Emotion-Sourced Variation in Service Operations

A dissertation presented by

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To

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EMOTION-SOURCED VARIATION IN SERVICE OPERATIONS

While multiple literatures suggest that emotion shapes behavior and satisfaction in experiences, there has yet to be a concerted effort to explicitly consider human emotion – whether from customer or employee -- as a source of variability in operations management (Karmarkar, 2015; Dasu and Chase, 2013). Environmental emotions, those that are endemic to the service, or emotions stimulated by operational design choices may each exert influences on service outcomes that providers and scholars alike have yet to consider. As scholarly work to arrive at an agreed upon theoretical foundation for the study of service operations has continued, open empirical questions remain about 1) the magnitude and predictability of emotion's influence on service outcomes, 2) the opportunity to affect emotional experience through service design and 3) the role that technology plays – particularly in self-service contexts (Berry et al, 2015).

This body of work uses both laboratory and field experimentation to understand the impacts of emotional sources of variability to operational performance and to investigate the potential for more empathic service design to improve customer engagement while preserving sought-after efficiencies. Across three investigations, set in the domains of financial services and ride-sharing, I show that anxiety, whether it is directly related to the decision at hand or not, is a source of variation that exerts a costly influence on choice satisfaction and decision-making that spills over to affect service relationships. I also find that these previously ignored effects can be mitigated through relatively low-cost service design choices.

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Finally, I say to the so many others that gave even the tiniest bit of themselves to recognize my humanity and offer a friendly face or word during my time in the doctoral program, I say: I see you and I thank you.

DEDICATION

This work is dedicated to:

My ancestors, whether resting in peace in Barbados or sitting in peace in Brooklyn, who set an example of perseverance for me to follow.

My parents, Henderson and Joycelyne Kinch, both of whom demonstrated that a love of learning transcends age and will still drop everything to shower me with love.

My brother, Antoine Kinch, and his family, who form a permanent cheering section whether there's something to cheer or not!

And of course, to my children: Greg Jr. and Elijah, who have inspired and challenged me every single day for the last 23 years (and counting) to be the very best Michelle I can be.

It is because of all of you that I am.

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PREFACE

Service operations scholars have long recognized that customer behaviors may introduce variability that could affect production system performance (Chase, 1981; Mills et al, 1983; Larsson and Bowen, 1989; Kelley et al, 1990, Lengnick-Hall, 1996) and that customer-introduced variability may be reduced or accommodated through operational changes (Frei, 2006). Accordingly, scholars have noted that there are likely psychological factors that influence operational process performance (Larson, 1987). While the field of behavioral operations has begun to take shape, it's primary focus thus far has been on accounting for departures from optimality in the modeling of canonical operations research models -- much like the field of behavioral economics has grown from departures from rationality in classical economics (Bendoly et al, 2007; Gino, Pisano, 2008).

The service marketing literature has established that emotion has an influence on customer perceptions of service quality and satisfaction, but sustained exploration of this area has been hampered by limitations in the measurement and predictability of emotion. As such, the study of emotions and decision-making has only recently emerged in earnest, solidifying the prospect of measurement accuracy and providing stronger theoretical bases to guide the empirical study of emotions in service encounters (Lerner et al, 2015).

While multiple literatures suggest that emotion shapes behavior and satisfaction in experiences, there has yet to be a concerted effort to explicitly consider human emotion – whether from customer or employee -- as a source of variability in operations management (Karmarkar, 2015; Dasu and Chase, 2013). Both environmental emotions (endemic to the operating environment) and emotion that is stimulated by operational design choices may affect the service outcomes. As scholarly work to arrive at an agreed upon theoretical foundation for the study of service operations has continued, open empirical questions remain about 1) the magnitude and predictability of emotion's influence on service outcomes, 2) the opportunity to affect emotional experience through service design and 3) the role that technology plays – particularly self-service technologies -- to reduce or heighten emotion in service delivery (Berry et al, 2015).

Ultimately, my research agenda seeks to understand the impacts of emotional sources of variability to operational performance and to investigate the potential for more empathic service design to improve customer engagement while preserving sought-after efficiencies. This body of work sets the stage as it is geared toward isolating and quantifying the impact of discrete emotions in service experiences as well as to understand the calming or exacerbating effects of certain operational design or procedural elements on service performance.

In Chapter One (co-authored with Ryan Buell at Harvard Business School), two laboratory experiments and one field experiment conducted in financial service contexts document the negative effects of anxiety on customer choice satisfaction, firm trust, and long-term engagement, and explore the impact of giving self-service consumers the option to interact with a person. Participants engaged in an online investing simulation who are made to feel anxious due to market downturns are less satisfied with their choices and report lower levels of trust in the firm. Providing participants with the opportunity to interact with an expert, or even another participant, dampens anxiety's negative effects on choice satisfaction and, by extension, firm trust. Interestingly, we find that very few participants who are offered the option to interact with a person take advantage of the opportunity, which is consistent with the idea that it is the mere availability of human contact that mitigates anxiety's deleterious effects. Finally, in a field experiment conducted with a credit union's self-service term loan approval process, the incorporation of access to human contact increased customer loan acceptance by 16%, suggesting that access to human contact can improve long-term service engagement.

Chapter Two (resulting from collaboration with Evgeny Kagan at Johns Hopkins Carey Business School and Yannis Stamatopoulos at the McCombs School of Business, University of Texas at Austin) uses two laboratory studies to show that price fluctuations stimulated by well-known dynamic pricing strategies in ride-sharing not only cause customer frustrations, but also stimulates anxieties. A growing literature stream in operations research touts the consumer welfare generating benefits of dynamic pricing in ride-sharing contexts, but empirical research on demand drivers in dynamic pricing contexts is lacking. We show that the anxiety that customers feel when facing surge pricing may engender risk and loss aversion. Further, we show that the mere mention of surge pricing causes participants to rate their trust in the company lower. Taken together, these insights suggest that price uncertainties reduces customer willingness to transact through emotional effects, a demand shift that scholars have heretofore ignored.

In Chapter Three, I integrate research across academic domains to examine links between anxiety and risk tolerance that may contribute to our understanding of observed inconsistencies in individuals' risk decisions and help us target service design interventions. In two controlled laboratory experiments, I document a pathway by which exogenous anxiety – unrelated to the decision task – influences risk tolerance and boosts a willingness to insure against known risks. Studies of insurance behaviors, an oft-used test bed for risk decisions, show that the rate at which American households buy life insurance suggests implausibly high levels of risk aversion and that households make insurance decisions inconsistently across product types. Prior studies of anxiety's relationship to risk-taking have delivered a mixed set of results. Scholars suggest that background risks or misperceptions might explain this “economic puzzle”, I submit that previously ignored emotion may be an important driving influence.

Understanding how emotion influences the willingness or ability of actors to engage with providers, participate in service production and subsequently evaluate their experiences, will refine our ability to model service operational processes and may challenge long held beliefs about how to manage customer contact in service operations. In operations, standardization and automations are used to increase efficiency and reduce operational costs, yet they depersonalize service experiences through a reduction in human contact.

My research examines settings where the myopic pursuit of efficiency may actually stimulate new service costs and may highlight that perhaps greater efficiency is found by introducing -- or at least allowing for – variability (e.g. customization) in the service operation rather than completely eliminating it. While any service setting could become emotional, certain settings have a higher likelihood of emotionally intense encounters such as financial services, healthcare, air travel, education and government social services – particularly those dealing with the welfare of children. In many of these settings, the stakes are high, outcomes are uncertain and not immediately assessed, and there is an asymmetry of information between consumer and service provider.

Through a greater understanding of how emotion influences customer decision-making and perceptions, and spills over to color service relationships, we can better predict and design service experiences to empathically optimize operational performance.

CHAPTER ONE:

MITIGATING THE NEGATIVE EFFECTS OF CUSTOMER ANXIETY THROUGH ACCESS TO HUMAN CONTACT

1. Introduction

Many service interactions are rife with anxiety. Patients often have to consider medical treatment options at the same time that they are processing the news of a serious condition. Airline passengers may be distressed about missing a flight or may simply be nervous about flying. Despite a wealth of evidence that anxiety may impair decision-making abilities (Gino et al. 2012, Lerner et al. 2015, Loewenstein and Lerner 2003, Pham 2007, Raghunathan and Pham 1999), firms face operational challenges as they increasingly deploy self-service technologies (SSTs) in these contexts (Bitner et al. 2002, Meuter et al. 2000). Although firms may introduce these technological service solutions with an eye toward improving profits, enhancing customer satisfaction and loyalty, or increasing sales, research suggests that their implications for customer experiences and firm performance may be equivocal (Buell et al. 2010, Campbell and Frei 2010, Xue et al. 2011). We submit that customer anxiety during SST encounters can ultimately exert a negative influence on service relationships that firms may not have factored into their operational design – that customers in such settings may be asked to take on more responsibility for service delivery when they feel least equipped to do so.

We focus our empirical investigation on customer interactions with financial services, an important sector of the U.S. economy with a long history of SST deployment that has attracted scholarly attention (Hatzakis et al. 2010, Yang and Ching 2014). Online investing, for example, is an area of financial services recognized as co-productive (Karmarkar and Pitbladdo 1995, Roels

2014), that may lead to higher incidence of stress and anxiety (Engelberg and Parsons 2016) and has provided context for prior study of decision-making satisfaction and trust formation in the absence of human interaction (Balasubramanian et al. 2003). We use both online investing and loan procurement scenarios as empirical settings for our studies.

This paper makes two specific contributions. First, we show that emotions can be an unobserved source of variation that influences service outcomes. In particular, we find that anxiety can exert a substantive negative influence on choice satisfaction in self-service settings. The dissatisfaction that customers feel with their own decision-making under anxiety – regardless of decision quality (Iyengar et al. 2006) – is often unexpressed, yet service providers may be penalized for the effects of anxieties that stem from factors that are outside of the firm's control. Although we are not the first to identify anxiety as an influencing factor in customer attitudes toward SSTs (Dabholkar and Bagozzi 2002, Meuter et al. 2003), we add to the nascent study of the role of emotions in operations (Ding et al. 2010, Karmarkar 2015, Urda and Loch 2013). By shedding light on how the short-term impact on choice satisfaction may carry over to have a long-term effect on the trust that customers place in their service providers, we add to a growing body of literature on the spillover effects of emotion in economic decision-making (Lerner et al. 2004, 2015).

Second, we find that operational design choices can mitigate the negative effects of customer anxiety even when the source of the anxiety may be beyond the control of the firm. In particular, we show that spillover effects from customer anxieties can be disrupted by incorporating the availability of human contact into SST encounters – even though the emotion persists and continues to adversely affect choice satisfaction. Importantly, we submit that the incorporation of human contact does not require firms to add costly service personnel. Rather, firms may improve customer choice satisfaction in high-anxiety settings by providing access to *other customers*, which may be virtually costless. Prior research has shown that the presence of other people may help or hurt customer-firm relationships during self-service (Collier et al. 2015, Li et al. 2013). We show that access to human contact is only a significant driver of customer satisfaction and trust, when customers feel anxiety. Thus, designing service experiences that remind anxious customers that human contact is available if needed allows those that value the option the most to self-select into human contact. This approach may avoid the cost and potentially detracting presence of other people during SST use in low-anxiety service settings. Our research suggests that firms may be able to avoid negative spillover effects to trust by providing access to human contact during SST use, which can be cost-effectively operationalized and need not require additional service employees to have desirable effects.

2. The effects of self-service and human contact in high-anxiety settings

SST has grown in prominence as firms have sought to reap potential productivity gains, improvements in service quality and profitability enhancements (Campbell and Frei 2010, Hitt and Frei 2002, Xue et al. 2007). Because of these potential operational efficiencies, technology-based self-service has become a key delivery model across industries – even those that have been associated with high levels of anxiety such as healthcare and financial services (Bitner et al. 2002, Botti and Iyengar 2006, Meuter et al. 2000).

In addition to efficiency gains, SST deployment is motivated by the increases in customer satisfaction that companies expect from offering customers greater convenience, reduced wait times, and higher levels of control over service outcomes (Bitner et al. 2000, Dabholkar 1996, Meuter et al. 2000, Xue et al. 2007, Xue and Harker 2002), however, the findings on realized costs and benefits of SST deployment due to customer behavior changes in these settings has been mixed. SST adopters exhibit greater product acquisition (Hitt and Frei 2002, Xue et al. 2011) and higher retention rates over longer time horizons (Buell et al. 2010), but on average, research in these settings show that SST adoption may result in lower satisfaction for some types of customers (Ding et al. 2010, Meuter et al. 2003).

