which corresponded to the earlier screener question). Within each experiment, they were randomly assigned to one of four treatments. The treatments consisted of a control, meaning that there was no explanation, description, or narrative of the underlying behavior; they were simply asked their intentions to engage in the behavior in the next six months. The fact-based prompt conveyed sterile, non-charged factual based information about the behavior. The positive-valence narrative used a narrative that focused on the positives (gain state) of engaging in the behavior. The negative-valence narrative used a narrative that focused on the negatives (loss state) of failing to engage in the behavior. Each of the narratives are provided below. After exposure to the treatment (or control), they were then asked questions about their intentions to engage in the behavior over the next six months.

Survey Design

The survey instrument had, in effect, 4 parts: (a) demographic questions, (b) regulatory focus questions, (c) treatment (narrative), and (d) post-treatment question about intentions. Each of those parts are now discussed. The full survey instrument is found in Appendix A.

Dependent Variables

The dependent variables were the post-treatment questions about intentions; the dependent variable in each experiment was the intention to engage in the applicable financial behavior in the next six months; this was done on a 7-point Likert-type scale, with 1 indicating very unlikely and 7 indicating very likely. The timeframe of six months was chosen to balance the concerns of providing sufficient time for the respondent to not be affected by scheduling concerns (like a timeframe of a few weeks may cause), but yet not long enough such that the respondent thinks eventually he or she will eventually engage in the behavior (e.g., a year or longer).

Independent Variables

Standard demographic control variables were included, such as age (continuous), gender (male/female), income (categorical), race (categorical), ethnicity (categorical), marital status (categorical), employment status (categorical), education (categorical), and financially dependent children (continuous). The categorical variables were then coded using a dummy variable approach. These variables were included, in part, for the regression-based analyses in case randomization did not work and to control for possible confounding effects. For example, disability insurance may be more salient for someone with full-time employment, and life insurance may be more salient for someone with children or a spouse. As well, retirement income planning may be more relevant to someone who was older and approaching retirement than someone who was younger.

Due to data accuracy concerns, net worth was not included (i.e., trying to have respondents quickly and accurately sum assets across classes and subtract all debts). Also, because the dependent variable questions regarded financial planning behavior intentions, express questions about financial planning behaviors (such as having a retirement plan, regularly saving, having a budget, etc.) were intentionally not asked due to salience and priming concerns (which could—perhaps albeit subconsciously—then affect their later answers about related planning behavioral intentions) and related consistency bias concerns.

Financial knowledge was included as an independent variable.[13] Measuring financial knowledge was achieved by using the “big three” financial knowledge questions designed by Lusardi and Mitchell (2011). Financial knowledge was important to include as a covariate because financial knowledge is generally associated with positive financial behaviors, such as retirement planning (Lusardi & Mitchell, 2007, 2008, 2009, 2011). Other variables—such as education, for example—are generally not good proxies for financial knowledge (Lusardi & Mitchell, 2011).

The motivating principles behind Lusardi and Mitchell’s (2011) financial knowledge questions were simplicity, relevance, brevity, and capacity to differentiate. The questions were

[13] Financial knowledge is different than financial literacy (Huston, 2010; Seay, Kim, & Heckman, 2016). The latter includes financial knowledge, but also incorporates the ability and confidence to implement that knowledge—that is, there is both a knowledge dimension and an application dimension (Huston, 2010; Seay et al., 2016).

purposefully not numerically or computationally difficult so that they may be used in various survey modalities (such as face-to-face or telephonically). These questions asked about interest compounding, inflation, and risk diversification. These questions have become the empirical benchmark to measure financial literacy, and they have been implemented in the Health and Retirement Survey (HRS), the National Longitudinal Survey of Youth (NLSY), the American Life Panel, and the Financial Capability Study (Lusardi & Mitchell, 2011). The questions answered correctly were treated as a continuous variable.[14]

Relatedly, subjective financial knowledge was included by asking the respondent on a 7-point scale to assess his or her overall knowledge about finances (with 1 indicating very low knowledge and 7 indicating very high knowledge).

Financial strain was included as an independent variable. Financial strain may be relevant because if respondents have difficulty in their day-to-day financial context (such as paying bills) it may be that they are less likely to engage in longer-term or more advanced financial planning behaviors. Financial strain was operationalized by asking respondents, in a typical month, how difficult is it for them to cover their expenses and pay all their bills. A 5-point Likert-type scale was used, with responses ranging from 1 (*not at all difficult*) to 5 (*completely difficult*); financial strain was indicated by a binary variable for those providing a response of 4 (*very difficult*) or higher.

Regulatory focus was assessed by the Regulatory Focus Questionnaire (RFQ) (Higgins et al., 2001). This scale is routinely used to measure regulatory focus (e.g., Camacho, Higgins, &

[14] "Don't know" (DK) responses were coded as incorrect answers. Although this is the traditional approach, recent literature as applied to financial knowledge examines this practice (Kim & Mountain, 2019). The effects of DK responses are perhaps most relevant to measuring intervention effects (e.g., effectiveness of a financial education intervention—that is, where financial knowledge is the dependent variable). Here, however, that was not the focus of this research. Moreover, due to the underlying randomization present in this study, any unobserved effects were assumed to be diffused across treatments.

Luger, 2003; Cesario & Higgins, 2008; Higgins et al., 2001; Molden & Higgins, 2004). This is an 11-item questionnaire, with two psychometrically distinct subscales, that asks how frequently specific events have occurred during the respondent's life, with 5-point Likert type responses; for example, "How often have you accomplished things that got you 'psyched' to work even harder?" and "Do you often do well at different things that you try?" (Higgins et al., 2001). The promotion subscale measures subjective histories of promotion successes (6 questions), and the prevention subscale measures subjective histories of prevention successes (5 questions).

In describing the initial psychometric testing of the scale, Higgins et al. (2001) explained the scale had good internal reliability, with Cronbach's alphas of 0.73 for the promotion scale and 0.80 for the prevention scale. Confirmatory factor analysis (with 268 undergraduate participants) showed an excellent goodness of fit index at 0.95 (0.93 for adjusted goodness of fit) (Higgins et al., 2001). A test-retest reliability study (with 71 undergraduate participants) showed that the promotion scale had a 0.79 correlation ($p < 0.0001$) and the prevention scale had a 0.81 correlation ($p < 0.0001$) (Higgins et al., 2001). Higgins et al. (2001) also explored the convergent and discriminant validity of the RFQ.

Predominant regulatory focus was computed by subtracting the prevention subscale score from the promotion subscale score (Camacho et al., 2003; Cesario & Higgins, 2008; Molden & Higgins, 2004). The resulting index (or difference) score was a continuous measure, "with positive numbers indicating predominant promotion focus and negative numbers indicating predominant prevention focus" (Cesario & Higgins, 2008, p. 417). Like Cesario, Grant, and Higgins (2004) and others (e.g., Memmert, Unkelbach, Ganns, 2010; Pula, Parks, & Ross, 2014; Tam, Bagozzi, & Spanjol, 2010), a median split of the difference scores was then used to classify respondents as predominantly prevention- or promotion-focused as compared to other respondents (i.e., a sample-relative median split). This method—median splitting the difference scores—can help mitigate small cell risk (i.e., not enough respondents of a particular focus). Cesario et al. (2004) also note other benefits to the median-split RFQ approach; first, making it categorical can simplify the analysis; and second, because the analysis and hypotheses at issue here regard fit (or nonfit) with a particular message framing, this, too, paired nicely with a categorical approach. Thus, in addition to the pure RFQ index score, a binary variable was created based on the RFQ median split, with respondents coded as one if promotion-focused (above the median scores) and zero if below the median.[15]

Treatments

There were three experiments, corresponding to the three behaviors: (a) retirement savings and income planning, (b) cash-flow/budget planning, and (c) insurance needs analysis. For each behavior, there were three treatments plus control—a positive-valence narrative, a negative-valence narrative, and a fact-based explanation. As shown in Table 3.1, and in line with Han and Fink (2012), each of the treatments were written to be similar in terms of number of words, number of sentences, average words per sentence, and Flesch-Kincaid Reading Ease and Flesch-Kincaid Grade Level. In each experiment, care was taken to ensure the same context and emotional appeal (e.g., effect on family or children); to minimize any subliminal gender or name effect, the protagonist's gender and her name were the same in each treatment narrative. Emotive appeals (like worry and stress) were not included in the fact-based treatment.

[15] Those that scored exactly at the median (here the median was zero) were removed from the analysis, as there were not enough respondents to be an independent reference group (i.e., neither relatively promotion- nor prevention-focused).

Table 3.1 Descriptive Statistics of Treatment Narratives

	Experiment 1 Retirement			Experiment 2 Budgeting			Experiment 3 Insurance		
	PN	NN	FB	PN	NN	FB	PN	NN	FB
Number of words	92	98	57	119	122	63	113	114	56
Number of paragraphs	1	1	1	1	1	1	1	1	1
Number of sentences	7	7	5	8	8	5	7	7	5
Avg. words per sentence	13.1	14	11.4	14.8	15.2	12.6	16.1	16.2	11.2
Avg. characters per word	4.2	4.5	4.5	4.4	4.4	4.8	4.7	4.4	5
Flesch Reading Ease	74.8	63.1	67.6	66.8	71.7	53	59.1	72	50.4
Flesch-Kincaid Grade Level	6	7.9	6.6	7.2	6.6	8.9	7.8	6	9

Note: PN = positive narrative; NN = negative narrative; FB = fact-based.
All calculations performed by Microsoft Word.

As shown, within each experimental block, the positive-valence and negative-valence narratives were roughly equivalent in terms of total words, sentence count, and measures of reading difficulty. However, across the blocks, the fact-based information was necessarily shorter, as it did not need to develop a plot or other narrative elements. Nevertheless, they were all still similar in terms of reading ease and reading grade level.

Moreover, a relevant issue noted in the framing literature is whether the exact phrasing of the gain- or loss-framed appeals acts as a moderator. As noted by O'Keefe and Jensen (2006) and others, these appeals can each take two forms, resulting in a 2x2 array of possibilities, i.e, whether the outcome is described as desirable (or not), and whether the outcome is attained (or avoided). For example, O'Keefe and Jensen (2006) provide an example of a gain-framed appeal as "If you perform the advocated action, desirable outcome X will be obtained," or "If you perform the advocated action, undesirable outcome Y will be avoided" (p. 5). On the other hand, a loss-framed appeal can take the form of "If you do not perform the advocated action, undesirable outcome X will be avoided," or "If you do not perform the advocated action, undesirable outcome Y will be obtained" (p. 5). It is admittedly unclear whether these different operationalizations matter; some evidence indicates that they do not (Devos-Comby & Salovey, 2002). Nevertheless, to ameliorate any effect in this vein, the treatment/narrative wording was consistent in its wording across narratives. The treatment language is provided below.

Retirement Income Planning (Prevention behavior)

Positive-valence narrative

Sally is a recently retired schoolteacher. She planned for her retirement. She set a savings goal based on what she wanted her retirement to look like. Based on that goal, she saved each month to meet it, and her retirement is now funded. Now that she is in retirement and has enough saved, she does not worry about making ends meet. She does not stress about money matters. She is able to do the things she wants to in retirement, such as travel, take on new hobbies, and visit with her family.

Negative-valence narrative

Sally is a recently retired schoolteacher. She did not plan for her retirement. She did not have a retirement savings goal based on what she wanted her retirement to look like. Without a specific goal, she did not save regularly each month, and her retirement is not funded. Now that she is in retirement and does not have enough saved, she constantly worries about making ends meet. She regularly stresses about money matters. She is not able to do the things she wants to in retirement, such as travel, take on new hobbies, and visit with her family.

Fact-based

There are several steps to planning for retirement. You set a goal about your retirement. Based on that, you set a savings goal. You then save over your working years to meet that goal. Properly saving for retirement will allow you to do those things you want in retirement, such as travel, hobbies, and visiting with family.

Cash Flow and Budgeting (Treatment behavior)

Positive-valence narrative

Sally is a schoolteacher. Money is tight, so she regularly monitors her monthly income and expenses. Based on that, she has been able to identify expenses that she can reduce and free-up additional monthly cash. She has established a budget. Due to this planning, she has been able to set aside funds for emergencies; if she had a sudden car repair or lost her job, she is comforted by knowing she has an emergency savings fund. With the budget, she is starting to save for long-term financial goals. Because of the monthly budget, she knows she can make ends meet each month. She does not regularly stress or worry about money matters because she has a plan in place.

Negative-valence narrative

Sally is a schoolteacher. Money is tight, but she does not regularly monitor her monthly income and expenses. Based on that, after her monthly expenses, she does not have extra additional monthly cash. She does not have an established budget. Due to this lack of planning, she has not been able to set aside funds for emergencies; she does not know where the money would come from if she had an unexpected car repair bill or if she lost her job. Without a budget, she is not saving for long-term financial goals. With no budget, she does not know whether she can make ends meet each month. She regularly stresses and worries about money matters because she has no plan in place.

Fact-based

Budgeting is the process of monitoring monthly income and expenses. With a budget in place, you can identify expenses that can be eliminated. This may free-up additional cash each month. Budgeting may allow you to set aside funds for an emergency, like an unexpected car repair bill or loss of a job. Budgeting may also help you start saving for long-term financial goals.

Insurance Needs Analysis (Detection behavior)

Positive-valence narrative

Sally is a school teacher. She is working with a financial advisor. A part of that process is insurance needs analysis—making sure she has the insurance protection she needs. Working with her financial advisor revealed that Sally did not have adequate insurance in place. She needed to increase her car insurance; take out a disability insurance policy (in case she became disabled); increase her life insurance policy (for the benefit of her kids); and take out an additional policy to protect her home and other assets. Now that she has identified these issues, she can fix them. Knowing that she is now protected, she does not worry and stress about these issues.

Negative-valence narrative

Sally is a school teacher. She does not work with a financial advisor. She has never analyzed her insurance needs, which would make sure she the insurance protection she needs. She does not know if she has adequate insurance in place.

She is unsure if her car is adequately protected; she is unsure if she is protected if she becomes disabled; she is unsure if her current life insurance is enough for her kids; and she does not know if her home and other assets are protected. Not knowing if she has enough in place, she does not know what needs fixed. Due to this uncertainty, she regularly worries and stresses about these issues.

Fact-based

An insurance needs analysis reviews if you have enough insurance. You review your current insurance policies. You also consider insurance you do not have but may need. Types of insurance include automobile, disability, life, casualty, and others. An insurance needs analysis is a first step in finding gaps and issues so that they can be fixed.

Missing Data

Respondents could stop and leave the survey at any time (albeit without pay). Those who started the survey, but did not finish, were not examined; only fully completed surveys were analyzed. Because no intrusive or personally invasive information was sought in the survey, survey attrition was treated as random and considered to not bias the results. Moreover, preferences to skip or not answer a question (or a "prefer not to say" answer) were not included in the survey design. Some fields use manipulation checks or trap questions to identify respondents not earnestly reading and responding to the questions. However, due to the possibility of injected bias, attention checks or trap questions were not used (e.g., Vannette, 2017). For example, Anduiza and Galais (2017) noted that manipulation checks may "aggravate the typical sample biases that plague nonprobabilistic samples" (p. 510). And, as noted earlier, Peer et al. (2014) found that MTurkers with high reputations rarely failed attention check questions. Similarly, Hauser, Ellsworth, and Gonzalez (2018) also noted that manipulation checks may affect a respondent's thought or emotional processes. As noted above, other failed quality checks (e.g., less than 60 seconds duration time) were listwise deleted. Consequently, there was no missing data.

Statistical Analyses

ANOVA & ANCOVA

The statistical analysis proceeded in several steps. First, descriptive statistics were examined for the survey as a whole and then individually for each experiment. Then, for each experiment, various statistical techniques were used. To determine mean differences in financial planning intentions by treatment groups, a one-way ANOVA was used. Because the treatment groups were unbalanced, a general linear model-based ANOVA technique was used, which was based on the basic linear model in Equation 2 (SAS, 2018a).

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \tag{2}$$

Consequently, the model used $\mathbf{X}$ as a (*n x p*) design matrix[16] and a vector $\mathbf{Y}$ (*n x 1*) of dependent variables (SAS, 2018a). The normal equations, $\mathbf{X}'\mathbf{X}\boldsymbol{\beta} = \mathbf{X}'\mathbf{Y}$, were solved using a generalized inverse, $\mathbf{X}'\mathbf{X}^{-1}$, which produced a solution, $\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-\mathbf{1}}\mathbf{X}'\boldsymbol{y}$ (SAS, 2018a). Naturally, since this was a least squares approach of estimation, errors were assumed to be uncorrelated with identical variances, which produce unbiased estimates (SAS, 2018a). GLM-based standard errors require errors to normally distributed (to be valid), but they are good approximations generally in the absence of normality (SAS, 2018a). Moreover, if the errors are

[16] The design matrix changes depending on the parameterization of the model, e.g., a one-way or two-way ANOVA (or other linear model); in short, a column is created in the design matrix for each effect in the model (SAS, 2018a).

normally distributed, the estimates are the equivalent to the maximum likelihood estimates (SAS, 2018a).

To test for homogeneity, Levene's test was used, which performed a one-way ANOVA on the absolute values of the residuals (or squared residuals) as found in Equation 3 (Milliken & Johnson, 2009; SAS, 2018a).

$$z_{ij}^2 = (y_{ij} - \bar{y}_i)^2 \quad (3)$$

A significant *F* test here, then, provided evidence that the residuals for one treatment was larger than the others (i.e., variances were not equal) (Milliken & Johnson, 2009). The Brown and Forsythe (1974) method was analyzed, too; here, this method is similar to Levene's test, but used group *medians* instead (Milliken & Johnson, 2009; SAS, 2018a).

If significant differences in treatment means were found, pairwise comparisons of group means were conducted. Contrasts were used to compare narrative effects generally to the control and fact-based treatments (i.e., an average of the narrative treatments compared to the fact-based group and control groups, separately). Due to the unbalanced nature of the data, least squares-means (LS-means) were used for all mean-based comparisons. Because multiple and simultaneous comparisons were made, moreover, various adjustments were implemented to control the error rates, namely the Tukey-Kramer method (Kramer, 1956; Milliken & Johnson, 2009; SAS, 2018a). The Tukey-Kramer method rejected the null hypothesis of mean equivalency if

$$\left|\hat{\mu}_i - \hat{\mu}_j\right| > q_{\alpha,t,v}\sqrt{\frac{\hat{\sigma}^2}{2}\left(\frac{1}{n_i} + \frac{1}{n_j}\right)} \quad (4)$$

where $q_{\alpha,t,v}$ was the upper percentile of a Studentized range statistic (Milliken & Johnson, 2009, pp. 49-50). Because a control group was also present, Dunnett's procedure was used, too, which controlled for the family-wise error rate (Milliken & Johnson, 2009). Under this test—which is similar to Tukey-Kramer—a treatment mean was different from the control mean if

$$|\hat{\mu}_i - \hat{\mu}_0| > d_{\alpha,t,v}\sqrt{\hat{\sigma}^2\left(\frac{1}{n_i} + \frac{1}{n_0}\right)} \tag{5}$$

where $\hat{\mu}_0$ was the control mean and $d_{\alpha,t,v}$ was the upper percentile of a "many-to-one t-statistic" (Milliken & Johnson, 2009, p. 53-54).

Similar to the one-way ANOVA, a two-way ANOVA was also conducted that incorporated regulatory focus (promotion or prevention) in addition to a treatment group effect. The model and formulas were the same as the above, but now the design matrix was different to accommodate the additional treatment effect. Due to the unbalanced nature, Type III sums of squares were examined, which were not functions of cell counts (SAS, 2018a). Main effects and interactions effects (with regulatory focus) were considered.

To control for the effect of RFQ difference (in case the randomization did not equalize the distribution of promotion and prevention respondents or their numerical distribution), an ANCOVA (analysis of covariance) was performed. ANCOVA combined elements of regression and ANOVA and adjusted for the covariate (here, RFQ differences), which was now introduced into the linear model (set forth above) (Rutherford, 2011; SAS, 2018a). Main effects and interactions effects (with regulatory focus) were considered.

OLS Regression

Next, ordinary least squares regressions were examined that predicted financial planning intentions, which took the following matrix form

$$\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{u} \tag{6}$$

where $\boldsymbol{y}$ was the (*n x 1*) vector of response variables, $\mathbf{X}$ was the (*n x k*) matrix of predictor variables (including intercept), $\boldsymbol{\beta}$ was the (*k x 1*) vector of parameters to be estimated, and $\boldsymbol{u}$ was the (*n x 1*) vector of error terms (disturbances) (Mendenhall & Sincich, 2012; Wooldridge, 2016). With lease squares estimation, then, $\widehat{\boldsymbol{\beta}}$ minimized the sum of the squared residuals as found in Equation 7.

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{y} \tag{7}$$

And, of course, the model assumes that it was linear it its parameters, there was no perfect collinearity (i.e., $\mathbf{X}$ was full rank), and the error had a conditional mean of zero with no serial correlation and homoscedastic variance (i.e., $\mathrm{Var}(\boldsymbol{u}|\mathbf{X}) = \sigma^2\mathbf{I}_n$, where $\mathbf{I}_n$ was the (*n x n*) identity matrix) (Wooldridge, 2016).

Moreover, for the OLS regression, heteroskedasticity-robust standard errors were used, which were based off the heteroskedasticity-robust variance matrix of $\widehat{\boldsymbol{\beta}}$, which took the form

$$\widehat{Avar}(\widehat{\boldsymbol{\beta}}) = (\mathbf{X}'\mathbf{X})^{-1}\left(\sum_{i=1}^{N} \widehat{\boldsymbol{u}}_i^2\, \boldsymbol{x}_i'\boldsymbol{x}_i\right)(\mathbf{X}'\mathbf{X})^{-1} \tag{8}$$

where diagonal elements were the White standard errors (Wooldridge, 2010). Importantly, as noted by Wooldridge (2010), these errors were "asymptotically valid in the presence of any kind of heteroskedasticity, including homoskedasticity" (p. 61). Additionally, residual-versus-fitted plots were examined.