An important source of the profitability and productivity gains that firms experience by introducing SSTs is the reduction of live operators as a part of the service encounter. However, this loss of human contact can have a material effect on customer perceptions and behaviors (Collier et al. 2015, Meuter et al. 2000). Although SSTs may be preferred by customers specifically to avoid service personnel (Dabholkar 1996, Dabholkar et al. 2003), studies have shown that SST adopters may simultaneously increase their use of traditional service channels (Campbell and Frei 2010). Increases in full-service channel usage may be due to deeper product penetration (Xue et al. 2011), or because self-service use provokes more complex needs or customer ambiguity (Kumar and Telang 2012).

The absence of human contact in SST channels may be especially discomforting for customers seeking service in high-anxiety service settings. When people are anxious, they are more likely to seek advice (Gino et al. 2012), and customer comfort, defined as reduced anxiety, plays an important role in the creation and maintenance of service relationships (Spake et al. 2003). To balance heterogeneous customer needs while preserving the efficiency potential of self-service, firms have begun to offer employee-assisted self-service (Froehle 2006) – adding back a portion of the cost of human servers that SST options are intended to reduce – but the lack of privacy engendered by the presence of store employees may in some cases exacerbate feelings of anxiety and reduce satisfaction (Collier et al. 2015, Dabholkar and Bagozzi 2002).

In the present research, we explore how making the availability of human contact salient in SST interactions – either with customers or employees – shapes customer perceptions and behaviors. This line of research is crucial in co-productive contexts, which rely on customers to be integrally involved in service delivery through their contributions of key information and/or labor (Roels 2014). Outcome quality in these settings is highly dependent on the quality of the customer's participation. Service operations scholars have long recognized that customer behaviors may introduce variability that affects production system performance (Chase 1981, Mills et al. 1983) and that customer-introduced variability may be reduced or accommodated by operational design (Frei 2006). We propose that emotions are a crucial driver of customer-imposed variability in SST settings. Emotions can play a dominant role in determining the quality of decisions people make (Lerner et al., 2015 offers a comprehensive review) and intense emotions, such as anxiety, can crowd out cognition, taking control of behavior (Loewenstein and Lerner 2003).

When people are anxious, their level of attention and their ability to process and evaluate information can be greatly reduced (Gino et al. 2012), lengthening the time it takes for them to make logical inferences (Pham 2007, Rick and Loewenstein 2008). Moreover, in high-stakes settings, anxiety has been shown to alter individual risk preferences, making people more risk averse (Raghunathan and Pham 1999) or more risk seeking (Mano 1994b), depending on their emotional state. The effects of anxiety may be especially acute in technology-based self-service settings where customers are conducting self-directed transactions or engaged in self-help. The empowerment that can attract customers to self-service options may also lead to increased decision difficulties – particularly in contexts marked by task complexity and low levels of consumer knowledge (Broniarczyk and Griffin 2014). Unmitigated choice freedom may result in an exhaustive search for the "best" outcome, which may increase the likelihood of feelings of regret and confound decision making (Iyengar and Lepper 2000). By designing SSTs to mitigate customer anxiety in self-service settings, firms may be able to help customers make more satisfying decisions.

By improving the experience of decision making for customers, interventions designed to counteract the negative effects of anxiety in SST settings may additionally bolster the long-term trajectory of the service relationship. Intense deliberation, which can confound decision making as described above, has also been linked to negative customer perceptions of choice quality (Carmon et al. 2003) and lower outcome satisfaction – regardless of how well those outcomes meet objective goals (Iyengar et al. 2006). Choice satisfaction in SST interactions has critical long-term implications for the trajectory of customer-firm relationships, since satisfaction is a precursor to customer trust (Garbarino and Johnson 1999), as is a sense of control over service outcomes (Dunn and Schweitzer 2005). Trust fosters relationship commitments and customer cooperation (Morgan and Hunt 1994) leading customers to engage more deeply with the service provider over time and enhancing long-term loyalty (Porter and Donthu 2008). Scholars have noted the heightened importance of trust as a facilitating factor in economic and social exchange in online environments (Urban et al. 2000), yet the study of trust formation in these contexts is still nascent (Porter and Donthu 2008). Since the loss of human interaction reduces the relationship-building capacity of customer-firm interactions (Balasubramanian et al. 2003), the study of how to build trust during self-service in emotional service settings is especially important. We contribute to this developing area of research by exploring how the provision of access to human contact in SST settings influences choice satisfaction and trust in high-anxiety settings.

3. Presentation of experiments

In three experiments, conducted in the lab and in the field, we study the effects of customer anxiety in self-service settings and its implications for choice satisfaction, trust, and engagement. The financial service industry provides an ideal setting to study the effects of anxiety on choice satisfaction and trust in co-production and the potentially mitigating role of human contact in SST design. The provision of financial services, which began as a largely face-to-face endeavor, has a long history of innovation with SSTs (Yang and Ching 2014). The present studies build on a rich stream of the extant empirical service operations literature that investigates self-service interactions in financial services (Buell et al. 2010, Campbell and Frei 2010, Xue et al. 2007, 2011). In the presentation of experiments that follow, we note how we determined our sample size, all data exclusions, and all measures collected (Simmons et al. 2012).

Experiments 1 and 2 simulate an online retirement portfolio management customer experience. Industry research identifies anxiety as a significant factor in retirement saving and investing (Greenwald et al. 2017). Indeed, portfolio management requires high-stakes decisions to be made based on complex and uncertain future scenarios (Zeidner and Matthews 2005), which may induce anxious feelings and increase the need for human interaction. Experiment 3 was conducted in the field in collaboration with a credit union based in the northeastern United States, and it focuses on the consumer loan application process. Facets of the consumer loan application process engender anxiety – for example, the pulling of a customer's credit report may stimulate anxieties associated with being evaluated (Zeidner and Matthews 2005) and uncertainty while waiting for potentially negative news – such as being denied for a loan - may produce more anxiety than facing the decision (Sweeny and Falkenstein 2015). Consistent with prior research (Karmarkar and Pitbladdo

1995, Roels 2014), we view the investment planning and consumer loan application processes to be forms of co-production, since key contributions need to be made by both the firm and the customer for the service to be delivered and for each to realize value from the interaction. In co-productive self-service interactions, we hypothesize that anxiety may undermine choice satisfaction, and in turn, trust in the firm and subsequent levels of engagement. We further hypothesize that incorporating the option of human contact into the design of self-service offerings can improve choice satisfaction and trust, leading to more productive engagement over the long term. The experiments that follow below test these hypotheses.

3.1 Experiment 1: Anxiety, Choice Satisfaction and Trust in Self-Service Interactions

As an initial test of the relationships among anxiety, choice satisfaction, and trust in self-service settings, we recruited participants to engage in an incentive compatible, online investment simulation task. We manipulated anxiety by varying the nature of the market conditions participants faced, measuring participants' subsequent anxiety levels, performance, choice satisfaction, and trust in the firm.

3.1.1 Participants. 160 participants were recruited on the Amazon Mechanical Turk platform in exchange for \$2.00 plus a bonus of \$0.25 for every \$100,000 earned during the investment simulation. Hence gains and losses in the task directly influenced participants' real compensation. Participants were informed that any bonus earned would be paid after the final round, but were not informed in advance of the precise number of rounds in order to minimize end effects (Rapoport and Dale 1966). As this was an initial study, the target sample size of 160 participants was chosen with the goal of capturing 75 observations per condition after exclusions. Participants who did not complete all tasks and questionnaires were dropped from the sample, resulting in a final dataset of 157 observations (M_{age} = 34.43, 44.23% Female).

3.1.2 Design and procedure. Participants engaged in an experimental task designed to simulate the flow of a typical online investment planning interaction. At the outset of the experiment, participants were told to imagine that they had an investment portfolio of $100,000 to manage for a long-term investment goal. Over a series of 12 rounds, where each round was meant to simulate a year of investing, participants were instructed to allocate a percentage of their portfolio to stocks, bonds, and cash.

During each round, participants could review their portfolio, conduct research about the performance of different asset classes over time, and allocate their investment among stocks, bonds, and cash. Mirroring real-world investment planning applications, the simulation with which participants interacted included three pages that provided real-time information for each round to inform their choices – *Your Portfolio*, *Research*, and *Take Action* (**Figure 1.1**). On the Your Portfolio Screen (Panel A), participants saw their balance, a pie chart of their portfolio as divided among their investment choices, investment commentary associated with the prior year's returns, and the portfolio's overall growth history. On the Research Screen (Panel B), participants were given an opportunity to learn about certain characteristics of each investment choice based on a rolling 20-year window. The information provided on this screen began with the most recent 20 years of historical data and was updated with each round based on the returns drawn by the simulation. The investment characteristics shown were average annual return, standard deviation, risk category of the fund, best / worst annual returns and the percentage of years with positive returns. Finally, the Take Action Screen (Panel C) allowed participants to enter their chosen percentage allocation to each investment in whole numbers from 0 to 100. After participants submitted their allocation decisions in each round, they experienced a brief pause to simulate the passage of time before progressing to the next round, and seeing how their portfolio fared in the market.

Since experiencing market downturns has been linked to anxiety in previous research (Engelberg and Parsons 2016), we manipulated anxiety by varying the probability that participants would face aversive market conditions. For participants in the low-anxiety condition, after they submitted their allocation decisions in each round, the simulation randomly drew a year between 1928 and 2014, and applied the historical returns for stocks, bonds, and cash from that year against the participant's balance and portfolio allocation, to calculate their starting position for the next round (**Figure 1.2**). For example, if the year 1946 was drawn, the application applied -8.43% to stocks, 3.13% to bonds and 0.38% to cash. In the high-anxiety condition, the simulation randomly drew a year between 1928 and 2014 with 50% probability, and randomly drew from the set of years where the stock market declined by 5% or more with 50% probability. Indeed, participants in the low-anxiety condition experienced average returns of 12.81% for stocks, 5.14% for bonds, and 3.46% for cash, while participants in the high-anxiety condition experienced returns of -3.12% for stocks, 5.41% for bonds, and 3.22% for cash.

A. Your Portfolio

Participants could use this screen to track their asset allocation, portfolio balance and portfolio growth over time as the simulation progressed. With each round, participants received commentary about economic forces that drove their investment results.

B. Research

Participants were given information about the historical performance characteristics of each asset class (e.g. cash, bonds, and stocks) to aid their decision making.

C. Take Action

Participants concluded each round by updating their portfolio allocation among cash, bonds, and stocks.

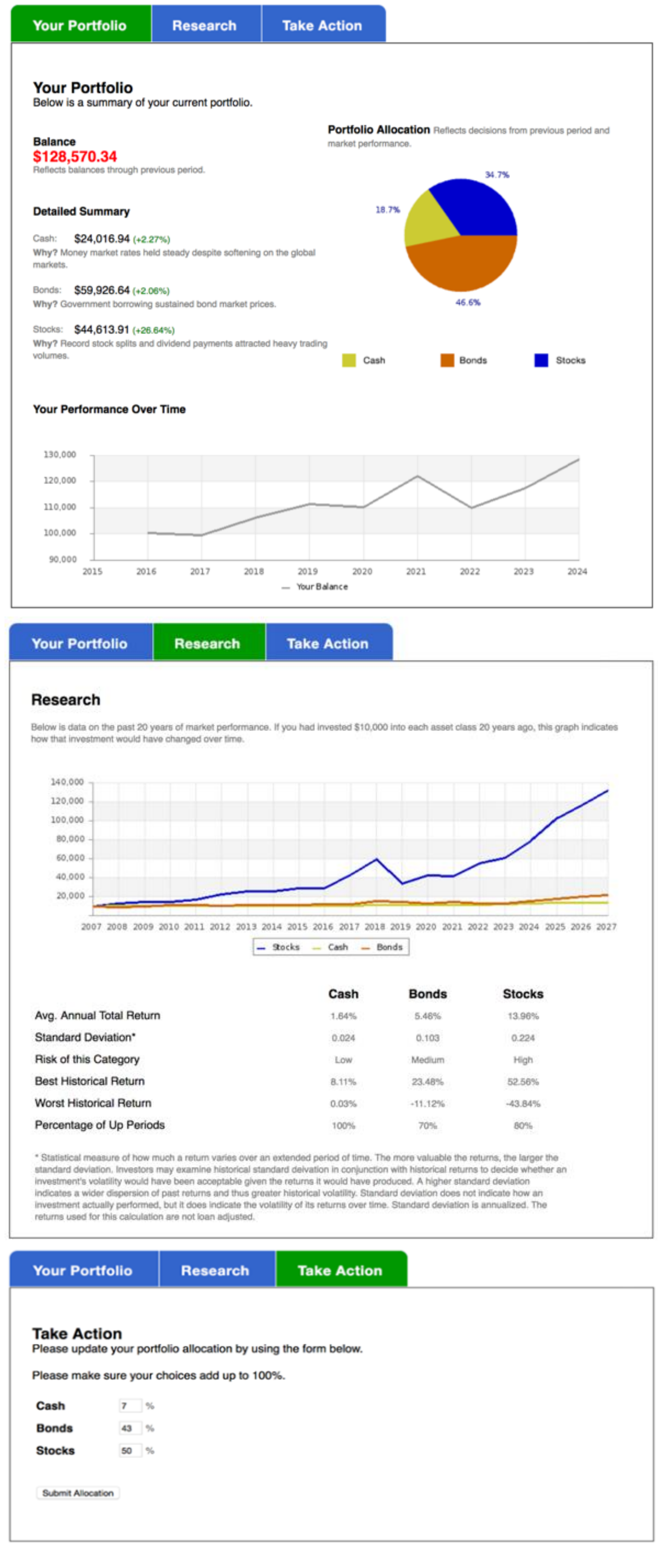

Figure 1.1: Screenshots of the participant experience in the investment simulation (Experiments 1 and 2). During each round, participants could review their portfolio (Panel A), research the performance of various asset classes (Panel B), and take action by updating their portfolio allocation (Panel C). Note: To facilitate the human contact manipulation in Experiment 2, the interface was augmented as depicted in Figure 1.4.

After submitting allocation decisions in rounds 3, 6, and 9, and before seeing how those choices performed, participants were asked to report their levels of anxiety and calmness, as well as their satisfaction with the investment allocation choice they just made. After completing the 12th round, participants were shown a final portfolio screen, and after 15 seconds, were redirected to the exit survey where they were asked about their feelings of trust toward the firm that provided the investment tool and to provide their demographic information.

3.1.3 Manipulation check. The six-item Short-form Spielberger State-Trait Anxiety Inventory ("STAI") (Marteau and Bekker 1992) instrument was used to measure pre-treatment levels of anxiety and calm and as a manipulation check to ensure that feelings of anxiety were indeed more prevalent in the high-anxiety condition, which as described above, sampled returns more heavily from years during which the stock market declined by 5% or more. We subtract the level of anxiety from the level of calm during each measurement round to arrive at our aggregated *Reported Anxiety* measure. By the end of the simulation, participants in the high-anxiety condition (M = 2.26, SD = 4.82), who faced adverse market conditions, reported over two and a half times the increase in anxiety relative to their baseline pre-treatment levels than participants in the low-anxiety condition, who faced normal market conditions (M = 0.86, SD = 3.20; $t(155) = -2.14$, $p < 0.05$). However, owing to anxiety-provoking nature of the investment task – characterized by outcome uncertainty, information asymmetry, and task complexity – participants in both conditions reported anxiety levels that were elevated over baseline rates ($ts(78) > 2.39$; $p < 0.02$).

3.1.4 Dependent measures. Prior research has established that anxiety increases advice seeking through a deterioration of self-confidence (Gino et al. 2012) and that outcome satisfaction and decision confidence are highly correlated with each other (Iyengar et al. 2006). Following the approach in Iyengar et al, 2006, we asked participants to separately rate, "how satisfied are you with your previous choices?" and "how confident are you that the decision you just made will produce a gain?" These two-items were rated on a scale of 1-7 (1 = Extremely dissatisfied/Not at all confident, 7 = Extremely Satisfied/Completely confident). Consistent with prior literature (Chernev et al. 2012), and confirmed by a Cronbach's Alpha (α = 0.85) indicating a high correspondence between these two measures, we used the average of these two responses as our choice satisfaction measure for each participant and label this variable *choice satisfaction*. At the end of the investment simulation, we asked participants to rate, on a 4-point Likert scale (1-None, 4-A Lot) "Based on this experience, how much do you trust the firm that offered this investment tool?" We use this single-item measure to capture feelings of *firm trust*.

3.1.5 Control measures. In order to isolate the effects of customer anxiety in this study, we control for the influence of investment performance outcomes on satisfaction ratings. However, since our manipulation directly influenced investment performance, we cannot use participant balances or raw investment returns as control measures. Instead, we calculated a measure of *relative underperformance* for each participant, subtracting the participant's personal rate of return (the linear combination of the performance of each asset class weighted by the participant's allocation choices) from the return of the highest performing asset class for any given round. In addition to this investment performance control, we include ex-ante *anxiety* and *calm* to account for pre-manipulation levels of emotion (as measured using the STAI), as well as *demographic controls* that are commonly linked to investment decision-making (age, income, gender and education).

3.1.6 Main Effects. Because the experiment is conducted over multiple rounds and we measure anxiety, self-confidence and choice satisfaction for each individual at intervals across the rounds, we have a panel of data for each participant. However, because *firm trust*, our final dependent variable, is collected at the end of the study, we collapse the data set using the means of our intervening variables. Reported Anxiety, Choice Satisfaction and Trust were then modeled using OLS regression with robust standard errors as a build up to a structural path analysis. Although random assignment should negate the need to include

individual-level controls, we nevertheless include them in our primary specification to control for potential failures of random assignment and for demographic influences on risky decision-making: age, gender, income and education (Kaufmann et al. 2013) . As shown in **Table 1.1**, Column 1, participants in the high-anxiety condition reported higher levels of anxiety, demonstrating that our manipulation was effective

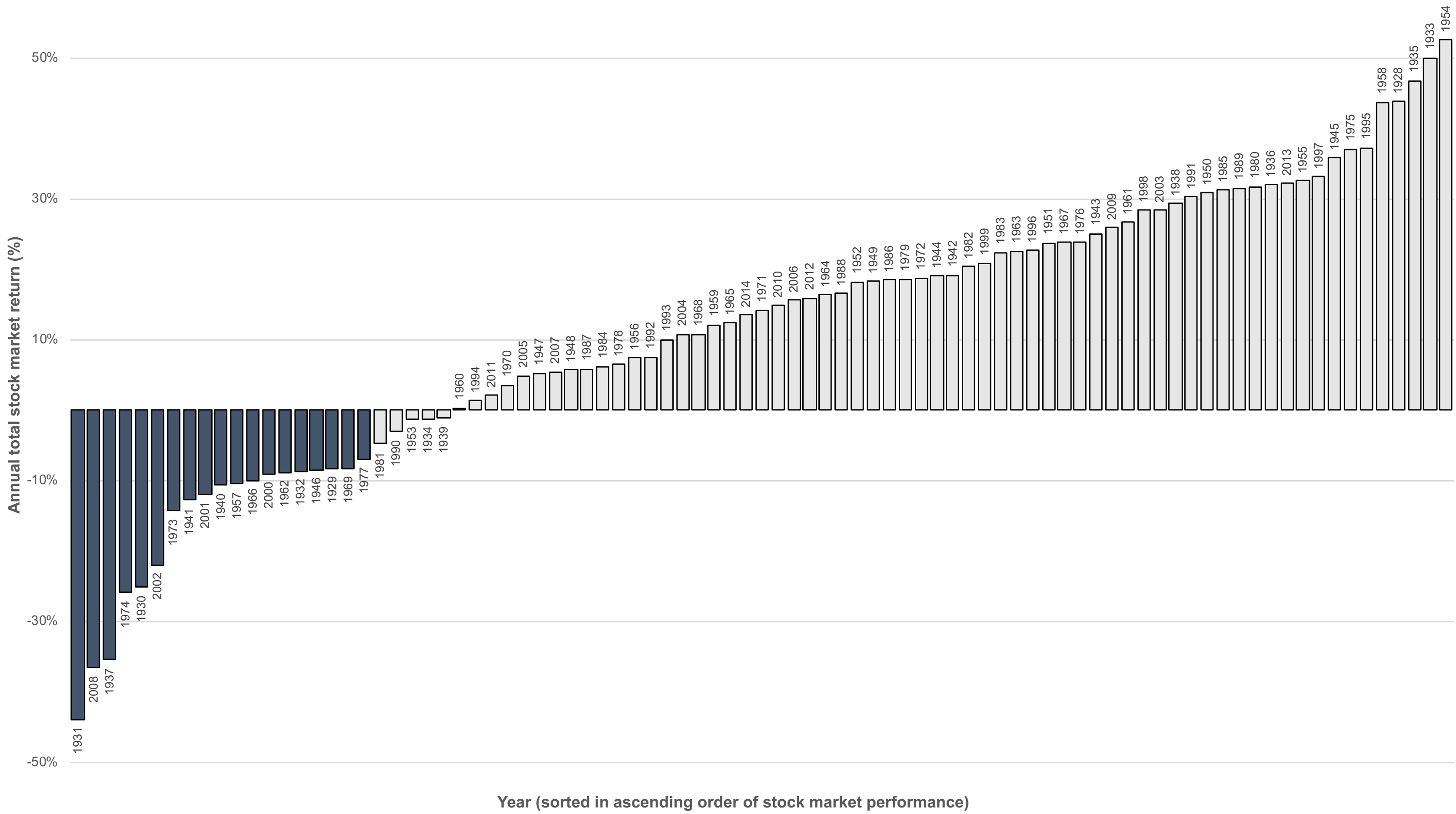

Figure 1.2: Annual returns of the Standard & Poor's 500 Index from 1928-2014 arranged in ascending order (Experiments 1 and 2). Years with returns lower than -5% are shaded in black. Participants in the low-anxiety condition for our investment simulation studies experienced market performance for all asset classes (cash, stocks, and bonds) that corresponded with returns from these years, drawn uniformly from the full distribution of years. Participants in the high-anxiety condition also experienced market performance that corresponded with returns from these years, drawn uniformly from the full distribution of years with 50% probability, and drawn uniformly from years with returns lower than -5% with 50% probability. Hence, participants in the high-anxiety condition experienced more severely negative stock returns at a higher frequency than participants in the low-anxiety condition. Prior research has linked market downturns to investor anxiety (Engelberg and Parsons 2016).

(β = 1.14, $p < 0.05$). In Column 2, we see that those in the high-anxiety condition exhibited diminished choice satisfaction (β = -0.38, $p < 0.05$) and in Column 3, we can see that those faced with higher likelihoods of a market downturn were also highly likely to report decreased levels of trust in the firm (β = -0.49, $p < 0.01$).

	(1) Reported Anxiety	(2) Choice Satisfaction	(3) Firm Trust
Anxiety Treatment	1.138**	-0.376**	-0.490***
	(0.525)	(0.187)	(0.135)
Age	-0.039**	0.013*	0.004
	(0.019)	(0.008)	(0.007)
Income Level	0.042	-0.025	0.047
	(0.124)	(0.046)	(0.033)
Education Level	0.332	-0.066	-0.171***
	(0.216)	(0.072)	(0.048)
Female Indicator	0.382	-0.234	-0.027
	(0.510)	(0.193)	(0.133)
Pre-Treatment Anxiety	0.621***	0.129*	0.080*
	(0.103)	(0.066)	(0.047)
Pre-Treatment Calm	-0.840***	0.207***	0.039
	(0.116)	(0.044)	(0.034)
Relative Underperformance	-0.962	-0.703	-4.943***
	(6.406)	(2.163)	(1.695)
Constant	1.004	2.771***	11.150***
	(1.777)	(0.748)	(0.577)
Observations	155	155	155
R-squared	0.495	0.198	0.193

Table 1.1: Feelings of anxiety diminish choice satisfaction and firm trust (Experiment 1).
All models are estimated with OLS regression, and robust standard errors are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Interestingly, choice dissatisfaction among participants randomly assigned to the high-anxiety condition existed despite the strength of their investment performance. Although participants in the high-anxiety condition faced a higher likelihood of market downturns and were more likely to miss opportunities, these participants outperformed the stock market they experienced over the 12 rounds, with an average return of 1.7% while the stock market on average fell by almost twice that amount, -3.12%. In contrast, those in the low-anxiety condition under-performed their stock market with an average portfolio return of 8.80% while their market on average went up by 12.81%. As expected, the relative underperformance of the respective stock market between groups is statistically significant ($M_{Low} = 0.04$, $SD_{Low} = 0.04$ vs. $M_{High} = -0.05$, $SD_{High} = 0.05$; $t(155) = 12.26$, $p < 0.01$).

3.1.7 Structural model. To formalize the relationships and test the theory that the diminished choice satisfaction of participants in the anxiety condition arose from their heightened anxiety, rather than from differences in their objective performance, we used structural equation modelling to conduct a path analysis, using the anxiety, choice satisfaction, and trust measures. We use bootstrapping to estimate robust standard errors and confidence intervals, to alleviate power concerns regarding possible asymmetric or non-normal sampling distributions of indirect effects (MacKinnon et al. 2007) and jointly estimate the equations to address potentially correlated error terms associated with endogenous variables.

As shown in **Figure 1.3**, participants in the high-anxiety condition, who experienced a higher probability of market downturns, were more anxious during their interactions with the investment simulator ($\beta = 1.14$, $p < 0.05$). This higher level of anxiety was in turn associated with diminished choice satisfaction throughout the task ($\beta = -0.19$, $p < 0.01$). Because choice satisfaction has a positive influence on trust in the firm ($\beta = 0.21$, $p < 0.05$), our model demonstrates that higher levels of anxiety are associated with lower levels of firm trust through diminished choice satisfaction. Because an indirect effect is calculated as the product of coefficients along the pathway, its distribution will be asymmetric. A bootstrap analysis can correct for bias and give us confidence about the statistical significance of this indirect effect of a pathway (MacKinnon et al.