Nonparametric Analyses

The above methods were all parametric analyses, which, among other things, assumed that the response variable (financial planning intentions) was continuous. The response variable here, however, was Likert-type data (on a seven-point scale). Although it is common in social science literature to treat this type of data as continuous, nonparametric techniques were analyzed too for additional robustness (confirmatory analyses).

The first nonparametric test conducted was the Kruskal-Wallis H-Test; this is the nonparametric equivalent of the one-way ANOVA (Korosteleva, 2014). The null hypothesis here was that all location parameters are the same (across k samples) and the alternative hypothesis was that they are not the same. In a Kruskal-Wallis test, all observations are pooled together and ranked (in increasing order; with ties assigned to the average rank it would have received had there been no tie) (Korosteleva, 2014). Assuming there were no ties, the H statistic was computed as:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{9}$$

where R_i denotes the sum of ranks in the ith sample (Korosteleva, 2014). In the event of a tie (m sets of ties), however, the formula was as follows:

$$H = \frac{\left[\frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1)\right]}{1 - \frac{\sum_{i=1}^{m} (T_i^3 - T_i)}{N^3 - N}} \tag{10}$$

where T_i denotes the number of ties in the ith set (Korosteleva, 2014). Using a large sample approximation (i.e., $n > 30$), the critical values follow a chi-square distribution (Corder & Foreman, 2014).

If the Kruskal-Wallis test was significant, then post-hoc tests were needed to isolate the treatment differences, which were now sets of two-sample comparisons. As such, Wilcoxon rank-sum tests were performed for each pair of samples. This test pooled the samples, ranked the observation, and computed the test statistics, W, which was the sum of the assigned ranks in the smaller sample. For large samples, the test statistic is approximately normally distributed

(Korosteleva, 2014), and, in particular, a standardized test statistic, z, was used with an asymptotic standard normal distribution (under the null hypothesis) (SAS, 2018b).

Logistic Regression (Cumulative, Multinomial, and Binary)

Lastly, logistic regressions were performed. For each experiment, a cumulative, multinomial, and binary logit were examined. These were performed—like the nonparametric techniques—because of the Likert-type nature of the response variable. The cumulative (sometimes referred to as an "ordered" logit) was appropriate for an ordered categorical variable, like a Likert-type response variable (Allison, 2012). The cumulative logit took the following form:

$$\log\left(\frac{F_{ij}}{1-F_{ij}}\right) = \alpha_i + \boldsymbol{\beta x}_i, \quad j = 1, \ldots, J-1 \tag{11}$$

where $\boldsymbol{\beta x}_i = \beta_1 x_{i1} + \cdots + \beta_k x_{ik}$ and $F_{ij} = \sum_{m=1}^{j} p_{im}$, where F_{ij} was the cumulative probabilities (i.e., that respondent i is in the jth category or higher) (Allison, 2012). The model was estimated by maximum likelihood (Allison, 2012). A critical assumption in the cumulative logit, though, was the proportional odds assumption, which regarded whether the effects (coefficients) of the predictor variables were the same across potential ways to dichotomize the response variable. In other words, whether the coefficients were invariant across dichotomizations (Allison, 2012). If this assumption was rejected, a cumulative logit was inappropriate, as there was no guarantee that the effects were consistent across levels of the response variable. To ameliorate that, the intentions were the collapsed into three categories (high, medium, and low), such that the proportional odds assumptions tended to not be violated. Indeed, the cumulative logit, with the three categories, was the ideal approach here, given the Likert-type response variable, but yet still being able to distinguish between varying levels of intentions.

Also, in those cases in which the proportional odds assumption was violated, a multinomial logit was examined. The multinomial logit took the following form:

$$\log\left(\frac{p_{ij}}{p_{iJ}}\right) = \boldsymbol{\beta}_j \boldsymbol{x}_i, \quad j = 1, \dots, J-1 \tag{12}$$

where $\boldsymbol{x}_i$ was a column vector of predictor variables and $\boldsymbol{\beta}_j$ was a row vector of coefficients (Allison, 2012). Furthermore, p_{ij} represents the probability that respondent *i* was in the *j*th category and was defined as:

$$p_{ij} = \frac{e^{\boldsymbol{\beta}_j \boldsymbol{x}_i}}{1 + \sum_{k=1}^{J-1} e^{\boldsymbol{\beta}_k \boldsymbol{x}_i}}, \quad j = 1, \dots, J-1 \tag{13}$$

which can also be expressed as,

$$p_{iJ} = \frac{1}{1 + \sum_{k=1}^{J-1} e^{\boldsymbol{\beta}_k \boldsymbol{x}_i}} \tag{14}$$

because probabilities must sum to unity (Allison, 2012). Consequently, after p_{ij} and p_{iJ} were determined, then, for any comparison between categories (levels) *j* and *k*, the logit equation was as noted in Equation 15 (Allison, 2012).

$$\log\left(\frac{p_{ij}}{p_{iJ}}\right) = (\boldsymbol{\beta}_j - \boldsymbol{\beta}_k)\boldsymbol{x}_i \tag{15}$$

A binary logit was also examined to model high intentions (defined as an intention score of six or seven) to non-high intentions. The binary logit took the form of

$$\log\left(\frac{p_i}{1 - p_i}\right) = \alpha + \boldsymbol{\beta} \boldsymbol{x}_i \tag{16}$$

where $\boldsymbol{\beta}\boldsymbol{x}_i = \beta_1 x_{i1} + \cdots + \beta_k x_{ik}$, that is, $\boldsymbol{x}_i$ was column vector of predictor variables and $\boldsymbol{\beta}$ was a row vector of coefficients (Allison, 2012).

Chapter 4 - Results

A complete descriptive table for the entire sample and by experiment is shown below (Table 4.1). Examining the subsamples for each experiment shows that each experiment was roughly equivalent to the sample as a whole. Looking at the entire sample, there was roughly an even split between males and females and the average age is 39. The vast majority (82%) of respondents were White, with Black being the next most common reported demographic (7.27%); the vast majority, moreover, reported non-Hispanic ethnicity (94%). A substantial percentage of respondents (90% plus) reported having at least some college experience, with over half reporting an earned degree (at any level). Almost half of the respondents reported being married, with single being the next highest reported marital status. The majority of respondents (57%) reported having full-time employment and a decent percentage (16.7%) reporting self-employment. The majority of respondents reported earning less than $60,000 in household income (with nearly 15% reporting annual income in excess of $100,000).

About 16% of respondents indicated financial strain. The average subjective financial knowledge score was 4.21, which was slightly more than the center response of 4. On average, they got two of the three financial knowledge questions correct. Of the three questions, 90% answered the compound interest question correctly; the inflation and stock risk questions were each answered correctly by approximately 80% of the respondents. 69% of respondents answered all three questions correctly and about 3.3% answered none of them correctly.[17]

[17] 9.52% answered one question correctly; 18.51% answered two questions correctly.

Table 4.1 Descriptive Statistics

	Entire Sample (n=1156)		Experiment 1 (n=367)		Experiment 2 (n=389)		Experiment 3 (n=400)	
Variable	Prop. (%)	M (SD)	Prop. (%)	M (SD)	Prop. (%)	M	Prop. (%)	M (SD)
Age		39.2 (12.14)		38.05 (11.7)		39.88 (12.47)		39.6 (12.2)
Male	48.79		40.87		50.39		54.5	
Female	51.21		59.13		49.61		45.5	
Race								
White	82.44		82.56		80.98		83.75	
Black	7.27		7.36		7.46		7	
Asian	6.4		5.45		9		4.75	
Other	3.89		4.63		1.54		4.5	
Ethnicity								
Hispanic	6.06		5.45		4.37		8.25	
NonHisp	93.94		94.55		95.63		91.75	
Education								
No HS	0.52		0.82		0.51		0.25	
High School	8.91		11.99		7.71		7.25	
Some Coll.	22.58		22.89		22.11		22.75	
Assoc.	11.51		11.99		9.77		12.75	
Bach.	40.92		39.78		41.13		41.75	
Post-Grad	15.57		12.53		18.77		15.25	
Marital Status								
Married	45.5		44.96		43.96		47.5	
Single	42.91		42.78		45.5		40.5	
Divorced	10.64		11.17		9		11.75	
Widow	0.95		1.09		1.54		0.25	
Children		.73 (1.10)		.74 (1.10)		.69 (1.02)		.75 (1.2)

Employment								
Full-Time	56.83		54.22		53.98		62	
Part-Time	11.51		11.99		13.37		9.25	
Self-Emp.	16.7		18.53		15.94		15.75	
Unemployed	10.29		10.90		11.05		9	
Retired	4.67		4.36		5.66		4	
Income								
< 20k	13.67		15.26		14.91		11	
20 to 40k	22.06		24.25		21.85		20.25	
40 to 60k	23.27		23.71		20.57		25.5	
60 to 80k	16.26		17.71		14.4		16.75	
80 to 100k	9.95		7.63		10.8		11.25	
Above 100k	14.79		11.44		17.48		15.25	
Financial Strain	15.66		17.44		17.48		12.25	
Subj Fin. Know		4.21 (1.3)		4.10 (1.3)		4.21 (1.3)		4.32 (1.2)
Obj Fin. Know		2.53 (.80)		2.43 (.86)		2.61 (.77)		2.54 (.76)
Prom. Score		3.45 (.68)		3.42 (.66)		3.45 (.71)		3.47 (.68)
Prev. Score		3.43 (.87)		3.41 (.88)		3.43 (.90)		3.47 (.85)
RFQ Difference		.01 (1.04)		.01 (1.02)		.03 (1.03)		.00 (1.07)
Promotion	49.13		49.05		49.1		49.25	
Prevention	50.87		50.95		50.9		50.75	

The average promotion scale and prevention scale scores were roughly the same, each about 3.4. Subtracting the prevention score from the promotion score meant that about 49% had positive difference scores, indicting a chronic promotion focus; about 51% had negative difference scores, indicating a chronic prevention focus; there were 36 respondents that had a difference score of zero, meaning they were neither chronic-promotion nor chronic-prevention.[18] The promotion scale had a Cronbach's alpha of .73, and the prevention scale had a Cronbach's alpha of .86, both of which were in acceptable ranges.

Research Question 1: Retirement Savings Planning

The first research question (Experiment 1, Retirement Savings Planning) concerned the effect of message framing on intentions to engage in retirement planning. In particular, whether narrative messages influenced these intentions (relative to a fact-based presentation or no information). Furthermore, whether the valence (positive or negative) of that narrative influenced intentions differently, which may be based on the underlying behavior. Then, whether that framing effect, if any, may be influenced by individual characteristics, such as regulatory orientation. Related to regulatory orientation, moreover, whether regulatory fit can enhance the appropriate framing effect—that is, the framing influence may be different depending on regulatory orientation (due to regulatory fit). In other words, looking at the main effects of narratives and regulatory orientation and then their interactions.

[18] Moreover, the median of the difference scores was zero before any listwise deletion; therefore, performing a median split would not have changed the classifications. Of the 36 respondents, 12 were from Experiment 1, 7 from Experiment 2, and 17 from Experiment 3. Theses respondents, moreover, were removed since they had neither a prevention nor promotion focus, which is central to many of the hypotheses examined. As well, their respective sizes would not have served as a reasonable reference group size (relative to those that were either promotion or prevention focused). Table 4.1 was presented after deletion of those respondents (as were the sample counts in Chapter 3).

ANOVA and ANCOVA

The first hypothesis (H1a) was that narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement savings. That is, there will be a difference in treatment means. To examine that preliminarily, a one-way ANOVA was analyzed. Table 4.2 reports the one-way ANOVA for Experiment 1.

Table 4.2 Experiment 1 One-Way ANOVA

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	6.24	2.081	0.68	0.565
Error	363	1110.87	3.06		
Corrected Total	366	1117.12			

Levene's test for homogeneity of the group variance was not rejected at the 1% (F(3, 363) = .63, p = .59), and the Brown and Forsythe test for homogeneity was not rejected either, F(3, 363) = .59, p = .62). The ANOVA showed a lack of a significant difference at the 5% level for the four groups, F(3, 363) = .68, p = .56. This indicated that the null hypothesis that all group intention means were the same cannot be rejected. Pairwise comparison of group means[19] using Tukey-Kramer adjustments for multiple comparisons produced similar results: none of the means were significantly different from any other. This means a lack of support for H1a. Indeed, this also means that there likely is not evidence in favor the other hypotheses, as they imply (and depend upon) a framing effect.

Also, to examine the effect of narrative message framing (compared to the control or to a fact-based prompt), a contrast was performed to compare the average effect of framing (positive and negative) to the control group. That contrast similarly reported no significant difference in intentions, t(363) = .63, p = .53, again indicating a lack of support for H1a. Similarly, a contrast

[19] Due to the unbalanced nature of the treatment groups, least-squares means were used for all mean comparisons.

comparing the average effect of framing to the fact-based group did not result in a significant difference, $t(363) = 1.41$, $p = .16$. Moreover, because there was a control group, mean differences using Dunnett's adjustment was performed, too; there were no significant mean differences compared to the control group. This, too, indicated a lack of support for H1a and the related hypotheses.

Similarly, the one-way ANOVA and contrasts inform hypotheses H1b and H1c. Hypothesis H1b posited that, due to the underlying nature of retirement planning (an analogy to the prevention behavior in the health literature), positive-valence (gain) narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement income. Here, however, there was no treatment effect, indicating a lack of support for hypothesis H1b. Similarly, hypothesis H1c advanced that negative-valence (loss) narrative message framing will be positively associated with intentions to actively plan for having sufficient retirement savings. Again, without a difference in treatment means, there was no support for this hypothesis. And, due to this being a prevention behavior, H1d posited that, positive-valence (gain) narrative framing will result in higher intentions to engage in an insurance needs analysis than negative-valence (loss) framing—in other words, the gain framing would be more effective than loss framing. Because there was not a treatment effect (relative to the control), this, too, indicated a lack of support for hypothesis H1d.

The one-way ANOVA was also performed on subsamples of promotion-only and prevention-only respondents, which informed hypotheses H1e and H1f. Hypothesis H1e posited that, for promotion-focus respondents, the positive-valence will be more effective than the negative-valence narrative due to regulatory fit. For promotion-focus only, the model was not significant, $F(3, 176) = .37$, $p = .78$. Similarly, none of the pairwise mean comparisons were significant. This indicated a lack of support for H1e.

Hypothesis H1f posited that, for prevention-focus respondents, the negative-valence narrative would be more effective due to regulatory fit. For prevention-focus only, likewise, the model was not significant, $F(3, 183) = .77$, $p = .51$; and none of the pairwise mean comparisons were significant. This, too, indicated a lack of support for H1f. For each subsample analysis, the same contrasts from the main one-way ANOVA were estimated; in each case, the contrasts were not significant at the 5% level.

Instead of a one-way ANOVA on the complete sample and then a subsample basis, another approach could be a two-way ANOVA that incorporated regulatory focus. Table 4.3 reports a two-way ANOVA (with Type III sums of squares) that incorporated both treatment group and chronic promotion or chronic prevention focus (with interactions).

Table 4.3 Experiment 1 Two-Way ANOVA (Treatment x Chronic Focus)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	5.80	1.934	0.63	.60
Focus	1	4.721	4.721	1.54	.216
Interaction	3	5.074	1.691	0.55	0.648
Error	359	1101.17	3.067		
Corrected Total	366	1117.12			

This model was not significant, $F(7, 359) = .74$, $p = .64$. Like the one-way ANOVA, this indicated a lack of support of H1a (framing effect), H1b (positive framing effect), H1c (negative framing effect), H1d (positive framing > negative framing), H1e and H1f (the regulatory focus hypotheses). In short, the framing effect, in this experiment, did not differ for regulatory focus (and, there was not even a framing effect to begin with).

However, perhaps the framing effect (and the regulatory fit phenomenon) was being influenced by the strength of the regulatory focus (and the variation was not being addressed by the random assignment). To control for that, Table 4.4 reports the one-way ANCOVA (with Type III sums of squares) for Experiment 1 using the RFQ difference as a covariate (and interacted).

Table 4.4 Experiment 1 ANCOVA (RFQ Difference Covariate)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	6.57	2.19	0.72	0.54
RFQ Diff	1	3.51	3.51	1.16	.28
Interaction	3	18.52	6.17	2.03	0.11
Error	359	1089.02	3.03		
Corrected Total	366	1117.12			

There was neither a main nor interaction effect, $F(7, 359) = 1.32$, $p = .24$. Because the model was not significant, additional analyses were not conducted.

Relatedly, and similar to the analysis for the one-way ANOVA, another analysis of interest was whether this changed for examining only promotion- or prevention-focused respondents as subsamples, controlling for the effect, if any, of RFQ strength. Therefore, an ANCOVA was analyzed on a subsample basis (type of focus). For promotion-focus-only respondents, the ANCOVA (with Type III sums of squares) table is presented in Table 4.5. Here, the F-test was not significant at the 5% level, $F(7, 172) = 1.85$, $p = .081$.

Table 4.5 Experiment 1 ANCOVA (RFQ Difference Covariate), Promotion Only

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment effect	3	6.911	2.30	0.81	0.491
RFQ Diff effect	1	7.58	7.58	2.66	0.105
Interaction	3	24.63	8.21	2.88	0.038
Error	172	490.78	2.85		
Corrected Total	179	527.66			

Nevertheless, further examining the model—because it was significant at the 10% level—the interaction was significant at the 5% level, $F(3, 172) = 2.88$, $p = .04$. Consequently, a traditional ANCOVA model cannot be used because the slopes for each group were not the same. Instead, separate slopes needed to be estimated for each treatment. Thus, mean differences were analyzed with Tukey-Kramer adjustments at two levels of absolute RFQ differences of 1 and 2 (i.e., at increasing differences in chronic promotion strength). Here, there were two significant mean differences, neither of which were at an RFQ difference level of 1. First, at RFQ difference level of 2, the positive-valence narrative treatment had a 2.13 higher intention score compared to the fact-based treatment, 95% CI [.15, 4.11], $p = 0.03$. Second, at RFQ difference of 2, the fact-based treatment had a 2.30 lower, 95% CI [-4.46, -.14], intention score relative to the control-group ($p = .03$); this was confirmed, too, using Dunnett's adjustment ($p = .017$).

The difference between the positive-valence and the fact-based treatment was of note, but the positive-valence was not significantly different than the control group. Thus, it could just be that the fact-based treatment had a negative impact on intentions. Looking at prevention-focused respondents only, the ANCOVA with RFQ difference[20] as a continuous covariate (and interaction) was not significant, $F(7, 179) = 1.05$, $p = .39$. Further analyses, therefore, are not discussed.

OLS Regression

To tease out (and control for) possible variation that was not captured by the random assignment, an ordinary least squares (OLS) regression analysis with various covariates (multiple linear regression) was examined to investigate the effect of the treatments on retirement planning intentions. Two models are presented in Table 4.6. First, is a model with main effects only, and second, a model with main effects and interactions. For categorical variables, cell sizes were examined to preserve power, and categories were collapsed as needed (e.g., white versus non-

[20] The regulatory differences were turned into absolute values (needed for the negative RFQ difference scores for prevention-focus) such that more positive values indicated stronger chronic prevention focus.

white; incomes less than $40,000 in the intercept and incomes above 80,000 collapsed; no college or college degree; married versus non-married; combining retired and unemployed)[21]. Second, is a model with main effects and interactions, in which the interactions are the RFQ difference score with each treatment group. The model is reported with robust standard errors. Variance inflation factors were examined for multicollinearity; in the main-effects model, all of the VIFs were between 1 and 2, except for the VIFs between the RFQ difference and dummy variable for promotion, which were slightly over three—this was not unexpected due to their relationships.[22]

Table 4.6 Experiment 1 OLS Regression for Retirement Intentions (n = 367)

Variable[23]	*B*	*SE*	*p*	*B*	*SE*	*p*
Intercept	3.018	0.497	<.0001	3.066	0.505	<.0001
Age	-0.002	0.008	0.766	-0.002	0.008	0.807
Male	-0.329	0.181	0.071	-0.351	0.182	0.054
Race: Non-white	0.484	0.218	0.027	0.453	0.216	0.037
College degree	0.245	0.182	0.180	0.233	0.183	0.205
Married	0.054	0.190	0.778	0.045	0.191	0.815
Self-employed	-0.658	0.246	0.008	-0.646	0.245	0.009
Part-time	-0.080	0.291	0.784	-0.087	0.291	0.765
Unemp/retired	-0.754	0.273	0.006	-0.741	0.274	0.007
40k < Inc. < 60k	0.015	0.234	0.948	-0.010	0.237	0.965
60k < Inc. < 80k	0.471	0.257	0.068	0.432	0.258	0.095
Income 80k +	0.756	0.276	0.007	0.735	0.279	0.009
Obj. Fin. Know.	0.014	0.106	0.893	0.002	0.106	0.987
Sub. Fin. Know.	0.197	0.071	0.006	0.202	0.071	0.005
Financial Strain	-0.529	0.250	0.035	-0.530	0.245	0.031
Promotion	0.291	0.283	0.304	0.277	0.281	0.325
RFQ Difference	-0.114	0.144	0.431	0.100	0.214	0.641
Fact treatment	-0.091	0.247	0.714	-0.106	0.246	0.666

[21] Categories were collapsed to achieve at least 10 (or as close thereto as possible) respondents in each cell for each level of the response variable (i.e., the intentions score), as long as the collapsing made theoretical and practical sense. However, that was not possible across all categories for all intention score levels.
[22] Of course, in the interaction model, some VIFs were higher between those involved in or related to the interactions.
[23] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Negative treatment	0.269	0.220	0.222	0.272	0.218	0.214
Positive treatment	0.275	0.227	0.226	0.259	0.224	0.249
Fact x RFQ Diff				-0.298	0.275	0.281
Neg x RFQ Diff				-0.350	0.241	0.148
Pos x RFQ Diff				-0.164	0.228	0.471
Adjusted R^2	.143			.142		

As shown, after controlling for these covariates, the treatments had no effect as main effects. Moreover, even after including the relative strength of the orientation effect (the interactions), there were still no treatment effects, which was consistent the earlier ANOVA and ANCOVA models. Therefore, the OLS regression did not provide support for any of the hypotheses; there was no treatment effect and that treatment effect did not differ based on RFQ difference. However, not related to this study's research questions (but perhaps possible future research), both financial strain and subjective financial knowledge were significant. Financial strain was negatively associated with retirement planning intentions and subjective financial knowledge was positively associated with retirement planning intentions.