2007). Our result shows that the bias-corrected confidence interval for the pathway of interest from anxiety to trust through choice satisfaction (95% CI: [-0.08, -0.01]) does not contain zero.

These results suggest that anxiety in self-service contexts may undermine choice satisfaction, with long term negative effects on firm trust. In Experiment 2, therefore, we'll investigate whether incorporating the potential for human contact into the design of self-service offerings can restore choice satisfaction, and in turn trust in the firm.

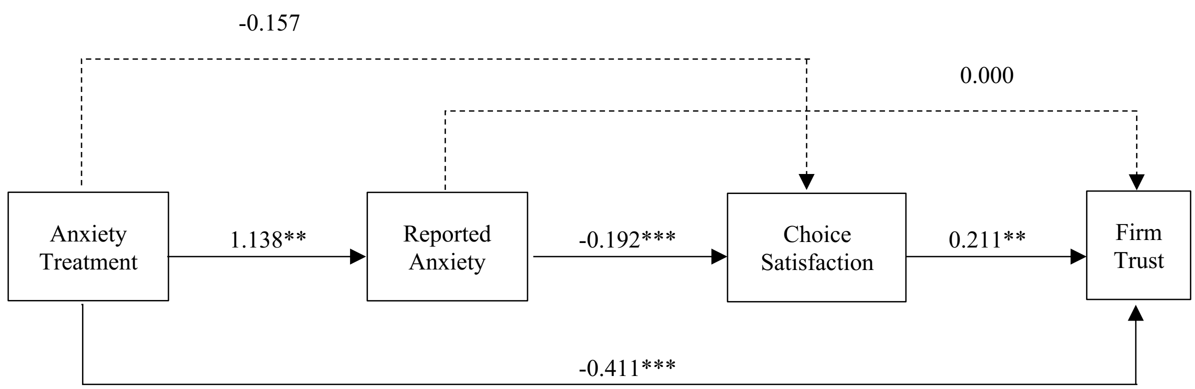

Figure 1.3: Structural links among anxiety, choice satisfaction, and firm trust (Experiment 1). Models control for age, gender, income, education, pre-treatment anxiety, pre-treatment calm, and relative underperformance, and were estimated with bootstrapped, robust standard errors with 1,000 repetitions. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

3.2 Experiment 2: The Effects of Access to Human Contact in Self-Service Transactions

Building on the prior results, in Experiment 2 we test the effects of two potentially cost-effective ways to introduce human contact into the design of SSTs: the integration of an online chat feature that connects participants to expert assistance or simply to their peers.

3.2.1 Participants. 266 participants were recruited to a university research laboratory in the northeastern United States to engage in a series of unrelated experiments in exchange for $15.00. Although we did not have direct control over the number of participants who attended these laboratory sessions, we sought at least 30 participants per experimental condition. Participants that did not complete all tasks due to time constraints as well as those that did not report their anxiety levels during the simulation were dropped from the sample, leaving 219 participants ($M_{age} = 23.45$, 50.92% Female) in the analysis. As with Experiment 1, to ensure incentive compatibility, participants were paid a bonus of $0.25 for every $100,000 earned during the investment simulation.

3.2.2 Design and procedure. We replicated the design of Experiment 1 with three important modifications. First, we incorporated three additional conditions in a factorial design, such that Experiment 2 featured a 2(anxiety: high, low) x 3(human contact: none, peers, experts) design. Anxiety was manipulated in a manner consistent with Experiment 1. Human contact was manipulated by means of a chat button, introduced in the top right corner of every page of the investment management platform for the two human contact conditions (**Figure 1.4**). In the "peers" condition, which was designed to simulate the experience of customers being given the option of chatting with other customers, the button read "Chat with Another Investor," and in the "expert" condition, which was designed to simulate the experience of customers being given the option of chatting with a service employee, the button read, "Chat with an Expert." Depending on the condition, clicking the button would connect the participant to a chat window where they could correspond with another participant, or with a research assistant, blind to our hypotheses, who interacted by means of a script. (See **Appendix 1** for a copy of the instructions and script for research assistants in the expert role.) Although it was not disclosed to participants, the "expert" was limited to providing scripted information about how to use the investment platform and reiterating information that was already available to all participants regardless of condition within the platform, so as not to inadvertently alter the efficacy of participant decision making across

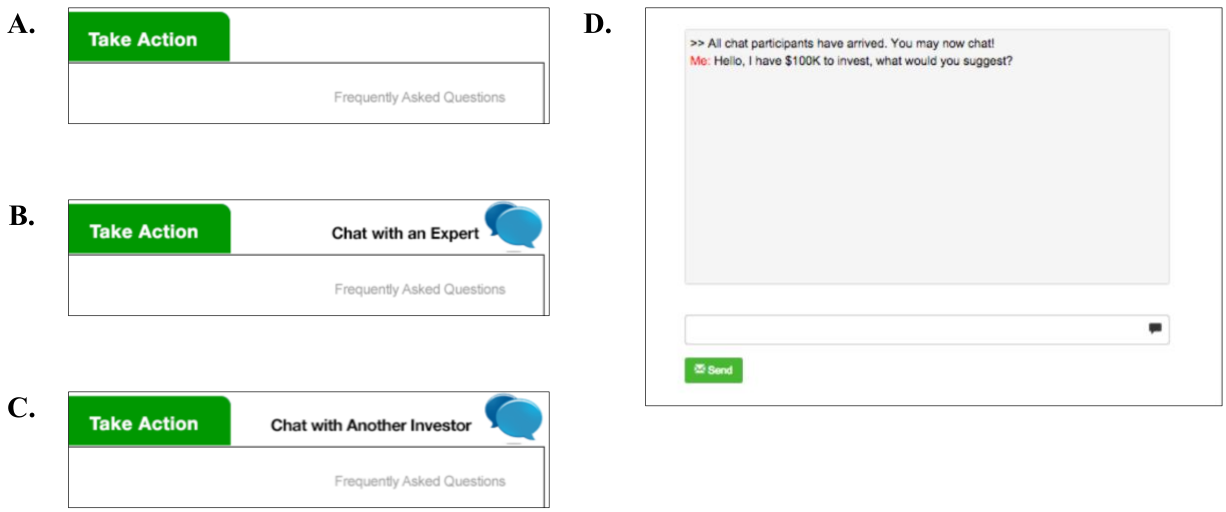

Figure 1.4: Screenshots of human contact manipulation (Experiment 2).
Participants were randomly assigned to one experimental condition in a 2(Anxiety: low, high) x 3(Human contact: none, experts, peers) design. Human contact was introduced by adding a clickable icon in the upper right-hand corner of every page of the investment simulation. Participants who did not have access to human contact (Panel A) saw no icon. Participants in the experts condition (Panel B) saw an icon that said "Chat with an Expert." Participants in the peers condition (Panel C) saw an icon that said "Chat with Another Investor." Clicking these icons would open a pop-up window (Panel D), which facilitated a real-time chat interaction. To ensure all participants had access to the same information, a Frequently Asked Questions link was also provided in the upper right-hand corner of each screen of the simulation.

conditions. Moreover, this design choice was consistent with regulatory requirements in the financial service sector, which precludes agents from providing investment advice without having completed extensive and costly training and obtained qualifying licenses, typically not found among platform support personnel (U.S. Securities and Exchange Commission 2008).

Second, to increase the probability that in-lab participants who were in the "peers" condition would have other participants still working on the task if they wished to chat, we extended the length of the simulation to 30 rounds. Extending the simulation in this way better mirrored a typical retirement investment horizon, and mapped appropriately with the degree of focus and attention afforded by the in-lab participants. Furthermore, extending the investment simulation to 30 rounds provided participants with a longer period of time during which to evaluate the investment platform itself, more carefully approximating a long-term perspective when soliciting the trust measure.

Third and finally, in order to prevent the possibility that participants in the "expert" condition would be afforded extra information that might separately affect their choice satisfaction, performance, or level of trust in the firm and thus confound our results, we added a "Frequently Asked Questions," section to the header of every page of the website, which included all of the information on the research assistant's script for the "expert" condition. This addition ensured that all participants had access to the same information across conditions, such that the only differences experimentally manipulated were the level of anxiety inherent in the service interaction and access to human contact.

3.2.3 Manipulation check. As in Experiment 1, we used the short-form STAI to compare ex-ante levels of anxiety and calm with levels of anxiety intermittently, this time after every five rounds of the investment simulation. Consistent with Experiment 1, participants in the high-anxiety condition ($M = 2.51$, $SD = 3.48$) reported more than twice the increase in anxiety over their baseline levels than participants in the low-anxiety condition ($M = 0.92$, $SD = 2.56$; $t(217) = -3.80$, $p < 0.01$) at Round 5 and at Round 10 ($M_H = 2.33$, $SD_H = 3.47$ vs. $M_L = 1.14$, $SD_L = 2.59$; $t(217) = -2.86$, $p < 0.01$). Owing to the 30-period length of Experiment 2, participants in the low-anxiety condition exhibited increasing levels of anxiety as the simulation progressed while those in the high-anxiety condition maintained the sharp increase in anxiety they initially reported throughout. As such, we observed converging levels of change in net anxiety after Round 10, consistent with acclimation and learning effects observed in prior service operations research (Gupta et al. 2016). Indeed, by the end of the task, participants in both the high-anxiety condition ($M = 2.68$, $SD =$

3.91, $t(108) = 7.16$, $p < 0.01$) and the low-anxiety condition ($M = 1.71$, $SD = 3.08$, $t(109) = 5.81$, $p < 0.01$) reported significant increases in anxiety over their baseline levels.

3.2.4 Dependent and control measures. We use the same dependent measures as we used in Experiment 1. However, once we replicate the structural relationship between anxiety and firm trust shown in Experiment 1, we home in on *choice satisfaction* as the main dependent variable to explore how the introduction of human contact affects service performance in high-anxiety settings. Since we measure choice satisfaction repeatedly for each participant in the study, utilizing it as our primary dependent measure affords us a more highly-powered panel data analysis in our main result for Experiment 2. With this shift to a repeated measures panel analysis, we necessarily cluster standard errors at the participant level and include a new *block number* control to address any fixed effects associated with the measurement intervals. Since choice satisfaction and confidence were shown to be highly correlated in Experiment 1, we felt that simply asking about choice satisfaction would streamline the participant experience without materially affecting the integrity of our results so we dropped the choice confidence question in Experiment 2. We again control for demographics (gender, age, education, income), pre-treatment emotion, and relative underperformance.

3.2.5 Analysis and results. Consistent with the analysis for Experiment 1, we first conduct OLS regressions to examine the main effects of our treatment assignments on our outcomes of interest. Moreover, we extend the analysis to examine the impact of human contact on these factors and on the structural model. **Table 1.2**, Column 1 serves as our manipulation check, showing that, consistent with Experiment 1, participants assigned to the high-anxiety condition reported higher levels of anxiety ($\beta = 1.00$, $p < 0.01$). This effect remains after controlling for the human contact conditions in Column 2 ($\beta = 1.02$, $p < 0.01$). Although directionally it appears that having access to human contact reduces anxiety, neither access to an expert nor access to other investors has a statistically significant effect on reported anxiety in this estimation. Including interaction terms in Column 3, however, reveals a marginal negative effect of access to experts on reported anxiety levels for participants in both conditions (β = -0.87, $p < 0.10$), though interestingly, access to an expert didn't exhibit a differential impact on the anxiety of participants in the high-anxiety condition (β = 0.32, p = NS).

Post-estimation means comparison tests reveal that the net increase in anxiety between participants in the high-anxiety treatment granted access to an expert, and participants in the low-anxiety treatment who are not granted human contact are statistically indistinguishable ($M_{L,No\ HC}$ = 1.95, $SD_{L,No\ HC}$ = 2.51 vs. $M_{H,Expert}$ = 2.02, $SD_{H,Expert}$ = 2.82 ; $t(69)$ = -0.10 p = NS). This pattern of results suggests that one way that access to human contact may be beneficial in self-service high-anxiety contexts is its capacity to mitigate the anxiety customers experience. In particular, we find that providing access to an expert, such as a service employee, has a marginally reductive effect on the level of anxiety participants report.

More interesting is the effect of access to human contact on choice satisfaction shown in **Table 1.3**. Columns 1 and 2 again show that our anxiety treatment - that is experiencing a market downturn - has a negative effect on choice satisfaction (β = -0.73, $p < 0.01$) that can be attributed at least partially to the anxiety that people feel, evidenced by the attenuation in the main effect of the anxiety treatment exhibited between Columns 1 and 2. Participants in the high-anxiety condition again reported lower choice satisfaction despite having produced positive investment returns of 2.10% on average in a downward trending environment where stocks returned -2.71%, while those in the low-anxiety condition underperformed their stock market with an average return of 7.59% vs. the stock market return of 11.37% on average and reported higher levels of choice satisfaction.

	(1) Reported Anxiety	(2) Reported Anxiety	(3) Reported Anxiety
Anxiety Treatment	1.003***	1.023***	0.421
	(0.368)	(0.367)	(0.603)
Access to Expert		-0.696	-0.866*
		(0.422)	(0.480)
Access to Peers		-0.088	-0.833
		(0.467)	(0.534)
Expert x Anxiety			0.315
			(0.821)
Peers x Anxiety			1.495
			(0.914)
Relative Underperformance	1.364***	1.353**	1.333**
	(0.522)	(0.523)	(0.521)
Pre-Treatment Anxiety	0.591***	0.594***	0.567***
	(0.150)	(0.155)	(0.161)
Pre-Treatment Calm	-0.708***	-0.702***	-0.718***
	(0.092)	(0.093)	(0.094)
Age	-0.103*	-0.123**	-0.124**
	(0.055)	(0.057)	(0.057)
Income Level	-0.120**	-0.111**	-0.110**
	(0.050)	(0.050)	(0.050)
Education Level	0.141	0.170	0.168
	(0.182)	(0.182)	(0.182)
Female Indicator	0.217	0.202	0.212
	(0.366)	(0.363)	(0.361)
Block Number 2	0.030	0.030	0.030
	(0.098)	(0.098)	(0.098)
Block Number 3	0.183	0.183	0.183
	(0.177)	(0.178)	(0.178)
Block Number 4	0.348	0.348	0.348
	(0.214)	(0.214)	(0.214)
Block Number 5	0.469**	0.469**	0.469**
	(0.224)	(0.224)	(0.224)
Block Number 6	0.518**	0.518**	0.519**
	(0.238)	(0.238)	(0.238)
Constant	3.050*	3.557*	4.140**
	(1.738)	(1.806)	(1.835)
Observations	5,590	5,590	5,590
Participants	215	215	215
R-squared	0.313	0.320	0.327

Table 1.2: Increasing access to human contact has a marginally negative effect on reported anxiety (Experiment 2). All models are estimated with OLS regression, and robust standard errors, clustered at the participant level, are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Once we account for access to human contact in Columns 3 and 4, we begin to see a trend towards the recuperation of these declines in choice satisfaction. There is a main effect of access to experts that attenuates this decline in choice satisfaction (Column 3) and is mediated by reducing the anxiety customers experience (Column 4). Interestingly, Columns 5 and 6 show that access to human contact mitigates the loss of choice satisfaction primarily during high-anxiety conditions (Experts×Anxiety: $\beta = 0.72$, $p < 0.05$; Peers×Anxiety: $\beta = 0.81$, $p < 0.01$). The main effect of access to human contact during relatively low-anxiety conditions points toward a reduction in choice satisfaction with access to peers having the strongest negative effect ($\beta = -0.37$, $p < 0.05$), consistent with prior research showing that the presence of other people during SST use may be a detriment to service quality perceptions (Li et al. 2013). In **Figure 1.5** , we can see the differential – and mitigating - effect of access to human contact on choice satisfaction during high-anxiety service conditions more clearly.

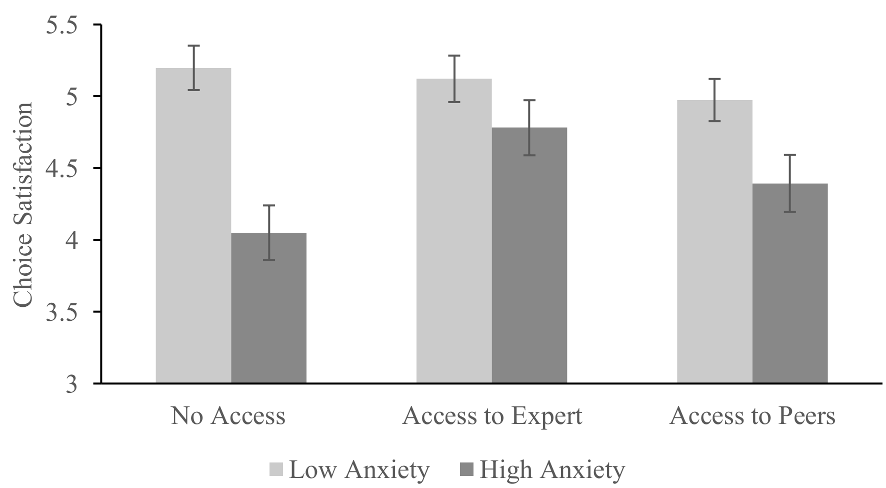

Figure 1.5: Access to human contact has a differential effect on choice satisfaction during high-anxiety service conditions.

	(1) Choice Satisfaction	(2) Choice Satisfaction	(3) Choice Satisfaction	(4) Choice Satisfaction	(5) Choice Satisfaction	(6) Choice Satisfaction
Anxiety Treatment	-0.727***	-0.560***	-0.735***	-0.567***	-1.141***	-1.070***
	(0.139)	(0.129)	(0.139)	(0.130)	(0.246)	(0.236)
Reported Anxiety		-0.166***		-0.164***		-0.168***
		(0.020)		(0.020)		(0.020)
Access to Expert			0.307*	0.193	-0.033	-0.178
			(0.171)	(0.166)	(0.223)	(0.207)
Access to Peers			0.051	0.036	-0.234	-0.374**
			(0.167)	(0.153)	(0.197)	(0.189)
Expert x Anxiety					0.666*	0.719**
					(0.345)	(0.327)
Peers x Anxiety					0.558	0.809***
					(0.340)	(0.308)
Relative Underperformance	-1.366***	-1.139***	-1.361***	-1.139***	-1.359***	-1.135***
	(0.248)	(0.222)	(0.250)	(0.223)	(0.250)	(0.220)
Pre-Treatment Anxiety	-0.126**	-0.028	-0.127**	-0.030	-0.125**	-0.030
	(0.055)	(0.048)	(0.056)	(0.049)	(0.055)	(0.047)
Pre-Treatment Calm	0.084**	-0.033	0.081**	-0.033	0.075**	-0.046
	(0.036)	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)
Age	-0.022	-0.039	-0.013	-0.033	-0.012	-0.033
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)	(0.024)
Income Level	0.015	-0.005	0.011	-0.007	0.007	-0.012
	(0.019)	(0.018)	(0.020)	(0.019)	(0.020)	(0.019)
Education Level	0.005	0.028	-0.008	0.020	-0.013	0.015
	(0.080)	(0.076)	(0.079)	(0.075)	(0.075)	(0.072)
Female Indicator	0.037	0.073	0.044	0.077	0.040	0.075
	(0.139)	(0.128)	(0.138)	(0.128)	(0.136)	(0.125)
Block Number 2	0.049	0.053	0.049	0.053	0.049	0.054
	(0.051)	(0.047)	(0.051)	(0.047)	(0.051)	(0.047)
Block Number 3	0.056	0.087	0.056	0.086	0.056	0.087
	(0.084)	(0.076)	(0.084)	(0.076)	(0.084)	(0.076)
Block Number 4	0.148	0.206**	0.148	0.205**	0.148	0.207**
	(0.093)	(0.083)	(0.093)	(0.083)	(0.093)	(0.083)
Block Number 5	0.242**	0.320***	0.242**	0.318***	0.242**	0.320***
	(0.102)	(0.089)	(0.102)	(0.089)	(0.102)	(0.088)
Block Number 6	0.254**	0.340***	0.254**	0.338***	0.254**	0.341***
	(0.111)	(0.097)	(0.111)	(0.097)	(0.112)	(0.097)
Constant	5.321***	5.828***	5.091***	5.673***	5.385***	6.080***
	(0.735)	(0.674)	(0.715)	(0.646)	(0.722)	(0.668)
Observations	5,590	5,590	5,590	5,590	5,590	5,590
Participants	215	215	215	215	215	215
R-squared	0.116	0.254	0.124	0.257	0.135	0.273

Table 1.3: Access to experts and peers improves choices satisfaction, particularly among individuals experiencing heightened anxiety (Experiment 2).
All models are estimated with OLS regression, and robust standard errors, clustered at the participant level, are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

3.2.6 Structural Models. Consistent with the analysis for Experiment 1, we use structural equation modelling to conduct a path analysis. Before incorporating the mitigating effects of human contact on choice satisfaction, we replicate our results from Experiment 1 to show that the pathway linking the high-anxiety service environment to trust through impacts to customer emotion and choice satisfaction remains. Again, since trust is measured at the end of the simulation and anxiety and choice satisfaction are measured repeatedly, we collapse our data set and use mean values for the intervening variables for this estimation as we did in Experiment 1. The path analysis presented in **Figure 1.6** provides converging evidence that market downturns induced customer anxiety ($\beta = 0.97$, $p < 0.01$), which in turn diminished choice satisfaction throughout the task ($\beta = -0.15$, $p < 0.01$). Choice satisfaction, in turn, enhanced firm trust ($\beta = 0.21$, $p < 0.01$). Having replicated the structural pathway shown in Experiment 1, we focus the rest of our analysis on how access to human contact affects choice satisfaction as our main dependent variable going forward.

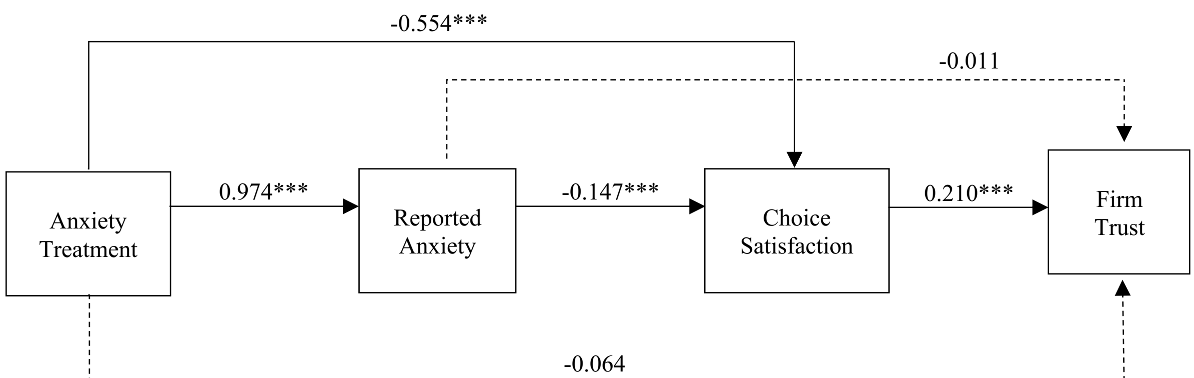

Figure 1.6: Structural links among anxiety, choice satisfaction, and firm trust (Experiment 2).
Models control for age, gender, income, education, pre-treatment anxiety, pre-treatment calm, and relative underperformance, and were estimated with bootstrapped, clustered standard errors with 1,000 repetitions. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

In **Figure 1.7**, we incorporate the main and moderating effects of our human contact interventions. The model reveals that although access to experts has a marginally reductive effect on reported anxiety (Experts: $\beta = -0.87$, $p < 0.10$), access to peers does not (Peers: $\beta = -0.83$, p = NS). Although anxiety still hinders choice satisfaction in the interaction ($\beta = -0.17$, $p < 0.01$), the ability to access an expert has no significant baseline effect on choice satisfaction (Experts: β = -0.18, p = NS), while, at least directionally, having access to other investors has a negative impact ($\beta = -0.37$, $p < 0.10$) on decision satisfaction. Access to expertise affects customer emotion while access to peers affects decision satisfaction under baseline, low-anxiety conditions.

However, when we examine interaction effects, we see that both forms of human contact have a strong positive effect on choice satisfaction during market downturns when anxiety is greatest (Experts×Anxiety: $\beta = 0.72$, $p < 0.05$; Peers×Anxiety: $\beta = 0.81$, $p < 0.05$). Although some of the moderating effect of access to human contact on choice satisfaction is mediated by anxiety, the majority of these effects are direct. Hence, having access to human contact makes people feel more satisfied with their decision making, rather than mitigating emotion in a high-anxiety service environment. In large part, participants still feel anxiety, but by offsetting declines in choice satisfaction, losses to firm trust can be stemmed.

Interestingly, the majority of participants that had access to human contact *did not actually opt to interact* with an expert or peer during the investment task. In the expert condition, 11 unique participants of the 71 that were assigned access (15.49%) actually chatted with the expert. In the peer condition, the level of interaction was even lower, with a total of 5 actual chat interactions by 3 unique participants of the 73 assigned (4.11%). This pattern suggests that the mitigating effects of access to human contact documented above were largely attributable to the mere opportunity to interact with human providers, rather than the choice to do so. Thus, the incorporation of human contact into SST platforms may be less costly and require lower staffing levels than conventional wisdom might suggest. Further, a logistic regression modelling the choice to pursue human contact, if offered, as a function of the full panel of control variables used in Study 2 showed that the greatest and only statistically significant predictor of whether a participant would take advantage of the option to chat was how anxious he or she felt before beginning the investment simulation ($\beta = 0.74$, $p < 0.01$). A description of this analysis and a full results table are presented in **Appendix 2**.