For additional robustness, OLS regressions were performed (not presented) using subsamples of only promotion- or prevention-focused individuals (like with the one-way ANOVAs). For promotion-focus only, the main-effects regression did not have a significant F-value, $F(18, 161) = 1.57$, $p = .07$; similarly, the interaction model was not significant either, $F(21, 158) = 1.58$, $p = .06$. For prevention-focus respondents only, the main effects model was significant, $F(18, 168) = 4.13$, $p < .0001$, but neither the treatment main effects nor the RFQ difference were significant (the variables of interest). The prevention-focus only interaction model was significant, $F(21, 165) = 3.75$, $p < .0001$, but none of the treatment main effects or interaction effects were significant at the 5% level. Though, the RFQ difference was significant, with a point estimate of -.79, indicating that as prevention focused increased, intentions decreased, 95% CI [-1.49, -.08]. In short, the OLS regression, including the separate subsample regressions, did not provide support for any of the treatment hypotheses.

Nonparametric Analysis

The foregoing analysis used parametric techniques (e.g., the ANOVA and OLS regression). Using parametric techniques, particularly ANOVA, is common in intentions-based studies (i.e., to treat the intentions index as a continuous variable). However, the dependent variable was still Likert-type data, and, consequently, parametric techniques may not be ideal. Therefore, as a robustness check, nonparametric techniques were examined, too.

The main test was the Kruskal-Wallis H-Test for several independent samples, which is the nonparametric equivalent of the one-way ANOVA (Korosteleva, 2014). The Kruskal-Wallis test found no significant difference in location parameters for the four groups, χ^2 (3, n = 367) = 1.91, p = .59. Because the null hypothesis was not rejected here, additional Wilcoxon rank-sum pairwise comparisons between treatment groups was not necessary. Consistent with the one-way ANOVA, this indicated no evidence for hypothesis H1a (i.e., no evidence of any treatment effect).

For the hypotheses with promotion-specific focus (i.e, H1e and H1g), examining only promotion-focused respondents similarly resulted in an insignificant Kruskal-Wallis H Test, χ^2 (3, n = 180) = .60, p = .90. The same was true for prevention-only (H1f and H1h) respondents too, χ^2 (3, n = 187) = 2.59, p = .46. Consequently, the nonparametric tests were consistent with the parametric ANOVAs above that, for retirement planning intentions, the treatments had no effect on intentions, and that this was true even when splitting the sample based on regulatory focus.

Logistic Regression (Cumulative, Multinomial, and Binary)

Next, logits were examined. This was done to, among other things, allay concerns with the Likert-type response variable. First, a cumulative logit was performed, which, like the above nonparametric analysis, was ideal with Likert-type data. The cumulative logit was first performed using all 7-levels of the intention scale. That cumulative logit is presented in Table 4.7, both as main-effects only and main effects with interactions (similar to the OLS regression).

Table 4.7 Experiment 1 Cumulative Logit of All Intention Levels (n = 367)

Variable[24]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept (7)	-4.075	0.613		<.0001	-4.096	0.614		<.0001
Intercept (6)	-2.559	0.580		<.0001	-2.579	0.582		<.0001
Intercept (5)	-0.993	0.567		0.080	-1.006	0.569		0.077
Intercept (4)	-0.359	0.565		0.525	-0.369	0.567		0.516
Intercept (3)	0.347	0.565		0.540	0.342	0.567		0.547
Intercept (2)	1.279	0.573		0.026	1.283	0.575		0.026
Age	-0.005	0.008	0.995	0.573	-0.003	0.009	0.997	0.688
Male	-0.374	0.199	0.688	0.061	-0.388	0.201	0.679	0.054
Race: Non-white	0.505	0.256	1.657	0.048	0.476	0.256	1.609	0.064
College Degree	0.241	0.206	1.273	0.241	0.233	0.207	1.262	0.262
Married	0.028	0.218	1.028	0.899	0.019	0.219	1.019	0.931
Self-employed	-0.663	0.266	0.515	0.013	-0.644	0.267	0.525	0.016
Part-time	-0.136	0.309	0.873	0.659	-0.153	0.310	0.858	0.621
Unemp/retired	-0.811	0.291	0.444	0.005	-0.797	0.295	0.451	0.007
40k < Inc. < 60k	-0.001	0.262	0.999	0.996	-0.046	0.263	0.955	0.862
60k < Inc. < 80k	0.574	0.295	1.776	0.052	0.531	0.296	1.701	0.073
Income 80k +	0.871	0.317	2.389	0.006	0.843	0.318	2.323	0.008
Obj. Fin. Know.	0.009	0.118	1.009	0.942	-0.003	0.119	0.997	0.981
Sub. Fin. Know.	0.219	0.078	1.245	0.005	0.229	0.078	1.257	0.003
Financial Strain	-0.639	0.262	0.528	0.015	-0.641	0.262	0.527	0.015
Promotion	0.276	0.325	1.318	0.396	0.265	0.326	1.303	0.416
RFQ Difference	-0.076	0.159	0.927	0.632	0.164	0.237	1.179	0.487
Fact Treatment	-0.139	0.267	0.870	0.602	-0.158	0.268	0.854	0.557
Neg. Treatment	0.310	0.267	1.364	0.246	0.307	0.268	1.359	0.252
Pos. Treatment	0.270	0.273	1.309	0.323	0.257	0.273	1.293	0.347

[24] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Fact x RFQ Diff		-0.316	0.278	0.729	0.257
Neg x RFQ Diff		-0.438	0.263	0.646	0.096
Pos x RFQ Diff		-0.175	0.270	0.839	0.516
Pseudo R^2 (Cox & Snell)	.181	.187			
AIC	1326.80	1329.91			
% Concordant	67	66.7			

Consistent with the earlier analyses, neither the treatment main effects nor the interaction effects were significant. Also, like before, the same model was performed on a subsample basis. For promotion-focus respondents only, the interaction model was significant, with a likelihood ratio test of χ^2 (21, n = 180) = 33, p = .046. Considering the model, though, none of the main effects or interactions were significant at the 5% level, which was consistent with the prior analyses.

In the prevention-only interaction model, which was significant (χ^2 (21, n = 187) = 74.14, p < .0001), the negative valence treatment/RFQ interaction was significant, with a point estimate of 1.43, χ^2 (1) = 4.71, p = .03. Although this may tend to support H1h—that, for prevention-focus respondents, the negative-valence effect increased with levels (strength) of prevention focus—the model was suspect due to the proportional-odds assumption being violated in this specification, χ^2 (105, n = 187) = 215, p < .0001. As such, for analytical purposes, this was not considered evidence in favor of H1h.

Due to indication of the proportional odds assumption being violated,[25] a multinomial logit (which has no similar proportional-odds assumption) was examined, too. The multinomial main-effects model (not presented due to the unwieldy number of category pairs), although significant, did not have any significant treatment effects in the main effects model. Similarly, in

[25] However, Allison (2012) notes that, with SAS, the test may reject the null hypothesis more often than needed. Allison (2012) further notes that, with many independent variables and larger sample sizes, in his experience, p-values of less than .05 are routinely returned.

the multinomial interaction model, which was significant (χ^2 (132, n = 367) = 200, $p < .0001$), none of the Type 3 analysis of effects chi-square tests were significant for the main effects or interactions, indicating that those variables had no effect on the outcome variable (Allison, 2012).

As a further check, a parsimonious multinomial logit was performed with only treatment-based regressors (regulatory focus, difference score, treatment, and interactions). Under this specification, the model converged, but there was not even a significant likelihood ratio test (χ^2 (48, n = 367) = 43.64, $p = .65$), and no Type 3 main effects or interactions were significant. In short, like the prior analyses, no support for any of the hypotheses.

To further strengthen the analysis from a statistical power perspective and to further account for possible issues with the proportional odds assumption,[26] instead of using all seven levels, the levels were collapsed into a low- (1 or 2), medium- (3, 4, or 5), or high-intention level (6 or 7). A cumulative logit, therefore, was performed with both main effects and interactions. Those results are reported in Table 4.8 (the reference group is Low). Importantly, with three levels instead of seven, the proportional odds assumption was not violated.[27] Similarly—and consistent with the prior results—neither the main effects nor interaction effects were significant. This, too, comported with the conclusions from the above parametric and non-parametric analyses.

[26] As well as the issue of potential smaller cells on the extremes of the intention measures (e.g., answers of 1 or 7).
[27] In the main-effects model, the proportional odds assumption test score was χ^2 (19, n = 367) = 22.40, $p = .26$; in the interaction model, the test score was χ^2 (22, n = 367) = 24.59, $p = .32$.

Table 4.8 Experiment 1 Cumulative Logit (High, Medium, Low)

Variable[28]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept (High)	-2.464	0.644		0.000	-2.447	0.646		0.000
Intercept (Med.)	0.456	0.627		0.468	0.480	0.630		0.446
Age	-0.008	0.009	0.992	0.396	-0.008	0.010	0.992	0.412
Male	-0.448	0.223	0.639	0.045	-0.452	0.224	0.636	0.044
Race: Non-white	0.562	0.284	1.754	0.048	0.541	0.285	1.717	0.058
College Degree	0.163	0.230	1.177	0.479	0.150	0.232	1.162	0.516
Married	-0.036	0.243	0.965	0.883	-0.034	0.244	0.967	0.890
Self-employed	-0.720	0.298	0.487	0.016	-0.714	0.299	0.490	0.017
Part-time	-0.272	0.345	0.762	0.430	-0.295	0.346	0.744	0.394
Unemp/retired	-0.718	0.325	0.488	0.027	-0.679	0.329	0.507	0.039
40k < Inc. < 60k	-0.102	0.293	0.903	0.728	-0.148	0.294	0.863	0.616
60k < Inc. < 80k	0.350	0.328	1.418	0.287	0.323	0.330	1.382	0.327
Income 80k +	0.848	0.353	2.334	0.016	0.811	0.354	2.249	0.022
Obj. Fin. Know.	-0.003	0.132	0.997	0.979	-0.008	0.132	0.992	0.952
Sub. Fin. Know.	0.231	0.087	1.260	0.008	0.234	0.087	1.264	0.007
Financial Strain	-0.687	0.292	0.503	0.019	-0.687	0.293	0.503	0.019
Promotion	0.460	0.363	1.584	0.204	0.464	0.364	1.591	0.202
RFQ Difference	-0.153	0.177	0.858	0.387	-0.011	0.263	0.989	0.966
Fact Treatment	0.085	0.297	1.088	0.776	0.058	0.299	1.060	0.845
Neg. Treatment	0.399	0.298	1.490	0.181	0.399	0.299	1.491	0.181
Pos. Treatment	0.393	0.304	1.481	0.196	0.373	0.305	1.452	0.222
Fact x RFQ Diff					-0.293	0.310	0.746	0.345
Neg x RFQ Diff					-0.275	0.292	0.760	0.346
Pos x RFQ Diff					-0.011	0.301	0.989	0.970
Pseudo R^2 (Cox & Snell)	.150				.154			
AIC	706.13				710.40			
% Concordant	69.9				69.6			

This interaction cumulative logit was also performed on a subsample basis. For promotion-focus respondents, the model was not significant, χ^2 (21, n = 180) = 27.08, p = .17; and, even considering it, none of the main treatment effects or interactions were significant, indicating a lack of support for H1e and H1g. For prevention-focus respondents, the interaction

[28] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

model was significant, χ^2 (21, n = 187) = 64.62, $p < .0001$, and the proportional odds assumption was not rejected, χ^2 (21, n = 187) = 23.26, $p = .33$. However, none of the main treatment effects or interactions were significant at the 5% level, indicating a lack of support for H1f and H1h.

Lastly, in addition to the cumulative logit, a binary logit[29] was performed to examine high intentions (compared to non-high intentions) both with main effects and interactions, which is presented in Table 4.9. Although the main-effects model was significant, the interaction-effects model's likelihood ratio test was marginally above the 5% level, χ^2 (22, n = 367) = 33.47, p = .056.[30]

Table 4.9 Experiment 1 Logit (High v. Non-High) (n = 367)

Variable[31]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept	-2.664	0.871		0.002	-2.645	0.872		0.002
Age	-0.013	0.013	0.987	0.305	-0.014	0.013	0.986	0.279
Male	-0.102	0.295	0.903	0.730	-0.084	0.297	0.920	0.778
Race: Non-white	0.588	0.341	1.800	0.085	0.596	0.343	1.816	0.082
College Degree	0.321	0.325	1.379	0.323	0.310	0.327	1.363	0.343
Married	-0.101	0.324	0.904	0.755	-0.091	0.325	0.913	0.779
Self-employed	0.055	0.410	1.057	0.893	0.073	0.411	1.076	0.859
Part-time	-0.198	0.482	0.820	0.682	-0.204	0.484	0.816	0.674
Unemp/retired	-0.035	0.439	0.965	0.936	-0.005	0.444	0.995	0.991
40k < Inc. < 60k	0.057	0.420	1.059	0.892	0.043	0.422	1.044	0.919
60k < Inc. < 80k	0.597	0.426	1.817	0.161	0.613	0.429	1.846	0.153
Income 80k +	0.993	0.446	2.698	0.026	0.978	0.447	2.659	0.029
Obj. Fin. Know.	-0.020	0.177	0.980	0.910	-0.014	0.178	0.986	0.935
Sub. Fin. Know.	0.260	0.120	1.296	0.030	0.258	0.120	1.294	0.032
Financial Strain	-0.696	0.482	0.499	0.148	-0.696	0.482	0.499	0.148
Promotion	-0.155	0.475	0.856	0.744	-0.145	0.478	0.865	0.762
RFQ Difference	0.188	0.239	1.207	0.430	0.142	0.365	1.153	0.698
Fact Treatment	0.443	0.401	1.558	0.269	0.418	0.404	1.519	0.301
Neg. Treatment	0.376	0.405	1.456	0.354	0.354	0.410	1.425	0.388
Pos. Treatment	0.277	0.419	1.319	0.509	0.258	0.425	1.295	0.544

[29] Collapsing the Likert-type data into a binary classification obviates any ordinal data concerns; respondents indicating a 6 or 7 intention score were classified as having strong intentions.
[30] The Score and Wald tests were likewise greater than .05.
[31] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Fact x RFQ Diff		-0.086	0.422	0.918	0.839
Neg x RFQ Diff		0.134	0.406	1.144	0.741
Pos x RFQ Diff		0.101	0.419	1.106	0.811
Pseudo R^2 (Cox & Snell)	.086	.087			
AIC	375.86	381.49			
% Concordant	71.2	71.5			

Like before, none of the treatment main effects or interactions were significant, indicating a lack of support for hypotheses H1a, H1b, H1c, and H1d. Subsample binary logits were performed, too. For promotion-focus only respondents, the interaction model was not significant, χ^2 (21, n = 180) = 17.07, p = .71. As such, this indicated a lack of support for H1e (if promotion-focused, positive-valence should be stronger) and H1g (if promotion-focused, positive-valence proportional to strength). For prevention-focus only respondents, the interaction model was significant, χ^2 (21, n = 187) = 35.01, p = .028, but none of the main effects or interactions were significant). As such, this indicated a lack of support for H1f (if prevention-focused, negative-valence should be stronger) and H1h (if prevention-focused, negative-valence proportional to strength).

In sum, then, across the analyses performed above (whether parametric or not), there was no general support for a general narrative treatment effect (either gain-framed or loss-framed). Moreover, there was no support for the hypotheses that advanced that any treatment effect may be influenced by either the regulatory focus of the respondent or even the relative strength of that focus.

Research Question 2: Budget & Cash-Flow Planning

The second research question (Experiment 2, Budget and Cash-Flow Planning) concerned the effect of message framing on intentions to engage in budget and cash-flow planning. In particular, whether narrative messages influenced these intentions (relative to a fact-based presentation or no information control group). Furthermore, whether the valence (positive or negative) of that narrative influenced intentions differently, which may be based on the underlying nature of the behavior. Then, whether that framing effect, if any, was influenced by individual characteristics, such as regulatory focus. Related to regulatory focus, moreover, whether regulatory fit can enhance the respective framing effect. In other words, looking at the main effects of narratives and regulatory orientation and then their interactions. The analysis proceeds in the same fashion as Research Question 1.

ANOVA and ANCOVA

The first hypothesis (H2a) was that, narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting (a general narrative effect). That is, at a minimum, there will be a difference in treatment means. To examine that preliminarily, Table 4.10 reports the one-way ANOVA for Experiment 2.

Table 4.10 Experiment 2 One-Way ANOVA

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	34.820	11.607	4.83	0.003
Error	385	925.638	2.404		
Corrected Total	388	960.458			

Levene's test for homogeneity of the group variance was not rejected at the 1% ($F(3, 385) = .44$, $p = .74$), and the Brown and Forsythe test for homogeneity was not rejected either, $F(3, 385) = .77$, $p = .51$. The ANOVA showed a significant group difference at the 5% level, $F(3, 385) = 4.83$, $p = .0026$. This indicated that that at least one group mean was different than the others. However, post-estimation tests were required to further elucidate any evidence in support of the hypotheses.

Consequently, pairwise comparison of group means using Tukey-Kramer adjustments for multiple comparisons showed two significantly different pairwise differences. First, the negative-valence narrative produced a .78 higher mean, 95% CI [.21, 1.35], compared to the control (p = .003), which was true with Dunnett's adjustment, too (p = .001); second, the negative-valence narrative had a .63 higher mean, 95% CI [.06, 1.21], compared to the positive-valence narrative (p = .0253). This supported hypothesis H2a that there may be a narrative effect and H2c for a negative valence effect.

Additionally, a contrast was performed to compare the average effect of the narratives (positive and negative) to the control group. That contrast indicated a significant difference in intentions, with a mean difference of .462, 95% CI [.09, .84], higher intentions for average narrative effect to the control group, $t(385) = 2.41$, $p = .016$. This also supported hypothesis H2a of a possible narrative effect (compared to control).

A contrast comparing the average effect of framing to the fact-based group, however, did not result in a significant difference, $t(385) = .07$, $p = .94$. And, when just looking at the treatment pairwise mean differences, there were not significant differences between the fact-based treatment and either the positive- or negative-valence narratives. The cleanest result would be for there to be a difference between both—that is, the narratives were different than the control and the fact-based treatment. On the other hand, the fact-based group was not significantly different than the control group. This created an ambiguity in interpreting the results: perhaps it was not strictly framing at play but priming and salience.

The one-way ANOVA and contrasts also shed light upon hypotheses H2b and H2c. Hypothesis H2b advanced that, positive-valence (gain) narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting. Here, however, the positive-valence narrative mean was not significantly different than the control, which does not provide support for H2b. Hypothesis H2c posited that, negative-valence (loss) narrative message framing will be positively associated with intentions to engage in monthly cash-flow budgeting. That is, there is still a narrative effect even with negative-valence framing. Here, the negative-valence narrative was positively associated with higher intentions relative to the control group, i.e., support indicated for H2c.

Due to the prevention nature of the behavior, the literature would hypothesize that gain (positive) framing should be more effective. Thus, hypothesis H2d posited that, positive-valence (gain) narrative framing will be result in higher intentions to engage in monthly cash-flow budgeting. Here, however, the negative treatment had the highest mean intention score (M = 4.72, SE = .16), compared to the positive treatment (M = 4.08, SE = .16). And, this difference was significant, $t(385) = 2.83$, $p = .03$. Therefore, this does not indicate support of H2d; that is, the positive narrative did not have a stronger treatment effect compared to the negative narrative.

The one-way ANOVA was also performed on a subsample basis. For promotion-focus respondents, the model was significant, $F(3, 187) = 3.88$, $p = .01$. Pairwise mean comparisons using Tukey-Kramer adjustments showed two significantly different mean pairs. First, the negative-valence treatment had a .79 higher, 95% CI [.01, 1.58], mean than the control, $p = .045$. This bolstered H2c (negative-valence effect), but this was opposite of the hypothesized direction for promotion-focus respondents, for which gain-framing should be more effective due to regulatory fit. Second, the negative-valence had a .93 higher mean, 95% CI [.10, 1.75], compared to the positive-valence treatment. Again, this is opposite of the hypothesized direction. As such, this indicated a lack of support for H2e.

For prevention-focus respondents, the one-way ANOVA was not significant, $F(3, 194) = 1.83$, $p = .14$. As such, additional analyses were not conducted; however, the lack of significance indicated a lack of support for H2f (if prevention-focus, negative valence should be more effective).

Next, a two-way ANOVA is reported in Table 4.11 that incorporates regulatory orientation, i.e., both treatment group and chronic promotion focus or chronic prevention focus (with interactions). This related to hypotheses H2e and H2f, which posited that, in accord with regulatory fit, the narrative treatment effect will be influenced by regulatory focus. That is, for promotion-focus respondents, gain framing (positive valence) will be more effective, and, for prevention-focus respondents, loss framing (negative valence) will be more effective. This model was significant at the 5% level, $F(7, 381) = 2.42$, $p = .02$.