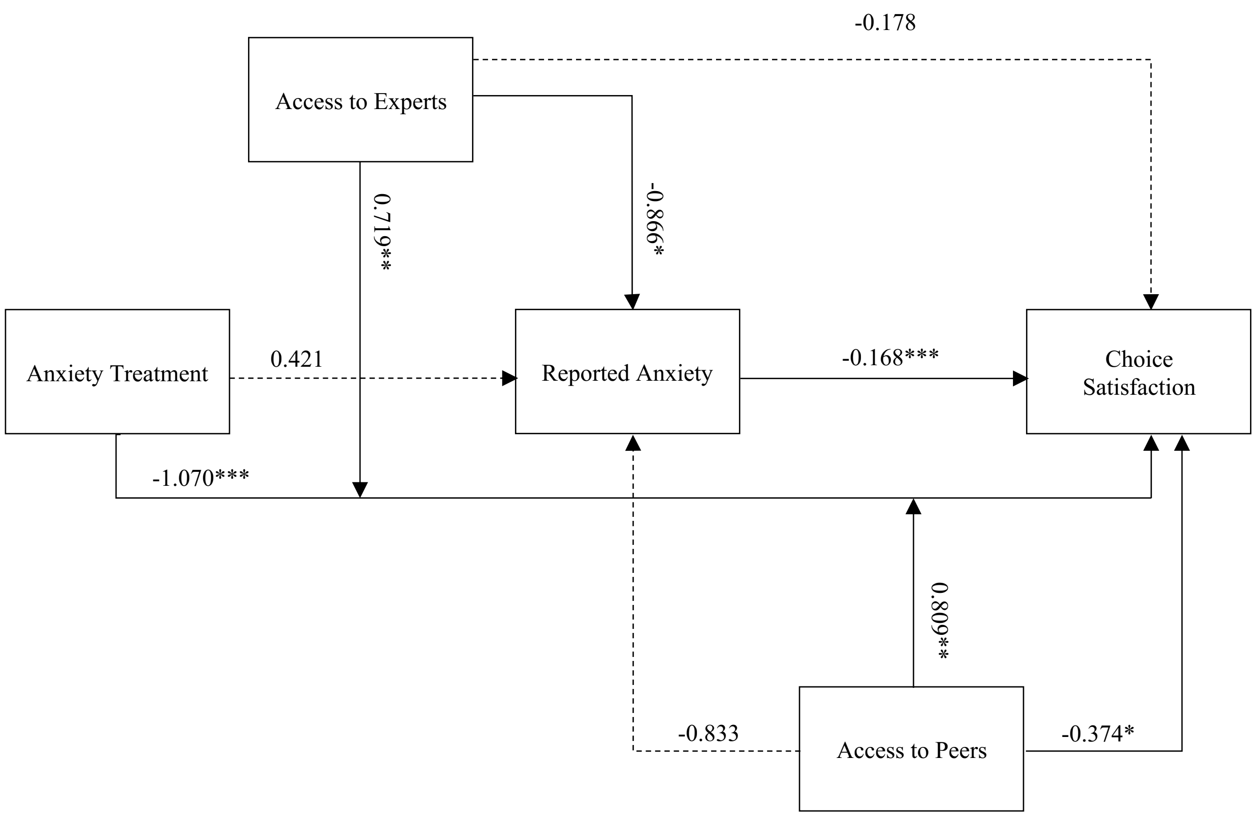

Figure 1.7: Structural links among anxiety and choice satisfaction differ among those granted access to human contact (Experiment 2).
Models control for age, gender, income, education, pre-treatment anxiety, pre-treatment calm, and relative underperformance, and a measurement interval fixed effect (owing to the repeated measure of reported anxiety and choice satisfaction), and were estimated with bootstrapped, clustered standard errors with 1,000 repetitions. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

This result dovetails with the earlier finding that access to human contact is beneficial to customers who are experiencing low levels of anxiety associated with the service task itself – hinting at the potential for a broad array of firms to improve customer experiences through the integration of human access in their self-service offerings.

Although sources of customer anxiety may be beyond the firm's control, our results imply that introducing the opportunity to connect with a human during anxiety-provoking service experiences could engender higher levels of choice satisfaction and trust. By designing cost-effective access to human contact, firms may be able to help anxious customers feel more confident in and satisfied with their contributions to the interaction, and in so doing feel more trusting of the firm itself.

3.3 Experiment 3: Introducing Access to Human Contact in the Field

Since the pattern of results in Experiments 1 and 2 suggest that providing access to human contact may enhance consumer confidence and firm trust in anxiety-provoking self-service interactions, and prior literature has shown that efforts to cultivate customer trust can lead to higher levels of customer satisfaction (Balasubramanian et al. 2003), loyalty and willingness to share information and engage in new product development (Morgan and Hunt 1994, Porter and Donthu 2008), it stands to reason that access to human contact may also lead to higher levels of customer engagement in a high-anxiety service setting. To test this hypothesis, and extend our analysis of these phenomena to the field, we partnered with a federal credit union in the northeastern United States, with four locations and over 10,000 members. The credit union had recently launched a self-service online loan application process and was pilot testing a new SMS messaging system to keep applicants abreast of updates to their loan application. By randomly assigning whether loan applicants would receive update messages that included or did not include access to human contact, we were able to investigate whether the provision of human contact increased subsequent levels of engagement with the firm – namely, whether customers whose loans were approved chose to move forward with the loan itself.

3.3.1 Participants. All customers and prospective customers who applied for a consumer loan with our partner credit union during a 20-week period during the Summer and Fall of 2016 were eligible for this study. During the time period, the credit union received 359 applications for consumer loans. We excluded applications for credit cards (*N*=53), which had a different approval process than other types of consumer loans offered by our partner institution. Moreover, owing to the relative ease with which credit cards may be acquired in the United States, we believed credit card applications may not induce as much customer anxiety as more conventional consumer loan applications. Of the 306 remaining eligible applications, we further excluded loan applications from our analysis that were incomplete (*N=5*), withdrawn by the customer before the approval process was initiated (*N*=9), or that were denied by the credit union (*N*=54). During our period of analysis, 78.29% of applications for eligible loans were ultimately approved. The resulting sample included 238 applicants. No inducements were offered for participation in this experiment, and although applicants in all experimental conditions were contacted 30 days after their loan was decisioned and given the opportunity to opt out of our analysis, none withdrew their data.

3.3.2 Design and procedure. The loan approval process at our partner institution had three stages. First, customers completed a loan application. Second, a loan officer, who was assigned to the application, completed the underwriting process. This process, which took an average of two business days, included reviewing the application, requesting additional documentation (if needed), verifying the applicant's income, and pulling their credit report to establish creditworthiness, before issuing a decision – which, if the loan was approved, included the loan amount, as well as its term and interest rate. Finally, the loan decision was communicated to the customer, who could choose whether or not to move forward with the loan.

Upon submission, applications were randomly assigned to one of three experimental conditions, which varied the level of messaging and access to human contact the customer received during the review process. Eligible applicants in the control condition (*N*=99) received no messaging or supplemental access to human contact during the decisioning process. Those in the messaging only condition (*N*=104) received SMS messages that provided status updates of actions taken by the credit union as the application progressed through the decisioning process (see **Figure 1.8** for the full text of each communication), but no supplemental access to human contact. Participants in the message only condition received three messages: 1) a communication acknowledging receipt of the application and introducing the loan officer in charge of the underwriting process, 2) a communication informing the applicant that the underwriting process was underway and that their credit report was being reviewed, and 3) a communication indicating the loan decision. These SMS messages were pre-programmed and were pushed out manually by the loan officer as the application's status changed throughout the review process. Finally, those in the messaging with human contact condition (*N*=101) received the same SMS messages above, with the addition of the telephone number of the loan officer handling the customer's loan application, along with an invitation to reach out should the customer have any questions. The provision of a phone number and the invitation for customers to contact the loan officer should they have any questions served as our experimental manipulation of interest.

Process Stage	Messaging Only	Messaging with Access to Human Contact
1. Application Receipt	Hi *John*, my name is *Rachel* and I will be working on your loan application. A decision will be returned to you by *Wednesday* and I'll text you updates along the way. Thank you for working with us!	Hi *John*, my name is *Rachel* and I will be working on your loan application. A decision will be returned to you by *Wednesday* and I'll text you updates along the way. Feel free to contact me at *555-5555* with any questions. Thank you for working with us!
2. Document Review	Hi *John*, just letting you know that I've pulled your credit report and am reviewing your request as a part of our process. If I need additional information, I'll give you a call. Thanks, *Rachel*.	Hi *John*, just letting you know that I've pulled your credit report and am reviewing your request as a part of our process. If I need additional information, I'll give you a call. If you need anything in the meantime, you can reach me at 555-5555. Thanks, *Rachel*.
3. Decision Reached	Congratulations, *John*! Your request has been approved. I will reach out to you to arrange a time to close. Thank you again for your business. *Rachel*	Congratulations, *John*! Your request has been approved. I will reach out to you to arrange a time to close. Thank you again for your business. *Rachel 555-5555*

Figure 1.8: Text messages sent to customers in messaging only and the messaging with human contact conditions during each stage of the loan approval process (Experiment 3).
Access to human contact was manipulated by inviting customers to reach out to the loan officer at each stage of the process, and by providing readily-available contact information.

Because we were interested in the effects of human contact on the choice of approved applicants to move forward with a loan, our experiment terminated three months after the applicant either accepted the loan, or the approval of the loan lapsed because the applicant chose not to move forward.

3.3.3 Manipulation check. Although we cannot directly check whether applicants in our field study felt anxious, prior research suggests that anxiety could play a role while awaiting news such as a decision (Sweeny and Falkenstein 2015). Moreover, we conducted an ex-post online pilot study (N = 224, M_{age} = 35.85, 43.30% Female) testing the effects of making an individual's evaluation transparent, in a manner similar to the loan approval process used by this credit union, on anxiety. Participants were primed with statistics indicating that most Americans were not financially savvy and were invited to take a financial literacy test. In addition to a participation fee, they were offered bonus payments for high scores. The sixteen-question exam (Lusardi and Mitchell 2017, van Rooij et al. 2011) was administered in three parts. Between modules, our treatment group experienced a "scoring countdown" where text on the screen disclosed which question was being scored as it was happening (e.g. "Now scoring question 1…", "Now scoring question 2…", and so on), while the control group was simply asked to wait for the next module to load. Although operational transparency, showing the hidden work taking place behind the scenes, has been shown to engender trust and engagement in other settings (Buell et al. 2018, Mohan et al. 2018), we find that making transparent the details of a person's evaluation increases reported anxiety relative to not doing so (β = 1.44, p < 0.01), after controlling for performance quality and demographic characteristics. Experimental stimuli and a full description of the methodological approach for this study are provided in **Appendix 3**. The results of this ex-post study support the idea that transparency in this context may have amplified any feelings of anxiety experienced by applicants awaiting news of their loan decisions.

3.3.4 Dependent measure. We coded loan acceptance as a binary measure, depending on whether loan proceeds had been disbursed to the customer as of March 2017, three months after the last loan application was completed in our study in order to allow plenty of time for the loans to be approved and closed. We note that random assignment was unrelated to the probability of loan approval and confirm that there were no statistical differences in the approval status among treatment cells (χ_2 (2, N = 304) = 0.20, p = NS).

3.3.5 Independent measures. In order to estimate the distinct effect of providing access to human contact on the customer's decision to proceed with a loan, if approved, we create indicator variables denoting whether the customer was in the baseline condition (no messaging or human contact), the messaging only condition (where messaging was provided without access to human contact), or the messaging and human contact condition (where messaging was provided with contact information and an invitation to connect). The identification of the effect of access to human contact in this estimation arises from directly comparing loan acceptance of participants in the messaging only condition with the loan acceptance of participants in the messaging with human contact condition. Hence, the messaging only condition is modelled as the excluded category in our specification, facilitating a direct interpretation of the coefficients.

3.3.6 Control measures. Although we rely on random assignment to control for any unobserved differences among our experimental groups, we were able to capture the applicant's *credit score*, as well as the *loan amount*, the *loan term (in months),* and the *loan interest rate* where applicable to the loan type which we believe are factors that may affect a customer's decision to accept the loan. Although treatment assignment was random and based on the order of application submission, we do observe significant differences when conducting means comparison tests among the average interest rate levels across our treatment cells. For this reason, we include controlled estimations to account for these differences. We note that their inclusion in our estimations does not affect the substance of our findings, but it does affect the power of the analysis as we lose observations due to missing data.

	(1) Loan Acceptance	(2) Loan Acceptance	(3) Loan Acceptance
Messaging and human contact condition	1.020*** (0.344)	1.192*** (0.354)	0.927** (0.426)
Baseline condition	0.281 (0.323)	0.479 (0.352)	0.205 (0.436)
Credit Score		0.008*** (0.002)	0.015*** (0.003)
Loan Amount			0.000 (0.000)
Loan Term (in Months)			-0.018* (0.010)
Loan Rate			12.503** (5.514)
Constant	0.147 (0.222)	-5.160*** (1.285)	-9.604*** (2.416)
Observations	238	238	195
Pseudo R-squared	0.031	0.090	0.136
Pr(Accept|Baseline)	60.53%	62.32%	68.43%
Pr(Acceptance|Messaging)	53.66%	51.58%	64.51%
Pr(Accept|Messaging and contact)	76.25%	76.23%	80.29%

Table 1.4: Increasing access to human contact improved the probability of loan acceptance (Experiment 3). All models are estimated with logistic regression, and robust standard errors are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively. Note: The messaging only condition is the excluded category. Marginal effect estimations for each condition are provided.

3.3.7 Analysis and results. In **Table 1.4**, we model loan acceptance as a logistic function of indicators for the messaging and human contact, and baseline conditions, as well as a vector of controls, as described above. Column 1 presents the basic specification, demonstrating that although there is an insignificant difference in loan acceptance among customers in the baseline condition and customers in the messaging only condition (β = 0.28, p = NS), introducing messaging with human contact has a positive and significant impact on the probability a customer will move forward with a loan (β = 1.02, p < 0.01). Column 2 shows that the effect of human contact remains significant after controlling for credit score, a crucial factor in the loan approval process and key driver of customer anxiety that was made salient in our messaging treatments. Further, our results are robust to the inclusion of control variables associated with the target loan which, as described above, reduce the power of the analysis due to missing data. The fully-specified model in Column 3 shows that providing status updates don't, on their own, improve loan uptake rates. In fact, controlling for other factors, the probability of uptake is nominally higher for customers in the baseline condition than for customers who receive messaging without human contact (β = 0.21, p = NS). Controlling for other factors, providing messaging without human contact reduces the predicted loan acceptance percentage from 68.43% to 64.51%. However, additionally incorporating an invitation for human contact increases the predicted probability that an applicant will accept the loan if offered to 80.29% (β = 0.93, p < 0.05), an increase in loan acceptance of 15.78%. These results provide converging evidence that supporting customers by offering them access to human contact in high-anxiety settings can improve the trajectory of long-term service relationships.

4. General discussion

The field of service operations has long recognized that customers can be viewed as "partial employees" whose participation in service production and delivery is a source of input uncertainty and whose management is therefore critical to maintaining the integrity of operational performance (Chase 1981, Larsson and Bowen 1989, Mills et al. 1983). Within service operations, research in the last decade has refined theoretical frameworks to define service models (Sampson and Froehle 2006) and optimize the design of these "co-productive services" (Roels 2014), but these frameworks have not yet considered the ways that informational, emotional or expectational asymmetries between customers and service providers may affect performance. The present research contributes to this literature by revealing how emotional factors like anxiety can undermine co-produced service performance, and how its deleterious effects can be mitigated by the introduction of access to human contact.

By definition, the success of co-production is dependent on the quality of customer participation and multiple research streams have examined the impacts of customer emotion on decision-making (Lerner et al. 2015). There is a substantial body of research on the impact of emotions on decision-making but there is limited research on the long-term consequences of these effects (Lerner et al. 2004) despite the fact that there is evidence to suggest that transient emotions on economic decision-making have enduring impacts that last well beyond the original decision (Andrade and Ariely 2009). Spillover effects from the influence of anxiety on customer perceptions of SST interactions may have implications for longer-term service relationships. Although the source of customer anxiety is unrelated to the firm's actions and the decisions made were the customer's own, firms may still be penalized for any negative effects through impacts to customer satisfaction or through influences on customer behaviors. Although scholars have recognized the need to reduce or accommodate customer-introduced variability in services (Frei 2006), the study of how service experiences can be designed to accommodate customer emotion is nascent (Dasu and Chase 2013).

In three studies, conducted in the lab and in the field, we demonstrate how anxiety engendered by facets of the service environment that are beyond the control of the operation, can undermine customer confidence in self-service settings, and in turn diminish their level of trust in the firm (**Experiment 1**). Building on recent research in social psychology, which shows how people become advice-seeking when they are anxious (Gino et al. 2012), we further demonstrate that adding access to human contact bolsters customer confidence in their own decision-making and in turn elevates their trust in the firm – and that the type of human contact, be it with an expert or peer, has differing effects on the customer experience.

We further show that these gains in choice satisfaction and trust need not be expensive to implement. Contact may be provided by employees, or even by other customers. Moreover, we find that very few participants actually initiate contact, which would keep the costs of implementation low. Nevertheless, the improvement in choice satisfaction is not dependent on the participant having sought contact; rather, the mere act of having been given access to human contact engenders greater confidence and trust (**Experiment 2**). Finally, in a field experiment, we demonstrate how providing access to human contact to applicants being considered for personal loans increased loan uptake by 16%, suggesting that the effect has external validity, having spillover effects that carry over to long-term customer engagement (**Experiment 3**).

Studies have shown that the introduction of SSTs to banking and healthcare settings may stimulate higher demand for live contact channels through an augmentation of customer behaviors (Campbell and Frei 2010, Kumar and Telang 2012), but have not delved into the mechanisms that might explain the phenomenon. Although not directly studied here, our findings hint to the possibility that customers may be seeking to alleviate the effects of customer anxieties by searching out human contact. A future study may investigate whether customer anxiety actually drives demand for human interaction in self-service settings. Even though participants in this research largely did not avail themselves of the opportunity to engage with the human contact offered to them, further study could examine whether and how actual human contact influences customer emotion and behaviors in high-anxiety service settings. Moreover, having found that access to different types of human contact had differing effects on the customer experience, future research could explore not only the impacts of other types of human contact, but also the optimal timing and approach to introducing human contact options during a self-service experience.

We believe these findings generalize to other domains that rely on strong customer participation for service quality, yet can be anxiety producing, personally involving, and complex such as healthcare, educational decisions, and certain government services. As more automated service processes are being deployed to engage customers across a range of emotional settings – from insurance sales to investment advice to delivering psychotherapy – an acute need to understand how best to balance technology with human contact in order to deliver satisfying, yet efficient service experiences is emerging (Huang and Rust 2018). We hope that this paper serves to spark a more robust avenue of inquiry – for the mutual benefit of customers and the companies that serve them.

CHAPTER TWO:

HIDDEN COSTS OF DYNAMIC PRICING

1. Introduction

Companies have deployed dynamic pricing strategies – where they change prices over time or across different types of consumers in order to maximize profit potential – for some time. Although some historical attempts at implementing variable pricing have been met with public outcry (for example, Coca-Cola attempted to adjust vending machine prices based on weather in the early 2000's), consumers have experienced variable pricing across many settings for some time: residential utilities, travel and hospitality, entertainment venues are just a few examples. While dynamic pricing is often touted as a mechanism to address supply-demand mismatches, much more research emphasis has been placed on the supply-side implications of using these pricing policies than on understanding the potential effects on demand. As variable prices have become more prominent in the everyday lives of consumers, more analytical attention is being paid to consumer welfare (Chen and Gallego 2019), but empirical research into the drivers and long-term cost of customer reaction remains limited. Here, we conduct a laboratory investigation to shed light on the costs that stem from emotional responses to dynamic pricing in the context of ride-sharing, a large and rapidly growing sector of the service economy whose use of dynamic pricing has garnered much attention (Benjaafar and Hu 2020, Cachon 2019, Cachon et al. 2020).

Researchers in the economics and operations management literatures have explored factors that drive companies to adopt dynamic pricing strategies, the efficacy of these strategies in capturing economic surpluses through price discrimination, as well as the implications on competition and market dynamics, primarily through setting up and solving economic models (Chen and Chen 2015). Many of the early models assume full consumer rationality or myopic customer behavior (i.e. that customers make a buy or wait decision at arrival according to how the spot price compares to their personal valuation) while placing emphasis on modeling the optimal pricing policy. Some of the recent models incorporate the behavior of strategic customers (i.e. customers who deliberately plan their purchase decisions) and how different types of information such as reference prices (Popescu and Yaozhong 2007) influences demand (Chen and Chen 2015, Shen and Su 2007). More recently, operations scholars have begun a concerted effort to model biases such as regret and probability misperceptions (Nasiry and Popescu 2012, Özer 2016), inertia (Su 2009), and loss aversion (Chen and Nasiry 2017, Hu and Nasiry 2018) in the revenue management literature.

While there has been a limited stream of controlled experimental work to understand decision-making in dynamic price environments, that work has centered on the systematic errors that managers make in inventory management (Bearden et al. 2008, Bendoly 2011). The empirical research stream which explores consumer reactions and behaviors within dynamic pricing environments remains understudied in operations (Baucells et al. 2017, Kremer et al. 2017, Li et al. 2014, Mak et al. 2014, Osadchiy and Bendoly 2015b).

Understanding these reactions and behaviors is more relevant than ever. As pricing algorithms and technologies advance, companies are not only better able to personalize and localize pricing but also better able to deliver instantaneous updates through electronic shelf labels (Stamatopoulos et al. 2018) for everyday purchases, which will make price fluctuations more salient and heighten consumer uncertainties.

While marketing research on consumer responses to dynamic pricing suggests that perceptions of fairness is a key driver of consumer decisions (Haws and Bearden 2006, Li and Jain 2016, Xia et al. 2004), which may have implications on trust in service relationships (Garbarino and Lee

2003), we submit that the anxiety induced by the uncertainties of dynamic pricing in certain settings may exist alongside feelings of frustration and exert differing influences on risk-taking, choice satisfaction and trust (Gino et al. 2012, Pham 2007, Raghunathan and Pham 1999, Shell and Buell 2019) -- implications that companies and researchers alike have overlooked.

In this paper, we ask: to what extent do dynamic pricing environments stimulate customer anxieties? Further, can we distinguish between anxieties that stem from price uncertainties and anger that may stem from perceptions of fairness in dynamic price environments? How is the anxiety stimulated by dynamic pricing related to risk and loss aversion? Finally, what are the service performance implications to unaddressed customer anxieties in dynamic pricing environments?

In two laboratory experiments, conducted in the domain of ride-sharing, we find that the recall of accepting a ride during a period of surge pricing was enough to induce strong emotional responses, affect risk perceptions and hurt service performance. First, we show that the experience of dynamic pricing can elevate both customer anxieties and anger, but it is primarily through elevated anxieties that trust in the ride-sharing firm is hampered. Interestingly, we find that the mere mention of surge-pricing – randomly assignment to a writing task that explicitly asks participants to recall a time where they paid for a ride when surge pricing was *not* in effect – resulted in lower trust ratings relative to our control group. While we are not the first to identify links between dynamic pricing and trust, we shed light on induced anxiety as an important mechanism. Our evidence suggests that anxiety is triggered by both the experience and the prospect of changing prices, suggesting that anxiety may be an important source of demand variation that has yet to be considered.

Second, we show that both risk and loss aversion are simultaneously impacted by dynamic pricing induced anxieties. Prior research has identified risk and loss aversion as important determinants of the effectiveness of dynamic pricing strategies (Nasiry and Popescu 2011), yet treat these factors as stable consumer traits and do not consider that the uncertainty of prices may induce short-term risk and loss aversion in all consumers. We leverage prior research showing that incidental anxiety can impact risk perceptions and long-term behaviors (Andrade and Ariely 2009, Habib et al. 2015, Raghunathan and Pham 1999) to address this gap and offer evidence to support the ongoing debate about whether anxiety drives loss aversion (Habib et al. 2015, Tom et al. 2007).

Together, these findings contribute an important insight – that stimulated anxiety is a root cause driver of demand-shifts in variable-pricing environments. This not only allows researchers to refine our analytic models but also enables companies to more effectively target service design interventions to minimize these unintended and previously unaccounted for costs.

2. Literature Review

Operations scholars have long recognized the need to understand and model customer behaviors in order for firms to optimize their pricing strategies (Shen and Su 2007), but only recently have scholars begun a concerted effort to incorporate the impact of psychological biases into theoretical models. Loss aversion, is an oft-studied demand function adjustment that scholars recognize as a driver of strategic decisions (Chen and Nasiry 2017, Nasiry and Popescu 2011, Popescu and Yaozhong 2007) or consumer inertia (Su 2009) in variable price environments. Scholars have also recognized that emotions, such as disappointment (Liu and Shum 2013) and regret (Nasiry and Popescu 2012) may exert important influences on consumer choices as prices change, but have yet to apply these insights to conduct empirical studies on the downstream implications to service relationships. Interestingly, scholars have conducted experimental investigations of how managerial decisions are affected by changing prices (Bearden et al. 2008, Kremer et al. 2017) as they evaluate company profits, even recognizing the potential for stress to affect pricing decisions (Bendoly 2011), but empirical research on consumer behaviors in dynamic pricing remains limited.