Table 4.11 Experiment 2 Two-Way ANOVA (Treatment x Chronic Orientation)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	35.839	11.946	4.95	0.002
Regulatory Focus	1	0.6791	0.679	0.28	0.596
Interaction	3	5.462	1.821	0.75	0.520
Error	381	919.564	2.414		
Corrected Total	388	960.458			

However, the interaction was not significant. Therefore, the two-way ANOVA without interaction was analyzed too (not presented). Although that model was significant, $F(4, 384) = 3.68$, $p = .006$, the main effect for chronic regulatory focus was not, $F(1, 384) = .25$, $p = .615$ (similar to the model with the interaction). This indicated a lack of support for hypotheses H2e and H2f; that is, the framing effect, in this experiment, did not depend on regulatory focus.

However, perhaps the framing effect (and the regulatory fit phenomenon) was being influenced by the strength of the regulatory focus (and the variation was not being addressed by the random assignment). Therefore, to control for that, the next model incorporated the RFQ difference as a covariate; Table 4.12 reports the one-way ANCOVA (with Type III sums of squares) for Experiment 2 using the RFQ difference as a covariate (and interacted).

Table 4.12 Experiment 2 ANCOVA (RFQ Difference Covariate)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	33.499	11.167	4.64	0.003
RFQ Difference	1	0.189	0.189	0.08	0.780
Interaction	3	8.165	2.722	1.13	0.336
Error	381	917.462	2.408		
Corrected Total	388	960.458			

The overall model was significant, $F(7, 381) = 2.55$, $p = 0.014$. However, because the interaction term was not significant ($F(3, 381) = 1.13$, $p = .34$), an equal-slopes model was estimated by removing the interaction term. Here, without the interaction term, the model was still significant, $F(4, 384) = 3.61$, $p = .007$. There was a main effect for the treatment group, $F(3, 384) = 4.81$, $p = .003$, but not for regulatory difference, $F(1, 384) = 0.00$, $p = .96$. After controlling for RFQ difference, there were two significant mean pairwise differences (with Tukey-Kramer adjustments). First, the negative-valence narrative had a .78 higher mean, 95% CI [.21, 1.35], than the control group, $p = .003$. Second, the positive-valence narrative had a .63 lower mean than the negative group, 95% CI [-1.21, -.05], $p = .03$. In short, the negative valence mean was higher than both the control and positive valence groups. This comported with the prior analysis; that is, there was not a stable positive treatment effect that resulted in an increased level of intentions, but there was a consistent (and positive) negative-valence effect. But after controlling for RFQ difference, the negative treatment mean was not significantly different than the fact-based treatment, which was the case, too, without incorporating the RFQ covariate.

To see if this changed when only the subsamples were examined, an ANCOVA was analyzed on a subsample basis (type of regulatory focus). For promotion-focus only respondents, the F-test for the model was significant at the 5% level, $F(7, 183) = 3.08$, $p = .004$. The ANCOVA (with Type III sums of squares) table is presented in Table 4.13.

Table 4.13 Experiment 2 ANCOVA (RFQ Difference Covariate), Promotion Only (n = 191)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	30.527	10.176	4.61	0.004
RFQ Difference	1	3.977	3.977	1.8	0.181
Interaction	3	19.203	6.401	2.9	0.036
Error	183	403.808	2.207		
Corrected Total	451.435				

Importantly, the interaction effect was significant, $F(3, 183) = 2.90$, $p = .036$. As such, an unequal-slope model was estimated with least squares mean differences calculated at different levels of absolute RFQ difference; mean differences were analyzed with Tukey-Kramer adjustments at two levels of absolute RFQ differences of 1 and 2, indicating little difference to greater difference in levels of chronic promotion focus. Analyzed at both levels, there were no significant mean differences. Also, compared to the control group, with Dunnett's procedure, there were no significant mean differences at the two RFQ difference levels. The contrast between the average narrative effect to the control was not significant, $t(183) = -.40$, $p = .69$; the contrast for the average narrative effect to the fact-based group was insignificant, too, $t(183) = 0$, $p = .99$.

Looking at prevention-focused respondents only, the ANCOVA with absolute RFQ difference as a continuous covariate was not significant, $F(7, 190) = 1.52$, $p = .16$.[32] Further analysis, therefore, is not discussed.

[32] This was true when even restricting it to a main-effects model (no interaction), $F(4, 193) = 1.94$, $p = .11$.

OLS Regression

Like with Experiment 1, a regression analysis with various covariates (multiple linear regression) was also examined to examine the effect of the treatments on cash-flow and budget intentions (and to control for possible variation not captured by the random assignment). Two models are presented in Table 4.14. First, is a model with main effects only, and second, a model with main effects and interactions. For categorical variables, cell sizes were examined to preserve power, and categories were collapsed as needed (e.g., white versus non-white; incomes less than $40,000 in the intercept and incomes above 80,000 collapsed; no college or college degree; married versus non-married; combining retired and unemployed).[33] The model is reported with robust standard errors. Variance inflation factors were examined for multicollinearity; in the main-effects model, all VIFS were under 3.0.[34]

Table 4.14 Experiment 2 OLS Regression for Budget Intentions (n = 389)

Variable[35]	*B*	*SE*	*p*	*B*	*SE*	*p*
Intercept	5.00	0.486	<.0001	4.995	0.482	<.0001
Age	-0.011	0.007	0.124	-0.011	0.007	0.136
Male	-0.139	0.165	0.401	-0.149	0.163	0.361
Race: Non-white	0.220	0.190	0.249	0.215	0.189	0.257
College Degree	0.068	0.178	0.702	0.046	0.176	0.792
Married	0.095	0.174	0.584	0.110	0.171	0.519
Self-employed	-0.059	0.244	0.809	-0.072	0.241	0.767
Part-time	0.153	0.230	0.507	0.131	0.233	0.575
Unemp/retired	-0.332	0.234	0.157	-0.354	0.233	0.130
40k < Income < 60k	0.334	0.239	0.164	0.314	0.235	0.184
60k < Income < 80k	0.321	0.226	0.156	0.296	0.221	0.182

[33] Categories were collapsed to achieve at least 10 (or as close thereto as possible) respondents in each cell for each level of the response variable (i.e., the intentions score), as long as the collapsing made theoretical and practical sense. However, that was not possible across all categories for all intention score levels. Thus, the cumulative logit with three ordered levels, discussed later, may be the ideal analysis.

[34] The highest VIFs were, of course, between the RFQ difference and the promotion dummy, which were still under 3.0. In the interaction model, all VIFs except those RFQ and the interactions were less than 2. The RFQ difference and promotion dummy had higher VIFs, which was not unexpected.

[35] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Income 80k +	-0.219	0.245	0.371	-0.232	0.240	0.335
Obj. Fin. Know.	-0.306	0.104	0.004	-0.301	0.103	0.004
Sub. Fin. Know.	0.072	0.073	0.325	0.072	0.071	0.311
Financial Strain	-0.075	0.225	0.740	-0.088	0.225	0.695
Promotion	-0.325	0.263	0.217	-0.279	0.262	0.287
RFQ Difference	0.135	0.145	0.351	-0.008	0.203	0.970
Fact Treatment	0.402	0.220	0.069	0.384	0.219	0.081
Neg. Treatment	0.778	0.211	0.000	0.764	0.210	0.000
Pos. Treatment	0.130	0.213	0.541	0.121	0.212	0.568
Fact x RFQ Diff				0.289	0.219	0.188
Neg x RFQ Diff				0.065	0.234	0.748
Pos x RFQ Diff				0.078	0.235	0.741
Adjusted R^2	.07			.07		

The main effects model was significant, $F(19, 369) = 2.54$, $p = .0004$; so too was the interaction model, $F(22, 366) = 2.30$, $p = .0009$. As shown, after controlling for these covariates in the interaction model, relative to the control (intercept), the negative treatment had a significant impact on intentions (consistent with the ANOVA and ANCOVA analyses), with the negative treatment mean of .76 higher than the control group, 95% CI [.35, 1.18]. The fact-based treatment was not significant at the 5% level but would be significant at the 10% level. This supported hypotheses H2a (of a narrative treatment effect) and H2c (negative-valence effect), but a lack of support for the other hypotheses (at least in terms of directionality).

To test H2d (positive-valence is greater than negative-valence effect) a linear hypothesis of parameter equivalence was conducted by a robust Wald test, which rejected the null hypothesis of equivalency, χ^2 (1, n = 389) = 8.95, $p = .003$ (under the main-effects only model).[36] As such, the parameters were not the same and the negative-valence parameter was significantly higher than the positive-valence parameter; thus, this indicated a lack of support for H2d. Using the interaction-effect model, a similar test was performed on the equivalency between the

[36] The same was true under the interaction model, χ^2 (1, n = 389) = 8.89, $p = .003$.

negative treatment coefficient and the fact-based treatment coefficient, χ^2 (1, n = 389) = 3.18, p = .07; although not rejected at the 5% level, it would be rejected at the 10% level, and fact-based coefficient was not different than zero in the underlying model at the 5% level.

Additional multiple OLS regressions were also performed (not presented) using only subsamples of promotion- or prevention-focused individuals only. This related to hypotheses H2e through H2h. For promotion-focus only respondents, the interaction model was significant, $F(21, 169) = 2.78$, $p = .0001$. Here, the positive treatment/RFQ difference interaction term was significant, $t(1) = 2.59$, $p = .01$, with an estimate of 1.27, 95% CI [.30, 2.23], indicating that, as promotion-focus strength increased, so too did the mean intention score for those in the positive treatment, which supported H2g (if promotion-focused, intentions in positive-valence related to promotion strength)—that is, regulatory fit. However, the underlying main effect for the positive treatment was -1.26, 95% CI [-2.21, -.31]. None of the other treatment main effects or interactions were significant at the 5% level.

A robust Wald test was used to test for the equivalency of the positive-valence and negative-valence main effect parameters; this test was rejected (χ^2 (1, n = 191) = 11.64, p = .0006); but, again, the positive main effect had a negative parameter estimate, which was contrary to the hypothesized direction. A robust Wald test was performed for the equality of the positive treatment and fact-based treatment, which was not rejected, χ^2 (1, n = 191) = 1.75, p = .19). Insofar as the positive-valence treatment, though, the Wald test results were less meaningful due to the significant positive interaction effect.

The disparate directionality between the main effect and interaction was less than ideal for support of H2e and H2g (the regulatory fit hypotheses for promotion respondents). For H2g and regulatory fit, though, the relationship of interest was really the interaction effect—that the positive effect depended on the strength of the promotion-focus, and that it increased with increasing levels of promotion focus. This indicated slight support for regulatory fit based on the OLS promotion-only subsample regression.

For prevention-only respondents, the main effects model was not significant, $F(18, 179) = 1.62$ $p = .06$. Nor was the interaction model, $F(21, 176) = 1.52$ $p = .076$. Considering the model, though, none of the interactions were significant. But, the fact-based and negative-valence main effects were both significant. The negative-valence main effect estimate was 1.23, 95% CI [.22, 2.23], indicating that prevention-respondents had higher intention scores when exposed to the negative-valence treatment. So, too, though was the fact-based treatment, 1.23, $t(1) = 2.41$, $p = .02$. Moreover, a robust Wald test could not reject the null hypothesis that the fact-based and negative-valence parameter estimates were equivalent, χ^2 (1, n = 198) = .00, $p = .99$. Thus, it was unclear whether the negative-valence effect was truly a framing effect or, say, a result of priming or salience. Given that the positive-valence treatment was not significant in this specification, that cuts against the difference being attributable due pure priming or salience (which would arguably be present in the positive-valence treatment, too). As such, there was tentative support for H2f (if prevention focus, negative valence is > positive valence). But, no support that the negative-valence effect is influenced by the prevention-focus strength (H2h). And, still, the model was not significant, so it should not be given great consideration.

Nonparametric Analysis

As was the case for Research Question 1, the foregoing analysis used parametric techniques (e.g., ANOVA and OLS regression). However, the dependent variable was still Likert-type data, and, consequently, parametric techniques may not be ideal. Therefore, as a robustness check, nonparametric techniques were examined, too.

Primarily, the Kruskal-Wallis H-Test for several independent samples was examined, which was relevant for H2a (general narrative effect). This test found a significant difference in location parameters for the four groups, χ^2 (3, n = 389) = 14.27, *p* = .003. This supported H2a in that the group location parameters were different. Consequently, two-sample Wilcoxon test were then conducted for each group-pair comparison.[37]

Comparing the control and fact-based groups, the Wilcoxon test was not significant, Z = 1.8, *p* = .067; for the control and negative valence, the test was significant, Z = 3.54, *p* = .0004,[38] with the negative valence having a larger Wilcoxon score (higher values). This supported the prior analyses, i.e., in support of H2c (negative-valence effect). For the control and positive valence, the test was not significant, Z = .48, *p* = .63, which indicated a lack of support for H2b (positive-valence effect); for the fact-based and negative valence, the test was not significant, Z = 1.56, *p* = .12; for fact-based and positive valence, the test was not significant, Z = -1.30, *p* = .19; finally, for negative and positive valences, the test was significant, Z = -2.89, *p* = .004, with the negative valence having a higher score (higher values), i.e., a lack of support for H2d (that positive-valence will be higher). In sum, then, the nonparametric analysis supported the parametric analysis insofar as the treatment parameters were not the same, and, in particular, the negative valence treatment resulted in higher intentions. And, contrary to the expectation from theory, the positive-valence was not higher than the negative-valence.

Similarly, examining only promotion-focused respondents resulted in a significant Kruskal-Wallis H Test, χ^2 (3, n = 191) = 10.39, *p* = .016. Related to H2d (for promotion, gain-framing should be more effective than negative-framing), then, a two-sample Wilcoxon test was conducted. The test was significant, Z = -2.81, *p* = .005, but the negative valence had the higher

[37] Due to the sample sizes involved, continuity corrections were not used.
[38] Two-sided (absolute value) *p*-values reported throughout.

score value (higher intention levels). Thus, this does not indicate support for H2d. For prevention-only respondents, the test was insignificant, χ^2 (3, n = 198) = 6.43, p = .093. This indicated a lack of support for H2f (for prevention-focus, negative valence should be stronger).

In sum, the nonparametric tests support the parametric ANOVAs and regressions above that, for cash-flow and budget planning intentions, the treatments had an effect on intentions. Alternatively, it could be that the nonparametric tests did not have sufficient power to isolate differences that the OLS regressions can.

Logistic Regression (Cumulative, Multinomial, and Binary)

Next, logits were examined. As before, this was done to allay concerns with using parametric techniques on a Likert-type response variable. First, a cumulative logit was performed, which, like the above nonparametric analysis, was ideal with a Likert-type response variable. The cumulative logit was first performed using all 7-levels of the intention scale. That cumulative logit is presented in Table 4.15 both as main-effects only and main effects with interactions (similar to the above OLS regression).

Table 4.15 Experiment 2 Cumulative Logit of All Intention Levels (n = 389)

Variable[39]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept (7)	-2.258	0.607		0.000	-2.255	0.609		0.000
Intercept (6)	-0.611	0.582		0.294	-0.600	0.584		0.304
Intercept (5)	0.773	0.582		0.184	0.794	0.584		0.174
Intercept (4)	1.524	0.586		0.009	1.549	0.588		0.008
Intercept (3)	2.483	0.595		<.0001	2.509	0.596		<.0001
Intercept (2)	3.846	0.626		<.0001	3.869	0.628		<.0001
Age	-0.014	0.008	0.986	0.086	-0.014	0.008	0.986	0.083
Male	-0.198	0.195	0.820	0.309	-0.191	0.196	0.826	0.330
Race: Non-white	0.298	0.236	1.347	0.206	0.295	0.236	1.342	0.212
College Degree	0.120	0.213	1.127	0.572	0.092	0.214	1.097	0.667
Married	0.063	0.204	1.065	0.756	0.085	0.204	1.089	0.676
Self-employed	-0.043	0.266	0.958	0.871	-0.076	0.267	0.927	0.776
Part-time	0.171	0.293	1.186	0.561	0.152	0.295	1.164	0.606
Unemp/retired	-0.365	0.279	0.694	0.191	-0.367	0.282	0.693	0.192
40k < Inc. < 60k	0.423	0.266	1.527	0.112	0.384	0.267	1.467	0.151
60k < Inc. < 80k	0.245	0.310	1.277	0.430	0.220	0.312	1.246	0.482
Income 80k +	-0.285	0.280	0.752	0.308	-0.294	0.281	0.745	0.295
Obj. Fin. Know.	-0.371	0.129	0.690	0.004	-0.366	0.129	0.694	0.005
Sub. Fin. Know.	0.137	0.079	1.147	0.082	0.133	0.079	1.142	0.094
Financial Strain	-0.092	0.262	0.912	0.726	-0.102	0.263	0.903	0.698
Promotion	-0.396	0.300	0.673	0.188	-0.337	0.302	0.714	0.265
RFQ Diff	0.179	0.148	1.196	0.227	0.048	0.225	1.049	0.831
Fact	0.472	0.257	1.603	0.066	0.451	0.258	1.571	0.080
Neg	0.931	0.261	2.536	0.000	0.930	0.261	2.535	0.000
Pos	0.123	0.257	1.131	0.632	0.124	0.257	1.132	0.628
Fact x RFQ Diff					0.317	0.241	1.373	0.188
Pos x RFQ Diff					0.078	0.261	1.081	0.766
Neg x RFQ Diff					-0.050	0.264	0.952	0.851
Pseudo R^2 (Cox & Snell)	.12				.122			
AIC	1409				1412			
% Concordant	63.4				63.8			

[39] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

In both models, the proportional odds assumption was not rejected at the 5% level.[40] Therefore, the multinomial logit was not examined. Examining the cumulative logit, none of the interaction effects were significant. Moreover, the negative valence was significant (p = .000), indicating a negative treatment effect, which was consistent with the prior analyses, and supportive of H2c (negative framing effect) and H2a (narrative effect generally). In particular, with an odds ratio of 2.5, this meant that, everything else being equal, those exposed to the negative treatment were more likely to express a higher intention level (compared to the control group). As well, like the OLS and ANOVA, this undercut hypothesis H2d, which posited that positive framing should be more effective than negative framing; this was not evident from the cumulative logit.

The cumulative logit was also performed on a subsample basis. For promotion-focus respondents only, although the interaction model was significant, χ^2 (21, n = 191) = 55.27, $p <$ .0001, the proportional-odds assumption was rejected, χ^2 (105) = 186.05, $p < .0001$. Nevertheless, examining the model, the positive-valence/promotion-strength interaction was significant, χ^2 (1) = 5.60, p = .02, with a point estimate of 1.44, indicating that the positive-valence increased in effect as promotion strength increased (H2g). However, like before, the positive-valence main effect was negative (B = -1.48). And, because the negative-valence parameter was not significant (i.e., could be 0), this could slightly support H2e, too (if promotion-focus, positive-valence is greater than negative-valence), at least at higher levels of promotion strength, due to the interaction effect. The fact-treatment/RFQ difference interaction was significant, too, χ^2 (1) = 3.97, p = .046. However, due to the proportional-odds assumption being rejected, additional analysis should be performed.

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[40] For the main effects model, the proportional effects score test was χ^2 (95, n = 389) = 105.12, p = .224; for the interaction model, it was χ^2 (110, n = 389) = 129.72, p = .097.

For prevention-focus only respondents, the interaction model was significant, χ^2 (105, n = 198) = 36, *p* = .02; however, like before, the proportional-odds assumption was rejected, χ^2 (105) = 231.2, *p* < .0001. Here, none of the interaction effects were significant at the 5% level. However, all the treatments main effects were significant; but a linear hypothesis test showed that they were not significantly different, χ^2 (1) = .73, *p* = .69. For instance, the negative-valence treatment had a point estimate of 1.82 (*p* = .005), which corresponds to an odds ratio estimate of 6.18, 95% CI [1.74, 21.97]. At first blush, this would normally indicate support for H2f, that, for prevention-focus respondents, the negative-valence will be more effective than the positive. But, due to the linear hypothesis test showing no significant difference between the parameter estimates, and, due to the proportional-odds assumption being rejected, additional analysis was still needed.

For the sake of comparison (across experiments) and to increase power (by reducing the number of cells and thereby increasing cell size count), the seven intention levels were collapsed into three (low, medium, and high) for a cumulative logit, which was performed with both main effects and interactions. Those results are reported in Table 4.16.

Table 4.16 Experiment 2 Cumulative Logit (High, Medium, Low) (n = 389)

Variable[41]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept (High)	-0.516	0.658		0.434	-0.519	0.661		0.432
Intercept (Med)	2.629	0.674		<.0001	2.638	0.676		<.0001
Age	-0.011	0.009	0.989	0.233	-0.011	0.009	0.989	0.241
Male	-0.190	0.223	0.827	0.394	-0.190	0.224	0.827	0.395
Race: Non-white	0.278	0.268	1.320	0.300	0.267	0.268	1.306	0.319
College Degree	0.060	0.242	1.062	0.803	0.029	0.244	1.029	0.905
Married	-0.035	0.232	0.966	0.880	-0.015	0.232	0.985	0.948
Self-employed	-0.084	0.303	0.919	0.781	-0.105	0.305	0.900	0.730
Part-time	0.178	0.335	1.195	0.594	0.167	0.337	1.182	0.620
Unemp/retired	-0.298	0.319	0.742	0.350	-0.301	0.322	0.740	0.349
40k < Inc. < 60k	0.449	0.303	1.567	0.139	0.426	0.304	1.531	0.162
60k < Inc. < 80k	0.284	0.353	1.329	0.421	0.266	0.355	1.305	0.454
Income 80k +	-0.071	0.319	0.932	0.825	-0.074	0.320	0.929	0.818
Obj. Fin. Know.	-0.469	0.147	0.626	0.001	-0.464	0.147	0.628	0.002
Sub. Fin. Know.	0.115	0.090	1.122	0.201	0.113	0.091	1.120	0.212
Financial Strain	-0.105	0.299	0.901	0.727	-0.114	0.300	0.892	0.704
Promotion	-0.236	0.342	0.790	0.491	-0.184	0.345	0.832	0.594
RFQ Diff	0.082	0.169	1.085	0.629	-0.068	0.257	0.935	0.793
Fact	0.572	0.296	1.772	0.053	0.555	0.296	1.741	0.061
Neg	1.137	0.300	3.119	0.000	1.131	0.301	3.097	0.000
Pos	0.043	0.294	1.044	0.884	0.038	0.295	1.039	0.897
Fact x RFQ Diff					0.323	0.276	1.381	0.242
Pos x RFQ Diff					0.134	0.299	1.143	0.655
Neg x RFQ Diff					-0.007	0.300	0.993	0.980
Pseudo R^2 (Cox & Snell)	.109				.113			
AIC	723				727			
% Concordant	67				67.2			

Similarly—and consistent with prior results—there were no significant interactions effects, but there was a significant negative valence effect, $\chi^2(1) = 14.14$, $p = .0002$. Again, indicating a negative narrative effect (H2c) and a narrative effect generally (H2a); those in the

[41] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

negative-valence narrative have three-times the odds of being in a higher level of intentions (compared to the control group). This supported H2c but did not support H2d.

For promotion-only respondents, the interaction model was significant, χ^2 (21, n = 191) = 50.73, p = .0003, and the proportional-odds assumption was not rejected (albeit marginally), χ^2 (21) = 32.5, p = .052. Here, the positive interaction effect was significant at the 5% level, but the main effect was negative. The significant positive interaction tended to support H2g (that, if promotion-focused, positive effect was related to promotion strength). And although the main positive-valence effect was negative—recall, given the model including the interaction, that main effect was assuming a promotion strength level of zero—after incorporating promotion strength, that could change due to the interaction, at least at higher levels of promotion strength. So, there was at least slight support for H2e (if promotion, positive treatment was greater than negative).

For prevention-only respondents, the interaction model was not significant, χ^2 (21, n = 198) = 31.25, p = .07,[42] and the proportional-odds assumption was not rejected, χ^2 (21) = 21.84, p = .41. But, the main effects-only model was significant (χ^2 (18) = 29.82, p = .04), and the proportional odds assumption was not rejected, χ^2 (18) = 17.73, p = .47. The negative-valence effect was significant (p = .003), with a point estimate of 1.34, corresponding to an odds ratio of 3.84, 95% CI [1.59, 9.18]. This indicated that, for prevention-focus respondents, negative-valence was effective (H2f), and, in particular, compared to the control, those with the negative narrative treatment had nearly four times the odds of being in a higher intention level. None of the other treatment main effects were significant. The linear hypothesis test found a significant difference between the negative-valence and the positive-valence (χ^2 (1) = 5.25, p = .02), again in support of H2f. No support, however, was found for H2h (that negative effect would be

[42] The interaction model was not significant under the Score or Wald tests either.

influenced by the negative-focus strength, i.e., the interaction and RFQ difference main effects were not significant).

Lastly, a binary logit,[43] as presented in Table 4.17, was performed to examine high intentions (compared to non-high intentions) both with main effects and interactions.

Table 4.17 Experiment 2 Binary Logit (High v. Non-High) (n = 389)

Variable[44]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept	-1.335	0.823		0.105	-1.303	0.831		0.117
Age	-0.014	0.012	0.986	0.222	-0.014	0.012	0.987	0.251
Male	-0.158	0.273	0.854	0.565	-0.174	0.277	0.840	0.528
Race: Non-White	0.277	0.309	1.320	0.369	0.265	0.312	1.303	0.396
College Degree	0.071	0.298	1.073	0.813	0.020	0.302	1.020	0.947
Married	-0.122	0.284	0.885	0.667	-0.094	0.287	0.910	0.743
Self-employed	0.168	0.362	1.183	0.642	0.113	0.368	1.120	0.759
Part-time	0.287	0.402	1.333	0.474	0.250	0.404	1.284	0.537
Unemp/retired	-0.166	0.415	0.847	0.690	-0.211	0.419	0.809	0.614
40k < Inc. < 60k	0.427	0.359	1.533	0.234	0.402	0.362	1.494	0.267
60k < Inc. < 80k	-0.162	0.443	0.850	0.714	-0.213	0.449	0.808	0.635
Income 80k +	-0.161	0.396	0.851	0.684	-0.198	0.400	0.821	0.622
Obj. Fin. Know.	-0.404	0.165	0.668	0.014	-0.390	0.165	0.677	0.018
Sub. Fin. Know.	0.239	0.115	1.269	0.037	0.224	0.115	1.251	0.052
Financial Strain	0.003	0.372	1.003	0.993	-0.021	0.372	0.979	0.954
Promotion	0.093	0.418	1.097	0.824	0.181	0.427	1.198	0.672
RFQ Diff	-0.160	0.204	0.852	0.434	-0.316	0.353	0.729	0.371
Fact	0.704	0.384	2.023	0.067	0.684	0.388	1.981	0.078
Neg	1.262	0.375	3.532	0.001	1.243	0.378	3.467	0.001
Pos	0.268	0.407	1.307	0.511	0.244	0.415	1.276	0.556
Fact x RFQ Diff					0.446	0.369	1.563	0.227
Pos x RFQ Diff					-0.140	0.434	0.870	0.747
Neg x RFQ Diff					-0.041	0.384	0.960	0.915
Pseudo R^2 (Cox & Snell)	.084				.093			
AIC	426.65				429.00			
% Concordant	68.8				69.9			

[43] Collapsing the Likert-type data into a binary classification obviates any ordinal data concerns; respondents indicating a 6 or 7 intention score were classified as having high intentions.
[44] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Like before, there was a negative-valence treatment effect; here, indicating that those in the negative-valence group have nearly 3.5 increased odds of being in a high intention group (strong likelihood) of engaging in cash-flow and budget planning compared to the control group. This supported H2a (narrative effect generally) and H2c (negative effect) but did not support H2d (that positive should be stronger than negative), as the positive treatment was not significant.

For promotion-focus only respondents, the interaction model was significant, χ^2 (21, n = 191) = 41.27, p = .005. However, none of the main effects or interactions were significant. Indeed, looking at the main-effects model only, none of the treatment main effects were significant (though, the negative-valence was marginally outside the 5% level, p = .051—which would comport with the prior results, i.e., a negative narrative treatment effect (H2c)).

For prevention-focus only respondents, the interaction model was not significant, χ^2 (21, n = 198) = 20, p = .52. This was true of the main-effects only model, too, χ^2 (18, n = 198) = 19.07, p = .39. Under this specification, then, there was a lack of support for H2f and H2h. As discussed more in Chapter 5, this was not necessarily a contradiction of the cumulative logit (with 3 categories), rather the variability could be between a different order of the levels and not at the high versus non-high distinction (i.e., how the variable was dichotomized); that is, the collapsing of intent levels 1 through 5 obscured the variability between, say, a level 1 and a level 5, which was isolated and identified in the cumulative logit.

In sum, then, across the analyses above, there was a generally narrative effect, which supported H2a that narratives can have an impact of cash-flow and budgeting intentions. Moreover, that effect was seemingly driven by the negative-valence narrative, which supported

H2c. And, there was some support for regulatory fit (e.g., H2e and H2g) from the cumulative logits.

Research Question 3: Insurance Needs Analysis

Lastly, the third research question (Experiment 3, Insurance Needs Analysis) concerned the effect of message framing on intentions to engage in an insurance needs analysis. In particular, whether narrative messages influenced these intentions (relative to a fact-based presentation or no information control group). Furthermore, whether the valence (positive or negative) of that narrative influenced intentions differently, which may be based on the underlying behavior. Then, whether that framing effect, if any, was influenced by individual characteristics, such as regulatory focus. In other words, looking at the main effects of narratives and regulatory orientation, and then their interactions. The analysis proceeds in the same fashion as Research Questions 1 and 2.

ANOVA and ANCOVA

The first hypothesis (H3a) was that narrative message framing will be positively associated with intentions to engage in an insurance needs analysis; that is, there will be a difference in treatment means—whether that arises from the positive or negative valence treatment. To examine that, a one-way ANOVA was analyzed. Table 4.18 reports the one-way ANOVA for Experiment 3.

Table 4.18 Experiment 3 One-Way ANOVA (n = 400)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	49.403	16.468	5.32	0.0013
Error	396	1225.387	3.094		
Corrected Total	399	1274.79			

The ANOVA showed a significant group difference at the 5% level, $F(3, 396) = 5.32$, $p = .0013$. Levene's test for homogeneity of the group variance was not rejected at the 1% ($F(3, 396) = 2.14$, $p = .09$), and the Brown and Forsythe test for homogeneity was not rejected either, *F*(3,

396) = 1.22 $p = .30$). The ANOVA indicated that at least one group mean was different than the others.

Post-estimation tests were conducted to further examine the hypotheses. Pairwise comparison of group means using Tukey-Kramer adjustments for multiple comparisons showed one significantly different pairwise difference. The negative-valence narrative produced a .99 higher mean compared to the control, 95% CI [.35, 1.64], $p < .001$, which was true with Dunnett's adjustment, too, $p = .0002$. This supported both hypothesis H3a (of a narrative effect) and H3c (negative valence will be effective). However, because the positive-valence treatment was not significantly different than the control, this did not provide evidence for H3b (that positive-valence framing will be positively associated with intentions). Furthermore, although the negative treatment reported a higher mean ($M = 3.92$, $SD = 1.88$) than the positive treatment ($M = 3.41$, $SD = 1.70$), their pairwise difference was not significant at the 5% level with the Tukey-Kramer adjustment ($p = .18$).[45] This indicated a lack of support for H3d (that negative framing will be more effective than positive framing).

To examine the average effect of framing, a contrast was performed to compare the average effect of the narratives (positive and negative) to the control group. That contrast indicated a significant difference in intentions, with a mean difference of .74 higher intentions for average narrative effect to the control group, 95% CI [.31, 1.17], $t(396) = 3.41$, $p <. 001$. Again, this supported H3a of a general narrative effect. A contrast comparing the average effect of framing to the fact-based group, however, did not result in a significant difference, $t(396) = .78$, $p = .43$. Like before, this could indicate that the narrative effect was due to priming and salience; additional analysis was needed.

[45] However, without the Tukey-Kramer adjustment, it was significant, $p = .04$.

A similar analysis was conducted at the subsample level. For promotion-focus respondents only, the one-way ANOVA was significant, $F(3, 193) = 2.67$, $p = .049$. However, none of the mean comparisons were significant at the 5% level (with Tukey-Kramer adjustments). Without the Tukey-Kramer adjustment, though, both the negative-valence and positive-valence were significantly different than the control, $p = .01$, $p = .02$, respectively. Based on the lack of significance with the Tukey-Kramer adjustment—a more conservative approach—however, indicated a lack of support for H3e (if promotion focus, promotion should be stronger).

Among prevention-focus respondents only, the one-way ANOVA was significant, $F(3, 199) = 4.51$, $p = .004$. There were two pairwise mean differences; first, the negative-valence mean was 1.11 higher than the control, 95% CI [.24, 1.99], $p = .006$, and .98 higher than the positive-valence treatment, 95% CI [.11, 1.84], $p = .02$, which indicated support for H2f (if prevention, negative-valence better than positive-valence).

The next model incorporated regulatory orientation as a factor. Table 4.19 reports a two-way ANOVA (with Type III sums of squares) that incorporates both treatment group and chronic regulatory state (promotion- or prevention-focus) and interactions. This model was significant, $F(7, 392) = 4.09$, $p = .0002$.

Table 4.19 Experiment 3 Two-Way ANOVA (Treatment x Chronic Focus) (n = 400)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	51.170	17.057	5.63	0.0009
Chronic Focus	1	26.426	26.426	8.72	0.0033
Interaction	3	11.0173	3.672	1.21	0.3051
Error	392	1188.011	3.031		
Corrected Total	399	1274.790			

Here, the treatment main effect was significant, indicating support for H3a. The pairwise means comparison still showed that the negative valence was significantly higher than the control. However, the interaction effect was not significant. Running the model without any interaction effect resulted still in a significant effect for chronic regulatory orientation, $F(1, 395) = 8.68$, $p = .0003$. Those that had a promotion chronic regulatory focus (as prevention was the reference), on average, had intention scores .51 higher than those who were chronically prevention oriented, 95% CI [.17, .86], $p = .003$.

However, perhaps the framing effect was being influenced by the relative strength of the chronic regulatory focus (the RFQ difference). To control for that, an ANCOVA (with Type III sums of squares) for Experiment 3 that incorporated both main effects and used the RFQ difference as a covariate (and interaction) was performed. The overall model was significant, $F(7, 392) = 4.79$, $p < .0001$. However, the interaction term was not significant ($F(3, 392) = 1.41$, $p = .24$), an equal-slopes model can be estimated by removing the interaction term. Consequently, Table 4.20 reports the model without the interaction term (with Type III sums of squares).

Table 4.20 Experiment 3 ANCOVA (RFQ Difference Covariate)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	51.124	17.041	5.67	0.0008
RFQ Difference	1	38.438	38.438	12.79	0.0004
Error	395	1186.948	3.005		
Corrected Total	399	1274.790			

Here, again, the model was significant, $F(4, 395) = 7.31$, $p < .0001$. There was a main effect for both the treatment group, $F(3, 395) = 5.67$, $p = .0008$, and regulatory difference, $F(1, 395) = 12.79$, $p = .0004$. Even accounting for the RFQ difference, there was still a significant mean difference, namely the negative valence treatment had 1.01 higher intention score than the control group, 95% CI [.38, 1.65], $p = .0003$. This, again, provided evidence for H3a (narrative effect generally) and H3c (negative-valence narrative effect).

Another analysis of interest, like in the prior experiments, was whether the results changed when examining on a subsample basis (i.e., only promotion- or prevention-focused respondents), which informed hypotheses H3e to H3g. In other words, among only promotion-focus respondents, whether the effect changed based on strength of the promotion focus. As before, the regulatory differences were turned into absolute values (needed for the negative RFQ difference scores for prevention-focus) such that higher values indicated stronger promotion or prevention focus, respectively. Here, for promotion-focused respondents, the *F*-test for the model was not significant at the 5% level, $F(7, 189) = 1.51$, $p = .168$. Additional analyses were therefore not performed on this specification.

Looking at prevention-focused respondents only, however, the ANCOVA with absolute RFQ difference as a continuous covariate was significant at the 5% level, $F(7, 195) = 4.09$, $p = .0003$. The interaction effect was significant, $F(3, 195) = 3.81$, $p = .011$. This is presented in Table 4.21.

Table 4.21 Experiment 3 ANCOVA (RFQ Difference Covariate), Prevention Only (n = 203)

Source	*DF*	*SS*	*MS*	*F*	*p*
Treatment	3	2.494	0.831	0.31	0.8204
RFQ Difference	1	2.853	2.853	1.05	0.3061
Interaction	3	30.982	10.327	3.81	0.011
Error	195	525.251	2.709		
Corrected Total	202	605.892			

Therefore, an unequal-slopes model was estimated with least squares mean differences calculated at different levels of absolute RFQ difference; mean differences were analyzed with Tukey-Kramer adjustments at two levels of absolute RFQ differences of 1 and 2, indicating an increasing change in chronic prevention strength. At an RFQ difference of 1, the negative valence treatment was 1.40 higher than the control, 95% CI [.49, 2.32], $p = .0006$; the negative valence treatment was also 1.26 higher than the positive valence treatment, 95% CI [.35, 2.16], *p* = .0023. At an RFQ difference of 2, there were two significant mean differences. First, the negative valence treatment was 3.35 higher than the control, 95% CI [1.32, 5.39], *p* = .0002. Second, the negative valence treatment was 2.77 higher than the positive valence treatment, 95% CI [.67, 4.88], *p* = .004. Both of these results provided support for H3d (negative-valence will be stronger than positive-valence) and H3f (among prevention-focus respondents, negative-valence will be more effective).

Comparing to the control group, with Dunnett's procedure, the results were similar. That is, there was significant differences between the control with the negative valence treatment at RFQ difference levels at 1 and 2. Both contrasts (the average narrative effect to the control and the average narrative effect to the fact-based group) were insignificant, $t(195) = -.81$, $p = .42$, and $t(195) = -.10$, $p = .92$, respectively.

OLS Regression

As before, to tease out additional variation (not addressed by the random assignment), an ordinary least squares (OLS) regression analysis with various covariates (multiple linear regression) was examined to ascertain the effect of the treatments on insurance needs analysis intentions. Two models are presented in Table 4.22. First, is a model with main effects only, and second, a model with main effects and interactions. For categorical variables, cell sizes were examined to preserve power, and categories were collapsed as needed, like the in the prior regression analyses (e.g., white versus non-white; incomes less than $40,000 in the intercept and incomes above 80,000 collapsed; no college or college degree; married versus non-married; combining retired and unemployed).[46] The model is reported with robust standard errors.

[46] Categories were collapsed to achieve at least 10 (or as close thereto as possible) respondents in each cell for each level of the response variable (i.e., the intentions score), as long as the collapsing made theoretical and practical

Variance inflation factors were examined for multicollinearity; most VIFs were under 2, and the highest were for the RFQ difference and the promotion dummy variable, which was not unexpected (even those were under 3).[47]

Table 4.22 Experiment 3 OLS Regression of Insurance Needs Analysis Intentions (n = 400)

Variable[48]	*B*	*SE*	*p*	*B*	*SE*	*p*
Intercept	3.080	0.553	<.0001	3.021	0.556	<.0001
Age	0.006	0.007	0.444	0.005	0.007	0.525
Male	-0.360	0.185	0.052	-0.358	0.185	0.054
Race: Non-White	0.557	0.247	0.025	0.617	0.252	0.015
College Degree	-0.035	0.196	0.860	-0.031	0.195	0.874
Married	0.053	0.189	0.780	0.073	0.188	0.699
Self-employed	-0.314	0.266	0.238	-0.307	0.262	0.243
Part-time	0.153	0.288	0.596	0.141	0.291	0.627
Unemp/retired	-0.625	0.251	0.013	-0.549	0.244	0.025
40k < Income < 60k	-0.220	0.241	0.362	-0.215	0.240	0.372
60k < Income < 80k	-0.128	0.258	0.618	-0.136	0.258	0.599
Income 80k +	0.191	0.251	0.449	0.214	0.250	0.391
Obj. Fin. Know.	-0.367	0.114	0.001	-0.350	0.114	0.002
Sub. Fin. Know.	0.193	0.084	0.022	0.193	0.083	0.020
Financial Strain	-0.139	0.264	0.600	-0.128	0.260	0.622
Promotion	0.060	0.272	0.825	0.087	0.269	0.745
RFQ Diff	0.174	0.139	0.211	0.184	0.169	0.278
Fact	0.500	0.233	0.032	0.502	0.231	0.031
Neg	0.925	0.235	0.000	0.918	0.235	0.000
Pos	0.449	0.225	0.046	0.460	0.224	0.040
Fact x RFQ Diff				0.051	0.214	0.811
Neg x RFQ Diff				-0.305	0.251	0.224
Pos x RFQ Diff				0.118	0.207	0.567
Adjusted R^2	.117			.118		

sense. However, that was not possible across all categories for all intention score levels. Indeed, small cell-related issues are ameliorated by the later logit analysis in which the dependent variable is defined by larger categories (e.g., high-, medium-, and low-intentions).

[47] In the interaction model, most VIFs were under 2, but the RFQ difference and promotion dummy had higher VIFs, which was not unexpected given their relationship.

[48] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

As shown, none of the interactions were significant. So, looking at the main-effects model, all the treatments (fact-based, negative-valence, and positive-valence) were significant at the 5% level. This supported hypotheses H3a (general narrative effect), H3b (positive-valence effect), and H3c (negative-valence effect). Using the main-effects model, a linear hypothesis test (for equivalency)—in particular, a robust Wald test—for the negative-valence treatment and the fact-based treatment parameters could not be rejected at the 5% level ($p = .084$),[49] i.e., cannot conclude they have different effects relative to the control. Also, this was consistent with the one-way ANOVA pairwise mean comparisons. A robust Wald test for the equivalency of negative-valence and positive-valence was rejected at the 5% level, $p = .044$, indicating support for H3d (that negative valence > positive valence). A robust Wald test for the equivalency of the positive-valence and fact-based parameters likewise could not be rejected, $p = .083$.

For robustness, additional multiple OLS regressions were also performed (not presented) using subsamples of only promotion- or prevention-focused individuals with the same main effects and interactions. For promotion-focus respondents only, the main-effects regression was significant, $F(18, 178) = 1.90$, $p = .019$. All treatments were significant at the 5% level with positive effects estimates of .65, 95% CI [.005, 1.30]; .84, 95% CI [.13, 1.55]; and .78, 95% CI [.10, 1.45] for the fact-based, negative-valence, and positive-valence, respectively, i.e., this directionality was the same as the whole sample. However, the robust Wald test on each pairwise difference could not reject the null hypotheses that they were different from each other. This indicated a lack of support for H3e (if promotion-focus, positive valence > negative valence).

The interaction model was significant, too, $F(21, 175) = 1.62$, $p = .049$; however, none of the interactions were significant at any commonly used significance level.[50] This indicated a lack

[49] Testing whether prevention = fact-based, χ^2 (1) = 3.01, $p = .092$.
[50] As well, in the interaction model, the main effects were no longer significant.

of support for H3g that, for promotion-focus, positive-valence was influenced by promotion strength (that is, a lack of an interaction effect); indeed, the RFQ difference main effect was not significant either.

For prevention-only respondents, the main-effects only model was significant, $F(18, 184) = 2.62$, $p = .0006$. In this model, only the negative treatment had a significant main effect, $t(1) = 3.25$, $p = .001$, with a positive estimate of .951, 95% CI [.37, 1.53]. This provided evidence of H3f that, for prevention-focused respondents, negative-valence (loss) narrative message framing would be more effective than positive-valence (gain) narrative for engaging in an insurance needs analysis—indicating support for regulatory fit. This was supported by a robust Wald test, too, which rejected their equivalence, $\chi^2(1) = 6.55$, $p = .011$.

The interaction model was significant, too, $F(21, 181) = 2.68$, $p = .0002$. Indeed, in the interaction model, the negative-valence treatment interacted with the RFQ difference, indicating that strong levels of prevention orientation, coupled with the negative valence treatment, led to higher intention scores, relative to the control group; the interaction effect was estimated at 1.69, 95% CI [.62, 2.77], $t(1) = 3.11$, $p = .0002$. This provided support for H3f and also H3h, which posited that, for prevention-focused respondents, as the strength of prevention focus increases, negative-valence (loss) narrative framing will be positively associated with intentions to engage in an insurance needs analysis; again, indicating support for regulatory fit.

Nonparametric Analysis

Like in the previous experiments, the foregoing analysis used parametric techniques (e.g., the ANOVA and OLS regression). And, like before, as a robustness check, nonparametric techniques were examined, too. The Kruskal-Wallis H-Test for several independent samples found a significant difference in location parameters for the four groups, χ^2 (3, n = 400) = 14.31, p = .003. Providing preliminary support for H3a (a narrative treatment effect).

Consequently, two-sample Wilcoxon test were then conducted for each group-pair comparison.[51] Comparing the control and fact-based groups, the Wilcoxon test was significant, Z = -2.16, p = .031, with the fact-based group having higher scores; for the control and negative valence, the test was significant, Z = -3.72, p = .0002, with the negative valence having a larger Wilcoxon score (higher values)—this provided support for H3c (negative-valence effect); for the control and positive valence, the test was significant, Z = -2.01, p = .045, with positive valence having higher scores—this provided support for H3b (positive-valence effect); for the fact-based and negative valence, the test was not significant, Z = 1.61, p = .11—consistent with the OLS regression parameter test results; for fact-based and positive valence, the test was not significant, Z = -.20, p = .84, again consistent with OLS robust Wald tests on the parameters; finally, for negative and positive valences, the test was not significant, Z = -1.86, p = .062. In sum, then, the nonparametric analysis supported the parametric analysis insofar as the treatment location parameters were not the same, but that the treatment effects may not be significantly different from each other.

Examining only promotion-focused respondents resulted in an insignificant Kruskal-Wallis H Test, χ^2 (3, n = 197) = 7.69, p = .052, albeit just marginally outside the 5% level. This would imply that the pairwise Wilcoxon should not be significantly different either. And, indeed, the Wilcoxon test for the negative- and positive-valence treatments were not significantly different, Z = .231, p = .82. This indicated a lack of support for H3e.

[51] Like before, continuity corrections were not implemented due to the sample sizes involved; reported p-values are two-sided.

However, for prevention-focused respondents only, the Kruskal-Wallis test was significant, χ^2 (3, n = 203) = 11.60, p = .009. The Wilcoxon test for a difference between the positive-valence and negative-valence the test was significant, Z = -2.76, p = .006, with the negative-valence having the higher scores (values). As such, this supported H3f (if prevention, negative-valence > positive-valence). Consequently, the nonparametric tests support the parametric ANOVAs and regressions above that, for insurance needs analysis, the treatment effects may depend on regulatory focus.

Logistic Regression (Cumulative, Multinomial, and Binary)

Next, logits were examined. First, a cumulative logit was performed, which, like the above nonparametric analyses, was ideal with Likert-type data. The cumulative logit was first performed using all 7-levels of the intention scale. That cumulative logit is presented in Table 4.23 both as main-effects only and main effects with interactions (similar to the above OLS regression). However, both the main-effect only and interaction models rejected the proportional odds assumption, so they should be examined cautiously.

Table 4.23 Experiment 3 Cumulative Logit of All Intention Levels (n = 400)

Variable[52]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept (7)	-3.984	0.620		<.0001	-4.075	0.622		<.0001
Intercept (6)	-2.696	0.587		<.0001	-2.788	0.589		<.0001
Intercept (5)	-1.319	0.575		0.022	-1.409	0.577		0.015
Intercept (4)	-0.688	0.573		0.230	-0.776	0.575		0.177
Intercept (3)	0.005	0.572		0.992	-0.080	0.573		0.889
Intercept (2)	1.032	0.574		0.072	0.953	0.576		0.098
Age	0.006	0.008	1.006	0.423	0.006	0.008	1.006	0.442
Male	-0.349	0.194	0.706	0.073	-0.347	0.195	0.707	0.076
Race: Non-white	0.583	0.255	1.791	0.022	0.638	0.259	1.893	0.014
College Degree	-0.028	0.212	0.973	0.896	-0.027	0.212	0.973	0.899
Married	0.078	0.201	1.081	0.700	0.094	0.202	1.098	0.642

[52] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Self-employed	-0.336	0.261	0.715	0.198	-0.322	0.261	0.724	0.217
Part-time	0.188	0.321	1.206	0.560	0.195	0.323	1.215	0.546
Unemp/retired	-0.713	0.286	0.490	0.013	-0.664	0.289	0.515	0.022
40k < Inc. < 60k	-0.186	0.256	0.831	0.468	-0.175	0.256	0.840	0.494
60k < Inc. < 80k	-0.072	0.289	0.931	0.803	-0.076	0.289	0.927	0.793
Income 80k +	0.171	0.270	1.186	0.528	0.188	0.271	1.206	0.488
Obj. Fin. Know.	-0.356	0.130	0.700	0.006	-0.345	0.131	0.708	0.009
Sub. Fin. Know.	0.225	0.086	1.252	0.009	0.226	0.086	1.254	0.008
Financial Strain	-0.087	0.288	0.917	0.764	-0.087	0.289	0.917	0.763
Prevention	0.025	0.292	1.026	0.931	0.077	0.293	1.080	0.793
RFQ Diff	0.243	0.141	1.275	0.085	0.257	0.194	1.293	0.185
Fact	0.509	0.254	1.664	0.045	0.509	0.255	1.664	0.046
Negative	1.016	0.261	2.761	<.0001	0.995	0.260	2.705	0.000
Positive	0.550	0.261	1.733	0.035	0.566	0.261	1.761	0.030
Fact x RFQ Diff					0.026	0.235	1.026	0.912
Pos x RFQ Diff					0.083	0.232	1.087	0.720
Neg x RFQ Diff					-0.354	0.250	0.702	0.157
Pseudo R^2 (Cox & Snell)	.156				.162			
AIC	1468				1471			
% Concordant	64.5				65.2			

In the above model, none of the interactions were significant. However, all three treatment effects were significant, indicating support for H3a (framing effect), H3b (positive-valence effect) and H3c (negative-valence effect). A linear hypothesis test of the equivalency of the positive-valence and negative-valence parameters could not be rejected (although it would be rejected at the 10% level, $p = .094$), indicating a lack of support for H3d (negative-valence > positive-valence). A linear hypothesis test of the equivalency between the fact-based and negative treatment was just marginally outside the 5% level, χ^2 (1, n = 400) = 3.699, $p = .054$.

For promotion-focus respondents only subsample analysis, the interaction model was significant, χ^2 (21, n = 197) = 34.22, $p = .034$. Yet, none of the main effects or interactions were themselves significant at the 5% level. The main-effects-only model was also significant, χ^2 (18, n = 197) = 33.74, $p = .014$. The negative-valence and positive-valence main effects were significant, $p = .01$ and $p = .02$, respectively. However, the linear hypothesis could not reject the null hypothesis that they were the same, i.e., indicating a lack of support for H3e (if promotion, positive-valence > negative-valence). And, again, the proportional-odds assumption was rejected (χ^2 (90) = 160.82, $p < .001$), indicating the model should be considered cautiously.

For prevention-only respondents, the interaction model was significant, χ^2 (21, n = 203) = 58.11, $p < .0001$. Although none of the main treatment effects were significant, the negative-valence/RFQ difference interaction was significant, with a point estimate of 2.46 (OR = 11.75, $p = .0006$), indicating support for H3h. Indeed, looking at the main-effects model only, which was significant, too, χ^2 (18, n = 203) = 46.57, $p = .0002$, the negative-valence treatment was significant, with a point estimate of 1.04 (OR = 2.83, 95% CI 1.33, 6.02, $p = .007$). A linear hypothesis test was just marginally outside the 5% level ($p = .055$) for the parameter equivalence between the positive-valence and the negative-valence; however, in the model, the positive effect was not significant and the negative effect was significant, which still indicates slight support for H3f. Though, as noted, the proportional-odds assumptions were violated in these models.

Consequently, due to indication of the proportional-odds assumption being violated in the above specifications,[53] a multinomial logit was examined, too. That analysis is not presented due to the unwieldy number of category pairs. Also, there was possible quasi-complete separation of the data (this was true in both the main effects and interaction model specifications), likely due to low cell size in the extreme values (e.g., scores of 7) in the treatment cells. Therefore, to alleviate that issue, a parsimonious multinomial logit was performed with just the treatment main effects as regressors, which allowed the model to converge. In this parsimonious specification,

[53] As noted earlier, Allison (2012) notes that, with SAS, the test may reject the null hypothesis more often than needed. And that, with many independent variables and larger sample sizes, in Allison's experience, *p*-values of less than .05 are routinely returned (Allison, 2012).

none of the Type 3 analysis of effects were significant for the main effects. And, only one level of the negative valence (level 6) was significant (which was being compared to the control group at an intention level of 1), which was not that remarkable (given these were extreme answer values).

Similarly, the full interaction model (with all previous covariates) suffered possible quasi-separation. Therefore, the parsimonious model of just main treatment effects and interactions was analyzed (without other covariates); this model was significant, χ^2 (36, n = 400) = 65.02, p = .002. Here, none of the Type 3 analysis of effects were significant for the main effects or interactions. But several individual interactions were significant, which tended to be at higher levels of intention scores, which makes sense given they were being contrasted with an intention level of 1 in the control group (the intercept). As noted in the prior experiments, there were some issues with this approach, however—namely that the reference level was the baseline level of one for intentions; it was natural, then, to expect some very large odds ratios for some of the treatment contrasts (e.g., someone indicating a 7 being compared to a 1) particularly with the endpoint values, which may have smaller cell size.

To further strengthen the analysis, increase power, and account for the proportional odds assumption, like in the prior analyses, instead of using all seven levels, the levels were collapsed into a low- (1 or 2), medium- (3, 4, or 5), and high-intention levels (6 or 7). A cumulative logit, therefore, was performed with both main effects and interactions. Those results are reported in Table 4.24. Importantly, with three levels instead of 7, the proportional odds assumption was soundly not rejected.[54] The reference condition was low intentions.

[54] For the main effects model, χ^2 (19, n = 400) = 24.23, p = .19; for the interaction model, χ^2 (22, n = 400) = 28.14, p = .17.

Table 4.24 Experiment 3 Cumulative Logit (High, Medium, Low) (n = 400)

Variable[55]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept (High)	-2.741	0.647		<.0001	-2.865	0.651		<.0001
Intercept (Med.)	-0.054	0.631		0.931	-0.158	0.633		0.803
Age	0.010	0.009	1.010	0.246	0.009	0.009	1.009	0.290
Male	-0.217	0.215	0.805	0.312	-0.218	0.216	0.804	0.314
Race: Non-white	0.610	0.281	1.840	0.030	0.687	0.287	1.987	0.017
College Degree	0.046	0.235	1.047	0.844	0.057	0.236	1.058	0.810
Married	0.117	0.223	1.124	0.600	0.145	0.224	1.156	0.518
Self-employed	-0.359	0.289	0.698	0.214	-0.346	0.291	0.708	0.235
Part-time	0.052	0.356	1.053	0.884	0.043	0.358	1.044	0.904
Unemp/retired	-0.659	0.319	0.518	0.039	-0.578	0.322	0.561	0.073
40k < Inc. < 60k	-0.374	0.284	0.688	0.187	-0.366	0.285	0.693	0.199
60k < Inc. < 80k	-0.329	0.321	0.719	0.304	-0.335	0.322	0.715	0.297
Income 80k +	-0.010	0.299	0.990	0.973	0.012	0.300	1.012	0.969
Obj. Fin. Know.	-0.308	0.144	0.735	0.032	-0.288	0.145	0.750	0.047
Sub. Fin. Know.	0.195	0.095	1.215	0.040	0.197	0.095	1.218	0.038
Financial Strain	-0.053	0.320	0.948	0.868	-0.050	0.322	0.951	0.877
Prevention	-0.080	0.323	0.923	0.805	-0.040	0.324	0.961	0.902
RFQ Diff	0.269	0.157	1.308	0.086	0.276	0.218	1.318	0.206
Fact	0.392	0.282	1.480	0.164	0.389	0.284	1.476	0.170
Neg	0.985	0.289	2.678	0.001	0.978	0.289	2.659	0.001
Pos	0.514	0.289	1.672	0.076	0.531	0.291	1.700	0.068
Fact x RFQ Diff					0.079	0.265	1.082	0.766
Pos x RFQ Diff					0.137	0.261	1.147	0.600
Neg x RFQ Diff					-0.394	0.279	0.675	0.158
Pseudo R^2 (Cox & Snell)	.120				.129			
AIC	774				776			
% Concordant	66.4				67.2			

In the main-effects model, the negative-valence treatment was significant at the 5% level, and the positive-valence treatment was significant at the 10% level. In the interaction model, however, none of the interaction effects were significant, but the negative treatment was still significant. This provided support for H3c (negative-valence effect) and H3a (framing effect

[55] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

generally). Moreover, in this model, the Wald test was rejected for the equivalency of the negative and fact-based treatment parameters,[56] indicating a true difference between the two. However, a Wald test could not reject the equivalency for the positive-valence and negative-valence (or fact-based treatment) in the interaction model. But the negative-valence was still significantly non-zero, which was not true for the positive-valence. This tended to support H3d.

Like before, separate subsample analyses were conducted, too. For promotion-only respondents, the interaction model was not significant, χ^2 (21, n = 197) = 28.73, p = .12; the main-effects only model was not significant either, χ^2 (18, n = 197) = 27.91, p = .064.[57] Even considering the main-effects model, the only significant parameter was for the negative-valence, with a point estimate of 1.02, corresponding to an odds ratio of 2.78, 95% CI [1.20, 6.48], p = .02. However, this did not indicate support for any hypothesis (other than a general negative valence effect), and even if considered, would not support H3e or H3g.

For prevention-only respondents, the interaction model was significant, χ^2 (21, n = 203) = 46.41, p = .001 and the proportional-odds assumption was not rejected, χ^2 (21) = 23.16, p = .34. Even though the negative-valence main effect was negative (B = -.747), the negative-valence-strength interaction was significant, with a point estimate of 2.32 (p = .005), indicating support of H3h (if prevention-focus, negative valence related to strength), at least at higher levels of prevention strength—that is, as prevention strength increased, so too did the effect of the negative-valence treatment. And, looking at the main-effects model, which was significant (χ^2 (18) = 37.08, p = .005), the negative-valence parameter was significant with a point estimate of .99 (OR = 2.69, p = .02), but none of the other treatments were significant, which indicated support for H3f (if prevention, negative-valence > positive-valence). However, the Wald test

[56] χ^2 (1, n = 400) = 4.40, p = .036.
[57] The model was not significant under Score or Wald tests either.

could not reject the null equivalency at 5% (p = .10), but again, the other parameter estimates were not significantly different than zero.

Lastly, in addition to the cumulative logit, a binary logit,[58] reported in Table 4.25, was performed to examine high intentions (compared to non-high intentions) both with main effects and interactions. As before, only the negative-valence treatment was significant, indicating support for H3c (negative-valence effect) and H3a (framing generally). As well, the Wald test rejected the null hypothesis that the negative and fact-based parameters were equivalent. A Wald test also rejected the null hypothesis that the positive-valence and negative-valence were equivalent, which supports H3d (negative-valence > positive-valence).

Table 4.25 Experiment 3 Logit (High v. Non-High) (n = 400)

Variable[59]	*B*	*SE*	*OR*	*p*	*B*	*SE*	*OR*	*p*
Intercept	-4.747	1.105		<.0001	-4.898	1.138		<.0001
Age	0.013	0.015	1.013	0.397	0.007	0.015	1.007	0.636
Male	-0.299	0.349	0.741	0.391	-0.268	0.355	0.765	0.450
Race: Non-white	0.748	0.409	2.114	0.068	0.879	0.420	2.409	0.037
College Degree	0.126	0.390	1.134	0.747	0.136	0.392	1.146	0.728
Married	0.172	0.359	1.188	0.632	0.216	0.364	1.241	0.553
Self-employed	-0.175	0.471	0.839	0.710	-0.219	0.478	0.804	0.647
Part-time	0.208	0.532	1.231	0.696	0.096	0.537	1.101	0.859
Unemp/retired	-1.218	0.690	0.296	0.078	-1.058	0.699	0.347	0.130
40k < Inc. < 60k	-0.553	0.479	0.575	0.249	-0.571	0.482	0.565	0.236
60k < Inc. < 80k	-0.152	0.503	0.859	0.762	-0.186	0.506	0.830	0.713
Income 80k +	-0.462	0.481	0.630	0.336	-0.419	0.488	0.658	0.391
Obj. Fin. Know.	-0.301	0.213	0.740	0.158	-0.253	0.218	0.777	0.246
Sub. Fin. Know.	0.446	0.163	1.561	0.006	0.456	0.167	1.578	0.006
Financial Strain	0.381	0.483	1.463	0.430	0.373	0.489	1.452	0.446
Prevention	0.353	0.520	1.423	0.498	0.540	0.544	1.716	0.321
RFQ Diff	0.130	0.253	1.138	0.608	0.141	0.488	1.151	0.774
Fact	0.847	0.569	2.332	0.137	0.931	0.612	2.538	0.128

[58] Collapsing the Likert-type data into a binary classification obviates any ordinal data concerns; respondents indicating a 6 or 7 intention score were classified as having high intentions.
[59] Reference groups were non-married, White, full-time employed, income less than $40,000, and in the control group.

Neg	1.852	0.544	6.369	0.001	1.901	0.581	6.694	0.001
Pos	0.830	0.581	2.293	0.153	0.470	0.692	1.600	0.497
Fact x RFQ Diff					-0.253	0.552	0.776	0.647
Post x RFQ Diff					0.611	0.591	1.842	0.302
Neg x RFQ Diff					-0.428	0.536	0.652	0.425
Pseudo R^2 (Cox & Snell)	.106				.118			
AIC	304.40				304.94			
% Concordant	76.3				78.4			

The logit was performed on the subsamples of promotion-focus-only and prevention-focus-only subsamples, too. For the promotion-focus subsample, the overall interaction model was significant, χ^2 (21) = 37.20, p = .02, but none of the treatment effects or interactions were significant. This indicated a lack of support for H3e (if promotion, positive-valence > negative valence) and H3g (positive-valence effect increases with RFQ score). And, in the main-effects model, the negative-valence was significant, with a point estimate of 1.78 (OR = 5.95, p = .01), again indicating a general negative narrative effect (H3c).

For the prevention-focus subsample, the interaction model was not significant, χ^2 (21, n = 203) = 31.05, p = .07 (this was true even upon removing the interaction effects, i.e., using only the main-effects model, χ^2 (18, n = 203) = 24.53, p = .14). This, too, indicated a lack of support for H3h (negative-valence effect increases with RFQ score). However, as described in Experiment 2, this could because the additional collapsing of categories obscured the variability between, say, those with a level 1 intention to those of a level 5 (or higher) intention value.

Summary

A summary table is presented in Table 4.26, which depicts the hypotheses examined and the resulting indication of supported (✓), not supported (x), or not applicable (—) by the several statistical analyses performed.

Table 4.26 Results/Hypotheses Summary Table by Experiment

Experiment 1								
Analysis	H1a (Framing)	H1b (PV)	H1c (NV)	H1d (PV > NV)	H1e (If Prom., PV > NV)	H1f (If Prev., NV > PV)	H1g (If Prom., PV α PromF)	H1h (If Prev., NV α PrevF)
ANOVA (incl. sub-sample ANOVA)	x	x	x	x	x	x	—	—
Pairwise Mean Comparisons	x	x	x	x	x	x	—	—
Linear Contrast	x	—	—	—	—	—	—	—
Two-Way ANOVA	x	x	x	x	—	—	—	—
OLS Regression (incl. sub-sample OLS)	x	x	x	x	x	x	x	x
Kruskal-Wallis test	x	x	x	x	x	x	—	—
Wilcoxon test	—	—	—	—	—	—	—	—
Cumulative Logit (7-levels) (incl. sub-samples)	x	x	x	x	x	x	x	x
Cumulative Logit (3-levels) (incl. sub-samples)	x	x	x	x	x	x	x	x
Binary Logit (incl. sub-samples)	x	x	x	x	x	x	x	x

✓ = support, x = no support, — = n/a; PV = positive-valence; NV = negative-valence;
PromF = promotion-focus strength; PrevF = prevention-focus strength

Experiment 2								
Analysis	H2a (Framing)	H2b (PV)	H2c (NV)	H2d (PV > NV)	H2e (If Prom., PV > NV)	H2f (If Prev., NV > PV)	H2g (If Prom., PV α PromF)	H2h (If Prev., NV α PrevF)
ANOVA (incl. sub-sample ANOVA)	✓	—	—	—	—	—	—	—
Pairwise Mean Comparisons	✓	x	✓	x	x	x	—	—
Linear Contrast	✓	—	—	—	—	—	—	—
Two-Way ANOVA	✓	—	—	—	—	—	—	—
OLS Regression (incl. sub-sample OLS)	✓	x	✓	x	x	x	✓	x
Kruskal-Wallis	✓	—	—	—	—	—	—	—
Wilcoxon	—	x	✓	x	x	x	—	—
Cumulative Logit (7-levels) (incl. sub-samples)	✓	x	✓	x	✓	x	✓	x
Cumulative Logit (3-levels) (incl. sub-samples)	✓	x	✓	x	✓	✓	✓	x
Binary Logit (incl. sub-samples)	✓	x	✓	x	x	x	x	x

✓ = support, x = no support, — = n/a; PV = positive-valence; NV = negative-valence;
PromF = promotion-focus strength; PrevF = prevention-focus strength

Experiment 3								
Analysis	H3a (Framing)	H3b (PV)	H3c (NV)	H3d (NV > PV)	H3e (If Prom., PV > NV)	H3f (If Prev., NV > PV)	H3g (If Prom., PV α PromF)	H3h (If Prev., NV α PrevF)
ANOVA	✓	—	—	—	—	—	—	—
Pairwise Mean Comparisons	✓	x	✓	x	x	✓	—	—
Linear Contrast	✓	—	—	—	—	—	—	—
Two-Way ANOVA	✓	—	—	—	—	—	—	—
OLS Regression (incl. sub-sample OLS)	✓	✓	✓	✓	x	✓	x	✓
Kruskal-Wallis	✓	—	—	—	—	—	—	—
Wilcoxon	✓	✓	✓	x	x	✓	—	—
Cumulative Logit (7-levels) (incl. sub-samples)	✓	✓	✓	x	x	✓	x	✓
Cumulative Logit (3-levels) (incl. sub-samples)	✓	✓	✓	✓	x	✓	x	✓
Binary Logit (incl. sub-samples)	✓	x	✓	✓	x	x	x	x

✓ = support, x = no support, — = n/a; PV = positive-valence; NV = negative-valence;
PromF = promotion-focus strength; PrevF = prevention-focus strength

Chapter 5 - Discussion

This chapter proceeds in four part. First, the research findings are summarized, synthesized, and analyzed. This is done on an experiment-by-experiment basis and then as a whole to discuss common themes and findings; particular care will be given to how the empirical findings comport with the expectations from theory and prior research and literature. Second, those findings are discussed for their implications for the financial-planning and related professions. Third, limitations of this study are discussed. Fourth, suggestions for future research are explored.

Research Findings

Retirement Savings: Experiment 1

Experiment 1 regarded retirement savings intentions. Despite the various statistical techniques used, no significant relations were shown. At first blush, this is surprising. Prior research has generally found support for relationships between psychological characteristics and savings behavior (e.g., Asebedo et al., 2019). For example, literature has discussed that psychological characteristics, such as time perspectives (Hershey & Mowen, 2000) and self-efficacy (Chatterjee, Finke, & Harness, 2011); affective states (Guven, 2012); and personality traits are associated with savings behavior or wealth accumulation (Asebedo et al., 2019; Nabeshima & Seay, 2015). Therefore, it was surprising that regulatory focus had no impact on savings behavior in this experiment.

Moreover, under the tripartite framework established from the medical framing literature, retirement savings behavior was modeled as a prevention behavior. From that literature, prevention behaviors allow individuals to *prevent* future harm (e.g., a future health malady) (Rothman & Salovey, 1997). Thus, the critical distinction between a detection behavior and a prevention behavior is the proximal risk (Detweiler at al., 1999); the risk is in the future for prevention behaviors, and the risk is current for the detection behavior.

Based on that distinction, then, theory indicated that gain framing should be ideal. However, this was basically a result by implication. Loss framing is not ideal in prevention behaviors because loss framing encourages risk-seeking (to avoid the loss). For prevention behaviors, there is no current risk, so loss framing would appear to be counter-productive—this leaves gain framing as the viable choice. And, indeed, as noted in Chapter 2, there has been empirical results that support gain framing for prevention behaviors (e.g., Christopherson & Gyulay (1981) for car seats, and Linville, Fischer, & Fischhoff (1993) for condom usage). But, O'Keefe and Jensen (2007) noted that the effect of gain framing for disease prevention behavior may be misleading. Here, the data did not support gain framing in Experiment 1.

Surprisingly—and unlike the other experiments—there was not a negative-valence framing effect either. Indeed, there was no significant mean intention difference in any of the treatments or control group. Due to the lack of *any* treatment effect (and this lack of treatment effect was consistent across model specifications—e.g., the binary high-low or cumulative three-category logits), this could be due to the fact that people basically know they need to save for retirement; that is, the public is generally aware of it and then social desirability bias takes over. It could also be that, unlike the other behaviors examined, the retirement horizon is so far off, it is not readily salient (e.g., "Yes, I'll do that eventually, but not now—I can do it later"). If that were the driving factor, though, there may be an age effect (as retirement becomes more salient). However, age was not a significant predictor in any of the models. Moreover, the lack of a significant framing effect was even true when the sample was split into prevention and promotion subsamples.

It may be that the retirement savings problem was not a suitable financial behavior proxy for a preventative behavior; that is, the narrative did not ably fit the theory. Even if that were the case, based on the other experiments, *some* treatment effect may be expected (at a minimum due the potential priming effect of the fact-based treatment relative to the control group). Yet, there was no effect across the experiment regardless of treatment or control. It could have also been that the Experiment 1 narratives were not as charged as the other narratives; that is, the story did not evoke the desired emotional response.[60] Stated simply, perhaps the loss and gain framing were not of significant magnitude to induce a framing response. Thus, it is unclear why Experiment 1 did not yield a significant difference across any treatment.

Cash-Flow and Budgeting: Experiment 2

Experiment 2 regarded budget and cash-flow planning intentions. This was modeled as a treatment behavior. Treatment behaviors remedy a current problem (Rothman & Salovey, 1997). Rothman and Salovey (1997) argued that undergoing the treatment is the risk-averse (safer) option compared to no treatment and suffering from the problem. Under prospect theory, then, to encourage the risk-averse option, gain framing should be used (because loss framing encourages risk-seeking choices).

There were four takeaways from Experiment 2. First, consistent support for a narrative effect; that is, one of the narratives were significantly different than the control; this was true across model specifications and statistical analyses. Second, there was a consistent *lack* of support for a positive-valence (gain) framing effect. This was contrary to the directionality hypothesized by theory; relatedly, the positive-valence effect, therefore, was not stronger than the negative-valence. Third, the framing effect was attributable to the negative-valence (loss)

[60] As noted more in the limitations section, manipulation checks should be used in future research to ensure the proper response was induced, i.e., the narrative conveyed the desired emotion.

narrative, which was generally consistent across models and specifications. Fourth, there was indication of regulatory fit, despite the lack a positive-valence main effect. Each will be addressed in turn.

There was a consistent framing effect, which emanated from the negative-valence narrative. In other words, across the sample as a whole, although there were negative-valence main effects, there was no positive-valence main effect. Based on the literature, this was unexpected. Recall that, for treatment behaviors, the literature predicted that gain-framing should be more persuasive than loss-framing—and there was empirical support for the gain-framing main effects (e.g., McNeil et al., 1982; Rothman & Salovey, 1997). Nevertheless, the negative-valence (loss) framing was consistently associated with higher intention levels (across models and specifications). There could be several reasons for that.

First, as noted in the literature review, was the possibility for negativity bias. In short, “bad is stronger than good” (Baumeister et al., 2001, p. 362). Derived from prospect theory, powerful negativity potency stems from the shape of the value function and loss aversion. Here, that negative potency could have been stronger than any effect in the gain frame. Second, the gain frame (i.e., the positive-valence) may not have been that “charged”—that is, it poorly implemented the perspective of a gain frame. However, upon review of the positive-valence narrative, it presented each item in the issue mix in a gain, positive outcome, or win; as such, this rationale is unlikely. Third is that budgeting and cash-flow planning may not have been an ideal financial behavior proxy for a treatment behavior. However, its selection was rooted in the theoretical nature of treatment and recuperative behaviors. The current problem was the monthly budget shortfall that created collateral problems; the treatment (the budget and cash-flow planning) ameliorated that problem in the positive-valence narrative, and the lack of the treatment exacerbated that problem in the negative-valence narrative. The selection of budget and cash-flow planning therefore had a basis in theory as a treatment behavior.

Experiment 2 also provided the first, albeit slight, indication of support for regulatory fit in this research. Regulatory fit refers to when a goal is pursued that is consistent with the underlying regulatory state (Idson et al., 2004). And the prior literature indicated that regulatory fit should enhance the message framing impact (e.g., Cesario et al., 2004, 2008). Based on theory, then, it was expected that gain framing (focusing on the benefits) would be more persuasive for promotion-focus respondents, and loss framing (focusing on the costs) for prevention-focus respondents (Spiegel et al., 2004). Although there was not consistent support for H2e and H2f (the regulatory fit main effects hypotheses), for promotion-focus respondents, there tended to be indication of a positive interaction effect between relative promotion strength and the positive effect (H2g). In other words, among promotion-focus respondents, the effect of the positive-valence narrative increased with the strength of the promotion focus (i.e., the RFQ difference). This comports with a regulatory fit rationale. Curiously, this was not true for prevention-respondents (H2h).

Insurance Needs: Experiment 3

Lastly, Experiment 3 examined intentions concerning performing an insurance needs analysis. This was modeled as a detection behavior. Detection behaviors are those that detect or identify a current problem. Detection behaviors examined in past studies included, for example, breast self-examinations, skin-cancer exams, and HIV testing—each of those behaviors give rise to the possibility of identifying a current problem. Here, in the narratives, the problem detected was a lack of adequate insurance protection (across various risk sources). Based on theory, then, loss framing was expected to be the more impactful framing choice. This is because detection behaviors are seen as risky at the time of the behavior (i.e., taking the test) because it exposes the person to a potential loss (being alerted to the problem). Because loss framing encourages risk-seeking behavior, therefore, loss framing should complement detection behaviors.

Surprisingly—and unlike in Experiments 1 and 2—there was indication of both a positive- and negative-valence effect. The positive-valence and negative-valence effects were consistent across model specifications. According to theory, the negative-valence (loss) framing should be more impactful than the positive-valence (gain) framing. There were mixed results in the analyses on this front. Three of the statistical methods indicated that negative valence was superior, but three did not. However, the pairwise comparison would have been significant without the Tukey-Kramer adjustment, and the nonparametric Wilcoxon test may not have had enough power to notice differences that were on the margin of significance (which may be the case given the Tukey-Kramer significance change). The other technique—seven-level cumulative logit—should not be given much deference due to the proportional-odds assumption being violated. Indeed, the ideal model to examine would be the three-level cumulative logit—due to the proportional-odds assumption not being violated and the naturally larger cell sizes (more power)—which did indicate that the negative-valence effect was larger than the positive-effect.[61]

Regarding regulatory fit, the Experiment 3 results were mixed. There was a consistent lack of support for the promotion-focus respondents and the positive-valence (i.e., the positive valence effect would be greater than the negative valence effect). One reason could be that, despite being promotion-focused, the negative-valence was particularly dominating here (i.e.,

[61] Though, the Wald tests in both the main effect and interaction model could not reject the null hypothesis of equivalency.

irrespective of the individual's chronic regulatory focus orientation).[62] For prevention-focus respondents, however, there was consistent support that the negative-valence was stronger than the positive-valence. However, this could just be the main effect (i.e., the negative-valence effect generally) rather than being specifically attributable to regulatory fit. But, when considering the similarly consistent results that, for prevention-focus respondents, the higher the level of prevention focus (i.e., stronger), lead to an increased negative-valence effect (H3h), which supported the presence of regulatory fit.

Narrative Effects

Experiments 2 and 3 both found some support consistent with a narrative effect. That is, compared to the control group, there were indications that those exposed to a narrative (either positive- or negative-valence) had higher mean intention scores. This was predicted by theory. Narrative framing (presenting information in a story-like manner) invokes emotional responses that are not present when merely processing fact-based information (e.g., Carlsson Hauff et al., 2014, 2016). Indeed, the narrative effect has been demonstrated in the financial decision-making context, too (Carlsson Hauff et al., 2014, 2016)

However, there was a possible confounding issue here—a potential priming effect; that is, reading about budgeting or an insurance needs analysis may naturally predispose someone to that behavior (as it is now more salient). Thus, comparing the narrative effects jointly and separately to the fact-based treatment is critical (to minimize the confounding influence, if any, of priming).

In Experiment 2, although there were pairwise mean comparisons significant relative to the control, neither the positive- nor negative-valence treatments were significantly different than

[62] This was noted as a limitation, too—the actual emotional effect of any narrative on the reader was indeterminate.

the fact-based treatment group. Similarly, although the narrative average effect contrast was significantly different than the control, it was not different than the fact-based treatment effect. This was borne out by the nonparametric analyses, too. So, it was unclear whether, at least in Experiment 2, what was the factor leading to the effect—was it truly the narrative or just priming and salience.

In Experiment 3, the picture, unfortunately, was not clearer. The narrative treatment effects, although significantly different than the control group, were not significant relative to the fact-based treatment (or the joint contrast either). In the various regression analyses, Wald tests generally could not reject the parameter equivalencies either between the narrative treatments and the fact-based treatment. However, in the three-level cumulative logit, the Wald test did reject the equivalency for the negative-valence and fact-based treatment; as did the same test in the binary logit. Thus, there was some support from Experiment 3 that the narrative effect is not solely attributable to mere priming and salience. As noted in the suggestions for further research section, this precise issue should be addressed in future research.

Framing Effects

The framing effects considered by this research were negative- and positive-valence narratives, which were akin to the hypothetical gain or loss framing that is present in the behavioral economics and related literature. Based on prospect theory, there was an expectation that, depending on how information was presented (i.e., its frame), the choice would be either be risk-seeking or risk-averse. The notion that choice is dependent upon the frame of information is antithetical to traditional rational expectation theory analysis. As prospect theory indicates and empirical studies routinely demonstrate, people view gains and losses differently—and different from their mere mathematical equivalencies. And, from that theoretical basis, losses tend to encourage risk-seeking behavior and gains tend to encourage risk-averse behavior.

Here, there was consistent support from Experiments 2 and 3 of framing effects. In both experiments, the negative-valence treatment had higher mean intention scores relative to the control groups. In Experiment 3, there was decent support for a positive-valence effect, too. These findings were generally consistent across statistical method, which adds to its robustness. However, for the same reasons discussed in the Narrative Effects section, it may be hard to isolate this effect from just priming. But, consider Experiment 2, in which there was a significant negative-valence effect but not a significant positive-valence effect. If, at bottom, the results were arising solely from priming and salience, it would be expected for both valences to be significant. Indeed, that only one valence is effective (and not the other) actually supports that the treatment effects may not be solely attributable to priming and salience. Though, this is a potential limitation that should be studied expressly in future research.

Moreover, as the core tenants of prospect theory have been examined empirically, a rich medical and public health literature has emerged, which is rooted in behavioral economics and prospect theory. That literature indicated that the framing effect can depend on the underlying nature of the behavior (was the behavior for prevention, treatment, or detection). Based on that framework, it was expected that the positive valence would be more effective in Experiment 2 and that the negative valence would be more effective in Experiment 3.[63] However, that result was not borne out here.

In Experiment 2, the positive-valence treatment was not significant, despite the prediction from the literature. And the negative-valence treatment was significant, which was not the

[63] The lack of any significance in Experiment 1 was relevant to the empirical validation of this framework applied to personal financial planning decision making, too.

theoretical expectation. In Experiment 3, both narratives were effectives. But, the real test, it seemed, for whether the theoretical expectation is accurate was whether the predicted framing effect was stronger. In Experiment 2 the positive-valence treatment was not more effective than the negative-valence treatment. In Experiment 3, the negative-valence treatment was more effective than the positive-treatment treatment, at least in the regression models. So, there was at least some support that negative-valence narratives are stronger than positive-valence narratives for prevention behaviors, which comports with the theoretical prediction. Future research should be conducted using different financial behaviors (but still under the three-behavior framework) to see if those empirical results are consistent with the theoretical predictions. At a minimum, though, Experiment 3 supports that negative-valence narratives can be effective to encourage risk-seeking behavior (the detection behavior) in the financial planning context.

Regulatory Focus and Regulatory Fit

This study joined the growing body of literature by applying psychological theory to inform financial planning research and financial behavior (e.g., Asebedo et al., 2019; Asebedo & Seay, 2014, 2015). Stated simply, regulatory focus theory posits that people "approach pleasure and avoid pain in different ways" (Higgins, 1997, p. 1282). Consequently, those who are promotion-focused achieve success by achieving positive outcomes; those who are prevention-focus achieve success by avoiding losses. Based on this theory, then, it was expected that promotion-focus respondents prefer gain states (and are motivated by achieving such end states), and prevention-focus respondents want to avoid loss states (and are motivating by avoiding such loss states). As such, gain framing should be effective for promotion respondents and loss framing for prevention respondents. This phenomenon is known as "regulatory fit"—when the goal pursuit matches (or sustains) the underlying regulatory focus.

There was some support for a regulatory focus and regulatory fit effect in Experiments 2 and 3, which arose from the subsample analyses.[64] In Experiment 2, the subsample OLS regression and the promotion-focus subsample cumulative logits had significant positive-valence/RFQ interaction effects for promotion-focused respondents, with positive point estimates, indicating that, as promotion strength increased, so too did the effect of the positive-valence treatment. This was consistent with a regulatory fit rationale. Also, for prevention-focus respondents, it was expected that negative-valence narratives would be stronger than the promotion-focus narratives. And, in Experiment 2, in the prevention-focus subsample cumulative logit (three level), the negative-valence effect was stronger than the positive-valence effect for prevention-focus respondents. Again, indicating support for regulatory fit as applied to narrative-based financial planning decision making.

In Experiment 3, had some mixed results, too, which indicated regulatory fit. The prevention-focus respondents still had a greater negative-valence effect—which was expected under the theory. But the promotion-focus respondents did not have a greater positive-valence effect. So, based on the prevention-focus respondents, there was still some support for regulatory fit.

Relatedly, under a regulatory fit rationale, as the respective promotion- or prevention-focus grew stronger, it may be expected that the respective narrative would be that much stronger, too; that is, the interaction effects. There were some indications of this phenomenon in Experiment 2 and Experiment 3. In Experiment 2's promotion-focus subsample, there was a significant interaction effect—that is, as the RFQ differential increased (became more positive), so did the slope of the positive-valence narrative effect (it became more positive, leading to

[64] Of course, as before, Experiment 1 resulted in null results across the board.

higher intentions). And, in Experiment 3, this phenomenon occurred for the prevention-focus respondents. Again, indicating additional support for regulatory fit.

In sum, based on these experiments, there was support for narrative effects, framing effects, and that those effects can depend upon underlying regulatory focus. These findings have implications for the financial planning profession, which are discussed next.

Implications

This research demonstrated that, in the financial decision-making context, framing matters, stories (narratives) are powerful, and that these effects can be different due to underlying psychological differences. These three findings can be used to advance the financial planning profession and related domains at both the individual and public levels. Each will be considered in turn.

First, framing matters. From a micro perspective (i.e., an individual client advising and counseling), advisors should be mindful of how they frame discussions and planning options to their clients. Related to the prior literature that has examined the impact of exact words used in describing financial planning techniques—for example, differences in using jargon or simple descriptions (James, 2018)—this study also demonstrated a difference between gain framing and loss framing in financial planning domains. Therefore, to increase financial planning behavior adoption and implementation, advisors should integrate framing into their client discussions.

Now, in choosing between loss framing and gain framing, loss framing tended to be pervasive (i.e., significant more often). But, in the insurance needs context, gain framing worked too. Nevertheless, as demonstrated in Experiment 3, the loss framing was typically stronger than the gain framing, which makes sense from a prospect theory and loss aversion perspective. If an advisor is unsure of which frame a client is more sensitive to, the advisor should, therefore, err on the side loss framing.

From a macro perspective (i.e., a public at large perspective), framing can be used in various public awareness campaigns. These approaches are prevalent in many domains already, such as in public health (consider, for example, the various well-known anti-smoking or anti-drug campaigns). Similarly, these public awareness campaigns should embrace loss framing, as the negative valence tended to be more significant more often (and more consistently). Embracing the loss framing is particularly true in public campaigns because the messages cannot be tailored for idiosyncratic psychological differences (such as regulatory focus).

In addition to just general public awareness campaigns—which may be sponsored by governments or nonprofits—the framing effect is also relevant to financial product creators, national advisories, and others that engage in advertising campaigns. Marketing can be used to both educate the public about financial products and services and coupled with a framing strategy can also shape and affect intentions to adopt and use those products and services.

Second, stories are powerful. This research has shown that, in the financial planning context, stories are powerful, and that people respond to stories. Although the narrative effect was not present in all three experiments, it was present in two of them, and there was no decrease in intentions in the first experiment due to the narratives (i.e., it was not counterproductive). Based on this research, the advisor loses nothing by using a narrative/story approach but may gain increased client implementation rates for some planning behaviors.

Consequently, advisors should think of ways to communicate financial planning advice through stories. Ideally, this could be in the form of client testimonials (stories); however, there are testimonial and ethical considerations that advisors should be mindful of. Other than direct client testimonials, advisors should communicate the value of financial planning recommendations in the form of a story. Good stories are memorable, vivid, and, as demonstrated, impactful—and can shape intentions. This is not to say that numerical calculations, forecasts, and Monte Carlo and stochastic modeling (and other math/number-based aspects of financial planning) are not important—they undoubtedly are! But they may not be the most persuasive way to get a client to engage in a healthy financial behavior.

A major implication of this research—particularly for the narrative effect—is marketing material (either at the individual advisor level or the mass-marketing level). As noted above with the framing, these findings can be applied to communicating the value proposition of financial planning and financial products. These value propositions should be communicated by stories rather than dry, sterile facts. This approach can be used by individual advisors and also by financial services companies. For individual advisors, these stories can be used in newsletters, mailers, waiting-area brochures, and the like. For financial services companies (i.e., product creators), their products and services should be marketed with strong story-based elements—for example, in commercials and written materials. Similarly, for the public awareness campaigns, strong story elements should be integrated.

Indeed, the maximum impact is achieved by combining the framing and narrative effects. Attention should be paid to which valence is applied to that narrative—that is, extolling the benefits of a particular financial behavior or focusing on the consequences for not doing so. Although some literature indicates that the valence should be determined by looking at the underlying nature of the behavior, there is some indication that framework may not fully square in the financial decision-making context. Despite that, there is a relatively consistent negative-valence effect at least across several financial behaviors (as demonstrated here, in budgeting and insurance domains). Therefore, story-based elements should be used with a negative valence (i.e., loss framing) in the aforementioned advertising and marketing strategies.

Third, these effects can be different due to underlying psychological differences. This means that, when possible, underlying individualized characteristics should be considered. Moreover, this research joined the growing application of psychological theory and examination of personality and psychological traits to inform financial planning behavior (e.g., Asebedo et al., 2019; Nabeshima & Seay, 2015). This research advanced the literature by examining regulatory focus theory, which basically regards how people find satisfaction (by achieving positive outcomes or by avoiding losses). However, this is also implied by prospect theory, too, which posits that reference points matter.

In accord with regulatory focus and regulatory fit, people can respond to those stories differently. Advisors may want to identify the regulatory focus of their clients. It is not uncommon for planners to administer questionnaires to their clients, such as to gauge risk tolerance. Therefore, planners and advisors may find utility in adding a regulatory focus questionnaire to their tests. Then, based on a client's determined regulatory focus, the planner can tailor communications to that. The impact of regulatory focus is broader than just to framing; planners may find regulatory focus orientation helpful information for tailoring client communication generally. Moreover, if a client is prevention focused, this may also inform the advisor's approach to the client's risk tolerance.[65]

In sum, there are many implications to the findings of this research that framing matters, stories are powerful, and people can respond differently to these. These implications range from one-on-one advisor-client counseling and advising to national marketing and public awareness

[65] Indeed, the interplay between regulatory focus and risk tolerance is another aspect that should be studied in future research.

campaigns. The goal on both levels is to increase adoption and implementation of healthy financial behaviors. This research can be used to advance that paramount goal by being strategic with how the value proposition of financial planning is communicated.

Limitations and Future Research

In this study, there were four main questions as related to financial planning decision making: (a) are narratives effective; (b) does the frame of the narrative manner; (c) does that effect, if any, depend on the underlying behavior; and (d) was that effect, if any, influenced by the individualistic characteristic of regulatory focus. In answering these questions, some limitations were noticed and suggestions for future research were indicated.

In any survey-based study, survey data quality was of paramount concern. Although MTurk-based surveys are becoming more common in social sciences, there may still be issues of data quality present. As noted earlier, trap questions were intentionally not used; if they were used, additional respondents may have been eliminated. But, as noted earlier, Peer et al. (2014) found that MTurkers with high reputations rarely failed attention check questions. Moreover, in this study, reasonable steps were taken (described in Chapter 3)—such as features available in MTurk (minimum entrance ratings) and Qualtrics (preventing ballot-box stuffing and timers)—to ameliorate these data quality concerns.

Related to general data quality, was also the data quantum. There was approximately 400 persons (per the survey design) in each experiment block, and, within that block, about 100 persons per treatment group (and control). When considering the seven-point Likert-type response variable, some of the cell counts may be less than desirable—this was particularly acute when looking at the subsamples. This was potentially true, too, when considering some of the explanatory variables (namely the categorical variables) when conducting the regressions (OLS and logits). The presence of small cells may affect statistical power to discern significant differences. Attempts were made to ameliorate this concern to collapse categorical cells when it made practical and theoretical sense. Nevertheless, future research should engage more respondents to increase cell size and thereby increase power.

Another potential limitation was the Likert-type response variable. Although its use is common in social sciences—and with OLS regression—a single Likert-type response is not truly continuous. Quantitative and methodological techniques were applied in this research to account for that—such as using nonparametric methods and logit-based models (in addition to the ANOVA and OLS regression techniques). Generally, the results from these techniques were consistent, which were favorable to their legitimacy. Yet, future research may want to use a truly continuous variable. There are several ways to accommodate that. One may be to use a Likert scale, which combines and averages several Likert-type responses, which, being a composite average, would be closer to a continuous and interval measure. Instead of a Likert-type response, a 100-point scale could be used with various descriptive anchors (James & Routley, 2016). Another approach may be to use a visual analog scale (or an average of VAS scores) for the response variable, which can be readily implemented in online surveys.

Another possible limitation was related to the narratives. The narratives used a third-party protagonist. The effect of a third-party protagonists may be different than if the narrative asked the respondent to place him- or herself into the narrative personally—that is, the narrative effect could be greater if it was more personalized to the respondent. Future research then should examine the narrative effects, if any, between a third-party protagonist and placing oneself into the narrative.

Relatedly, the narratives consistently used a female schoolteacher as the protagonist. Future research should examine whether the effects are different based on the protagonist. That is, those in that profession may relate more to the protagonist (and those in dissimilar professions may not be able to relate to the protagonist). With a schoolteacher protagonist, moreover, some respondents may have felt (or thought) that the teacher had other pension plans or other benefits typically afforded to teachers, which may have impacted their response and connection to the narrative. Alternatively, perhaps narratives that do not use professions should be examined too.

Similarly, the narratives and underlying theory assumed that engaging in the financial behaviors were the rational choice to make. However, there may be situations in which *not* engaging in the behavior could be considered rational. For example, someone who was financially strained may not be able to save for retirement, regardless of the narrative treatment they were exposed to. Hopefully, some of this possible confounding was ameliorated by the regressions. But the possibility remains that, for some, it may have been perceived as completely rational to not engage in the behavior, perhaps due to some other immediate financial need or financial strain. In that vein, although some literature indicates that regulatory focus is a stable characteristic, a particular focus can be temporarily induced (Latimer et al., 2008). It may be the case then that, for some respondents, perhaps financial strain or other change-in-circumstance affected their regulatory focus. Fortunately, as others have noted, due to the nature of the RFQ questions asking about subjective histories, it is unlikely that chronic RFQ changes based on short-term changes in circumstances (Latimer et al., 2008). In any event, financial strain was controlled for in the various regressions.

Another limitation that arose in analyzing the results was ascertaining a difference between a valence treatment or the fact-based treatment. Sometimes, those differences were not significant. A possible confounding effect, then, may be priming and salience. By discussing and reading about the behavior, the respondent may be more prone to respond favorably to a prompt concerning the behavior. This can also be affected by the sample size, which, as already noted, should be increased in future work. Additional research should focus on the difference between the fact-based treatments and the valence-based treatments.

Related to that was whether the respondents viewed the prompts as intended by the researcher. In other words, whether the positive-valence narrative actually communicated a gain frame (or positive affect) and whether the negative-valence narrative actually communicated a loss frame (or negative affect). In short, did the intended emotional or affective response take place. A manipulation check (measuring the affective response) should be included in future research.

Lastly, another limitation—and one rooted in the underlying theoretical lens—is that prospect theory studies are necessarily reference-point dependent (Tonsor, 2018). Many prospect theory-based studies consider only one reference point or a common reference point (Tonsor, 2018). Yet reference points can and do differ—indeed, they are expectations-based can change with time (e.g., Koszegi & Rabin, 2006, 2007; Tonsor, 2018). As such, respondents' loss aversion may be different due to their underlying (individual) reference point. Similarly, reference points are typically assumed to be known (and known with certainty!) (Caputo, Lusk, & Nayga, 2019).

Here, data was not collected in attempts to derive or construct underlying reference points or to assess their certainty. Although some data collected could be used for that (e.g., income data), due to its categorical nature, it would only be a crude proxy for a numerical reference point. As well, those reference points (and loss aversion) could be rooted in past experience or events (e.g., the loss of a loved one who did not have insurance—and even how recent that experience was). Hopefully, some of these effects, if any, were ameliorated by the experimental design and randomization. Nevertheless, future research should investigate, if possible, the difference in these framing effects due to underlying variability in reference points.

Conclusion

Although the mathematical elegance and tractability of *homo economicus* is alluring, behavioral economics and related social science research demonstrates that, empirically, it is naïve and often divergent from real world decision making. As such, behavioral economics offers keen insights to how real people make real decisions—and how those decisions can be shaped and affected.

Stories and narratives have been integral to culture, religion, and society at large since time immemorial. This dissertation demonstrated that narrative message framing—a behavioral economics phenomenon—can be used to increase financial planning intentions. And that the narrative effect can depend on the underlying financial behavior and underlying psychological characteristics of the individual. Naturally, shaping intentions is a first step to changing actual behavior. Thus, financial planners and policymakers should explore ways to use narrative messages as nudges to increase implementation of healthy financial behaviors on the micro (client-level) and macro (public) scales.

In sum, this dissertation found support for the propositions, as applied to financial planning, that stories are powerful, framing matters, and these effects can be enhanced by incorporating underlying psychological differences. Critically, then, these insights should be applied to increase objectively healthy and desirable financial planning behaviors—to nudge healthy financial behaviors. As such, these findings are important for a variety of constituencies, ranging from individual advisors to national financial services firms, non-profits, and governments.

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Appendix A - Survey Instrument

Examining Financial Planning Intentions

This survey involves research and is being used to gather information regarding financial planning and intentions regarding financial behavior; the purpose of this research is to inform potential improvements for financial planning behavior implementation.

You may not derive a direct personal benefit from this research, but we hope this research will improve and advance the financial planning field.

To participate in this study, you must (a) reside in the United States, (b) read and speak fluent English, and (c) be at least 18 years old. Additional eligibility criteria are screened early in the survey.

This survey should take about 10-15 minutes to complete and is performed online. If you agree to participate, you will answer a series of questions and may read short prompts or stories and answer related questions. You may proceed at your own pace.

We believe there are minimal risks with this survey and study. With any electronic research study, however, a risk of breach of confidentiality always exists. All responses will be kept confidential to the best of our ability. Your MTurk worker ID may be collected for purposes of distributing compensation. You are encouraged to review the MTurk Privacy Policy at https://www.mturk.com/mturk/privacynotice.

After completion of this study, your MTurk worker ID may be removed from your responses, and the information may be used for future research studies or distributed to other investigators for future research without additional informed consent from you and without additional compensation.

If you satisfactorily and fully complete the survey, you will receive $0.50 (fifty cents). Payment is dependent upon answering all questions. There may be quality control measures built into the survey. Failure to satisfactorily meet the quality checks will end the survey and no compensation will be paid. The first few questions contain screener questions. If you do not meet our full eligibility criteria, the survey will end, and no compensation will be paid. If the survey is not satisfactorily completed, you will not be compensated. It may take several days after you complete the survey for us to approve and process the payment.

Participation is voluntary; you do not need to be in this study. There is no penalty for refusal to participate. You may stop the survey at any time by simply closing and exiting your browser; however, if you do not satisfactorily complete the survey, you will not be compensated.

For questions about the study, please contact Tim Todd (tmtodd@ksu.edu) or Martin Seay (mseay@ksu.edu). You may also contact Rick Scheidt, Chair, Committee on Research Involving Human Subjects, 203 Fairchild Hall, Kansas State University, Manhattan, KS 66506, (785) 532-3224; Cheryl Doerr, Associate Vice President for Research Compliance, 203 Fairchild Hall, Kansas State University, Manhattan, KS 66506, (785) 532-3224.

By clicking "I Agree" and continuing to the survey, you affirm that (a) reside in the United States, (b) read and speak fluent English, (c) you are over 18 years old, (d) have read and understand these terms, and (e) agree to such terms.

○ I consent and agree to the terms above

○ I do not consent

Please select the answer that best describes you or fill in the blank as indicated. All questions must be completed.

1 Age:

2 Gender:

○ Male

○ Female

3 My country of current residence is:

○ Outside of the United States

○ The United States

○ Other

4 I can read, speak, and write in English fluently.

○ True

○ False

5 Marital Status

○ Married

○ Single

○ Divorced or Separated

○ Widowed/Widower

[Behavior Screeners]
6 Do you currently have a written plan with a set savings goal in place to save for retirement?

○ Yes

○ No

6 Do you currently have a written monthly budget that you try to follow?

- ◯ Yes
- ◯ No

6 In the last two years, have you performed an insurance needs analysis (an insurance needs analysis reviews if you have enough insurance across various types of loss)?

- ◯ Yes
- ◯ No

7 Which best describes your race?

- ◯ White or Caucasian
- ◯ Black or African-American
- ◯ Asian
- ◯ Other

8 Which best describes your ethnicity?

- ◯ Hispanic
- ◯ Non-Hispanic

9 Which best describes your current employment and work status?

- ◯ Self-employed
- ◯ Full-time employee
- ◯ Part-time employee
- ◯ Unemployed
- ◯ Retired

10 How many children do you have who are financially dependent on you or spouse/partner? (Include children not living at home and step-children, too, if they are financially dependent):

11 What is the highest level of education that you have completed?

- ◯ Did not complete high school
- ◯ High school (or GED)
- ◯ Some college, no degree
- ◯ Associate’s degree
- ◯ Bachelor's degree
- ◯ Post-graduate degree (e.g., master’s or doctorate)

12 What is your (or household's, if married) approximate annual income? This includes all sources of income, such as wages, tips, investments, public benefits, retirement plans, etc.

- ○ Less than $20,000
- ○ At least $20,000 but less than $40,000
- ○ At least $40,000 but less than $60,000
- ○ At least $60,000 but less than $80,000
- ○ At least $80,000 but less than $100,000
- ○ $100,000 or more

13 In a typical month, how difficult is it for you to cover your expenses and pay all of your bills?

- ○ Not at all difficult
- ○ Not very difficult
- ○ Somewhat difficult
- ○ Very difficult
- ○ Completely difficult

14 On a scale of 1 to 7 (where 1 means very low and 7 means very high), how would you assess your overall financial knowledge?

- ○ 1 (Very Low)
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7 (Very High)

15 Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- ○ More than $102
- ○ Exactly $102
- ○ Less than $102
- ○ Do not know

16 Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today
- Do not know

17 Please tell me whether this statement is true or false. “Buying a single company’s stock usually provides a safer return than a stock mutual fund.”

- ○ True
- ○ False
- ○ Do not know

This set of questions asks you **HOW FREQUENTLY** specific events actually occur or have occurred in your life. Please indicate your answer to each question by selecting the appropriate number below it.

18 Compared to most people, are you typically unable to get what you want out of life?

- ○ (1) never or seldom
- ○ (2)
- ○ (3) sometimes
- ○ (4)
- ○ (5) very often

19 Growing up, would you ever “cross the line” by doing things that your parents would not tolerate?

- ○ (1) never or seldom
- ○ (2)
- ○ (3) sometimes
- ○ (4)
- ○ (5) very often

20 How often have you accomplished things that got you “psyched” to work even harder?

- (1) never or seldom
- (2)
- (3) a few times
- (4)
- (5) many times

21 Did you get on your parents’ nerves often when you were growing up?

- (1) never or seldom
- (2)
- (3) sometimes
- (4)
- (5) very often

22 How often did you obey rules and regulations that were established by your parents?

- (1) never or seldom
- (2)
- (3) sometimes
- (4)
- (5) always

23 Growing up, did you ever act in ways that your parents thought were objectionable?

- ○ (1) never or seldom
- ○ (2)
- ○ (3) sometimes
- ○ (4)
- ○ (5) very often

24 Do you often do well at different things that you try?

- ○ (1) never or seldom
- ○ (2)
- ○ (3) sometimes
- ○ (4)
- ○ (5) very often

25 Not being careful enough has gotten me into trouble at times.

- ○ (1) never or seldom
- ○ (2)
- ○ (3) sometimes
- ○ (4)
- ○ (5) very often

26 When it comes to achieving things that are important to me, I find that I don’t perform as well as I ideally would like to do.

- ○ (1) never true
- ○ (2)
- ○ (3) sometimes true
- ○ (4)
- ○ (5) very often true

27 I feel like I have made progress toward being successful in my life.

- ○ (1) certainly false
- ○ (2)
- ○ (3)
- ○ (4)
- ○ (5) certainly true

28 I have found very few hobbies or activities in my life that capture my interest or motivate me to put effort into them.

- ○ (1) certainly false
- ○ (2)
- ○ (3)
- ○ (4)
- ○ (5) certainly true

[Experiment 1: Retirement Income Planning]

[Fact-Based]
29 Please read the following:

There are several steps to planning for retirement. You set a goal about your retirement. Based on that, you set a savings goal. You then save over your working years to meet that goal. Properly saving for retirement will allow you to do those things you want in retirement, such as travel, hobbies, and visiting with family.

In the next six months, how likely are you to establish a retirement savings goal and begin to take steps to accomplish that goal?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Positive-Valence]
29 Please read the following:

Sally is a recently retired schoolteacher. She planned for her retirement. She set a savings goal based on what she wanted her retirement to look like. Based on that goal, she saved each month to meet it, and her retirement is now funded. Now that she is in retirement and has enough saved, she does not worry about making ends meet. She does not stress about money matters. She is able to do the things she wants to in retirement, such as travel, take on new hobbies, and visit with her family.

In the next six months, how likely are you to establish a retirement savings goal and begin to take steps to accomplish that goal?

- ◯ Very Unlikely
- ◯ Unlikely
- ◯ Somewhat Unlikely
- ◯ Undecided
- ◯ Somewhat Likely
- ◯ Likely
- ◯ Very Likely

[Negative Valence]
29 Please read the following:

Sally is a recently retired schoolteacher. She did not plan for her retirement. She did not have a retirement savings goal based on what she wanted her retirement to look like. Without a specific goal, she did not save regularly each month, and her retirement is not funded. Now that she is in retirement and does not have enough saved, she constantly worries about making ends meet. She regularly stresses about money matters. She is not able to do the things she wants to in retirement, such as travel, take on new hobbies, and visit with her family.

In the next six months, how likely are you to establish a retirement savings goal and begin to take steps to accomplish that goal?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Control]
29 In the next six months, how likely are you to establish a retirement savings goal and begin to take steps to accomplish that goal?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Experiment 2: Cash Flow and Budget Planning]

[Fact-Based]
29 Please read the following:

Budgeting is the process of monitoring monthly income and expenses. With a budget in place, you can identify expenses that can be eliminated. This may free-up additional cash each month. Budgeting may allow you to set aside funds for an emergency, like an unexpected car repair bill or loss of a job. Budgeting may also help you start saving for long-term financial goals.

In the next six months, how likely are you to establish and follow a monthly budget?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Positive Valence]
29 Please read the following:

Sally is a schoolteacher. Money is tight, so she regularly monitors her monthly income and expenses. Based on that, she has been able to identify expenses that she can reduce and free-up additional monthly cash. She has established a budget. Due to this planning, she has been able to set aside funds for emergencies; if she had a sudden car repair or lost her job, she is comforted by knowing she has an emergency savings fund. With the budget, she is starting to save for long-term financial goals. Because of the monthly budget, she knows she can make ends meet each month. She does not regularly stress or worry about money matters because she has a plan in place.

In the next six months, how likely are you to establish and follow a monthly budget?

- ◯ Very Unlikely
- ◯ Unlikely
- ◯ Somewhat Unlikely
- ◯ Undecided
- ◯ Somewhat Likely
- ◯ Likely
- ◯ Very Likely

[Negative Valence]
29 Please read the following:

Sally is a schoolteacher. Money is tight, but she does not regularly monitor her monthly income and expenses. Based on that, after her monthly expenses, she does not have extra additional monthly cash. She does not have an established budget. Due to this lack of planning, she has not been able to set aside funds for emergencies; she does not know where the money would come from if she had an unexpected car repair bill or if she lost her job. Without a budget, she is not saving for long-term financial goals. With no budget, she does not know whether she can make ends meet each month. She regularly stresses and worries about money matters because she has no plan in place.

In the next six months, how likely are you to establish and follow a monthly budget?

- ◯ Very Unlikely
- ◯ Unlikely
- ◯ Somewhat Unlikely
- ◯ Undecided
- ◯ Somewhat Likely
- ◯ Likely
- ◯ Very Likely

[Control]
29 In the next six months, how likely are you to establish and follow a monthly budget?

- ◯ Very Unlikely
- ◯ Unlikely
- ◯ Somewhat Unlikely
- ◯ Undecided
- ◯ Somewhat Likely
- ◯ Likely
- ◯ Very Likely

[Experiment 3: Insurance Needs Analysis]

[Fact-Based]
29 Please read the following:

An insurance needs analysis reviews if you have enough insurance. You review your current insurance policies. You also consider insurance you do not have but may need. Types of insurance include automobile, disability, life, casualty, and others. An insurance needs analysis is a first step in finding gaps and issues so that they can be fixed.

In the next six months, how likely are you to perform an insurance needs analysis?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Positive Valence]
29 Please read the following:

Sally is a school teacher. She is working with a financial advisor. A part of that process is insurance needs analysis—making sure she has the insurance protection she needs. Working with her financial advisor revealed that Sally did not have adequate insurance in place. She needed to increase her car insurance; take out a disability insurance policy (in case she became disabled); increase her life insurance policy (for the benefit of her kids); and take out an additional policy to protect her home and other assets. Now that she has identified these issues, she can fix them. Knowing that she is now protected, she does not worry and stress about these issues.

In the next six months, how likely are you to perform an insurance needs analysis?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Negative Valence]
29 Please read the following:

Sally is a school teacher. She does not work with a financial advisor. She has never analyzed her insurance needs, which would make sure she the insurance protection she needs. She does not know if she has adequate insurance in place. She is unsure if her car is adequately protected; she is unsure if she is protected if she becomes disabled; she is unsure if her current life insurance is enough for her kids; and she does not know if her home and other assets are protected. Not knowing if she has enough in place, she does not know what needs fixed. Due to this uncertainty, she regularly worries and stresses about these issues.

In the next six months, how likely are you to perform an insurance needs analysis?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[Control]
29 In the next six months, how likely are you to perform an insurance needs analysis?

- ○ Very Unlikely
- ○ Unlikely
- ○ Somewhat Unlikely
- ○ Undecided
- ○ Somewhat Likely
- ○ Likely
- ○ Very Likely

[End of Experiment]

Thank You Please make note of this 7-digit code.

[Random Code]

You will input this code through Mechanical Turk to indicate your completion of the survey.

Then click the button on the bottom of this page to submit your answers. You will not receive credit unless you click this button and submit your answers.