Although operations scholars assume strategic, or forward looking, customer behaviors exist in settings where prices fluctuate, documenting direct evidence of its existence has only recently begun in earnest. Li et al. (2014) analyze longitudinal data across distribution outlets in the airline industry to identify when and under what pricing conditions customers exhibit strategic behaviors. Mak et al. (2014) lends support, using an experimental study to trace customer learning as buyers adjust to changing prices. Osadchiy and Bendoly (2015a) conduct an experimental study to investigate how certain information affects the risk perceptions of potential buyers as they wait before making a purchase. Baucells et al. (2017) leverages insights from other decision sciences to model and experimentally test psychological tradeoffs that strategic customers may make as they consider when to buy in a retail markdown setting. While our work is related to this literature, we pursue a different goal – to identify an underlying influence on demand in dynamic price environments and to shed light on the downstream costs that operations scholars and companies alike have overlooked when modeling the profit potential of these pricing policies.

To build our hypotheses about customer reactions and behaviors in the face of price uncertainties, we integrate findings from the marketing and the judgement and decision-making literatures. While operations scholars recognize that consumers may use reference prices as a basis for calculating whether changing prices represent gains or losses (Popescu and Yaozhong 2007), marketing scholars recognize that reference price dependencies can generate perceptions of inequity, which may incite consumer anger and erode customer satisfaction (Bolton et al. 2003, Campbell 1999, Haws and Bearden 2006), particularly in "take-it or leave-it" price settings, like ride-sharing. One early study linking dynamic pricing to firm trust showed that exposure to price discrimination, e.g. offering different prices to different consumers for the same item, has negative implications on trust in firms through a loss of perceived benevolence (Garbarino and Lee, 2003).

Since it is well established that overall satisfaction and trust are separate and distinct pre-cursors to a customer's commitment to a firm (Garbarino and Johnson 1999), it stands to reason that factors introduced by an operational choice that undermine satisfaction or deter trust formation would also decrease the long-term gains associated with that choice. Emotional reactions are critical factors. Incidental emotions influence trust and in particular, negative emotions such as anger and anxiety can have a detrimental effect (Dunn and Schweitzer 2005, Shell and Buell 2019). While perceptions of unfairness may evoke anger as prices fluctuate, these uncertainties may stimulate anxiety, with both emotions intensifying as the need to transact increases. While it is oft-cited that surge pricing entices more drivers to meet demand for service at critical times and in underserved areas, consumers may not be able to suppress the negative emotions that spiking prices generate -- and the impacts of these emotions may endure (Andrade and Ariely 2009).

Although both are negative and may be difficult for people to differentiate within themselves, it is well understood in psychology that anger and anxiety are discrete and are predicted to have different impacts on decision-making in risk environments (Lerner and Keltner 2000, 2001). Anger is characterized by a sense of certainty and a belief that individuals are in control of outcomes, while anxiety is characterized by a sense of uncertainty and a belief that circumstances dictate, thus the two emotions are predicted to result in different responses to risk - with anger tending to weaken risk aversion and anxiety tending to strengthen it in certain choice environments (Habib et al. 2015, Lerner and Keltner 2000, Raghunathan and Pham 1999). Recognizing that framing biases effect risky decisions, researchers have long attempted to understand whether negative emotions drive loss aversion and the results remain inconclusive (Habib et al. 2015, Tom et al. 2007). Further, these differences lead us to expect anger to have a greater impact on evaluative measures related to past experiences such as satisfaction, and for anxiety to have a greater influence on measures associated with the potential for future engagement, like trust.

3. Presentation of Experiments

Experiment 1: Emotional Responses and Impacts to Service Performance

The goal of our investigation is to document the presence and influence of customer anxiety in variable price environments. Surge pricing, where companies raise prices to match supply and demand characteristics based on time and location needs, has garnered much attention from academics and the popular press. A growing literature stream in operations research touts the consumer welfare generating benefits of dynamic pricing in ride-sharing contexts, but empirical research on the demand drivers in dynamic pricing contexts is lacking (Benjaafar and Hu 2020, Cachon 2018, Castillo 2018). We set this research in the domain of ride-sharing to maximize the likelihood that participants would have recent experience to draw on for our memory recall writing task and begin, in Experiment 1, to document the presence of anxiety during surge pricing.

3.1.1. Participants. 150 participants were recruited to complete a memory recall task on the Amazon Mechanical Turk platform in exchange for a $1.00 participation fee. Since this was an initial test to examine the links between dynamic pricing and emotion, the target sample size of 50 participants per condition was chosen in expectation of unusable observations due to noncompliant participants. Those that failed to comply with the writing instructions were dropped from the sample, resulting in final dataset of 118 observations (M_{age} = 35.18, 68.64% Male).

3.1.2. Design and Procedure. We set this initial study in the context of ride sharing services, which commonly employ dynamic pricing algorithms to address supply-demand mismatches found during peak demand times and in typically underserved locations. After reading a brief description of ride sharing services, participants were randomly assigned to one of three writing tasks where they were asked to write a short paragraph in as much detail as they could remember about a recent ride-sharing experience. Autobiographical Emotional Memory Tasks are often used to experimentally induce emotional responses (Siedlecka and Denson 2019). Here, we use the recall task to determine whether negative emotions are induced due to the memory of making a ride-sharing purchase decision during surge pricing.

In our control condition, participants were asked to describe a recent experience where they paid for a ride-share (“Control”, $N = 44$). In the “Surge On” condition, participants were prompted to recall a time when they paid for a ride share when surge pricing was in effect ($N = 38$). Finally, in the “Surge Off” condition, participants were prompted to write about a time when they paid for a ride share when surge pricing was not in effect ($N = 36$). **Figure 2.1** shows the instructions given to participants.

Condition	Writing Prompt
Surge On	Aiming for 5-7 sentences, please take a few minutes to describe, in as much detail as you can remember, a time when you paid for a ride-share when **SURGE PRICING <u>WAS</u> IN EFFECT**. For example, what was the situation? What factors drove your decision to accept the price that was offered? How did you feel about the decision you made to accept the price at that time?
Surge Off	Aiming for 5-7 sentences, please take a few minutes to describe, in as much detail as you can remember, a time when you paid for a ride-share when **SURGE PRICING <u>WAS NOT</u> IN EFFECT**. For example, what was the situation? What factors drove your decision to accept the price that was offered? How did you feel about the decision you made to accept the price at that time?
Control	Aiming for 5-7 sentences, please take a few minutes to describe, in as much detail as you can remember, a time when you paid for a ride-share. For example, what was the situation? What factors drove your decision to accept the price that was offered? How did you feel about the decision you made to accept the price at that time?

Figure 2.1: Surge Pricing Writing Prompts.

3.1.3. Dependent Measures

Emotion. Immediately after completing the writing task, we asked participants to report the extent to which they felt anxiety, anger or calm on a 4-point Likert Scale using the Spielberger Short-form State-Trait Anxiety Inventory (Marteau and Bekker 1992) and the Felt Anger Subscale of the State-Trait Anger Expression Inventory (Spielberger and Reheiser 2009). *Anxiety* was calculated as the average of self-reported ratings of "tense", "upset" and "worried" plus the average of reverse-coded ratings of "calm", "relaxed" and "content". *Anger* is the average of "mad", "burned up", "irritated", "angry" and "furious". For the purpose of being able to compare the effects of anger and anxiety, we standardize these variables in our regression tables.

Because both anxiety and anger are negatively-valenced, and prior research has investigated the extent to which dynamic pricing engenders perceptions of unfairness (Haws and Bearden 2006), we felt it important to measure both emotions to determine the extent to which one may dominate the other in this initial study. All items were asked at once on a single page and counterbalanced to avoid any ordering effects. Although the two measures are highly correlated ($r(116) = 0.65, p < 0.01$), we analyze their effects separately to determine whether we can draw any distinction between their effects.

Change in Usage Frequency. We asked participants to separately rate how often they used the ride sharing company before and after the experience they wrote about on a 5 point scale (1 = Once in a while , 5 = Daily) and we calculated the difference between these measures to create the variable *usage_delta* to determine whether the experience had an effect on loyalty.

Overall Satisfaction and Trust. Participants were asked to separately rate their overall satisfaction with and the level of trust they feel toward the company they wrote about, both on a seven point scale (1= Extremely dissatisfied/Extremely low , 7= Extremely satisfied/Extremely high).

3.1.4. Control Measures. Demographic information (age, gender-identity, education level and income level) was collected as control measures. Two-sample independent means comparison tests, pairwise, showed that treatment cells were balanced across each of these measures (all *p-values* > 0.28).

3.1.5. Results

Emotions. In **Figure 2.2**, we can see a clear pattern of results. Participants prompted to recall a time when they paid for a ride share during surge pricing reported higher levels of negative emotion than those in the Surge Off condition and those in our control group, who were not given a surge pricing prompt at all. Interestingly, our Surge Off treatment group rated anger in approximately equal measure to our control group, while we begin to see greater variation across the groups in reported anxiety.

We use Wilcoxon's Rank Sum tests for our statistical testing. First, comparing those who were asked to write about a time when surge pricing was in effect to those who were given no surge pricing prompt ("Surge On" vs "Control"), we find significant differences in reported anxiety ($z = 1.82$, $p < 0.10$) and anger ($z = 2.25$, $p < 0.05$).

When we compare those who were explicitly asked to write about a time when surge pricing was not in effect to those who were not given a surge pricing prompt ("Surge Off " vs "Control"), we do not see significant differences in anxiety ($z = 0.59$, p = NS) or anger ($z = 0.38$, p = NS).

Comparing the two groups that were given a writing prompt that mentions surge pricing ("Surge On" vs. "Surge Off"), we find marginally significant differences in anger ($z = 1.83$, $p < 0.10$) and do not see significant differences in anxiety ($z = 0.99$, p = NS). Taken together, these results point to a phenomenon where the experience of actually buying during a price surge may result in customer frustrations, but indistinguishable anxiety levels whether participants wrote about a time when surge pricing was in effect or not suggests that the mere mention of surge pricing was enough to elevate customer anxiety.

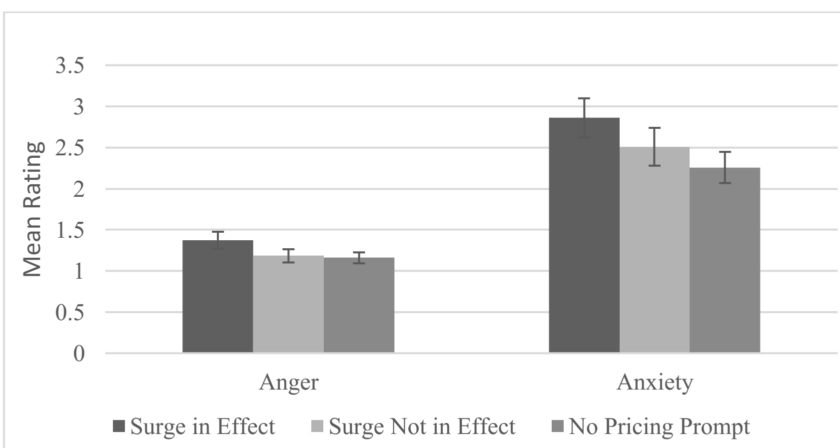

Figure 2.2: Emotional Responses to Surge Pricing Recall Task (unstandardized measures)

Regression Estimations. Controlled OLS regression results (**Table 2.1**) corroborate the pattern of emotional responses we observed and allows us to investigate how dynamic pricing might impact service relationships. In Columns 1 - 3 , we see that, relative to our control group, random assignment to the Surge On condition results in higher levels of anxiety ($\beta = 0.48$, $p < 0.05$) and anger ($\beta = 0.47$, $p < 0.05$), while assignment to the Surge Off condition does not. Participants across conditions reported no significant differences in how often they used ride-sharing services as a result of the recent experience they recalled. However, Columns 4 and 6 show that measures of satisfaction ($\beta = -1.48$, $p < 0.01$) and trust ($\beta = -1.32$, $p < 0.01$) were hampered by whether participants were asked to recall a time of surge pricing or not. Interestingly, Column 6 shows that when participants were explicitly asked the write about a time when surge pricing was *not* in effect, they reported lower trust in the firm ($\beta = -0.65$, $p < 0.05$) relative to our control group, whose prompt makes no mention of surge pricing at all. Columns 5 and 7 show that these main impacts to both service relationship measures persist after controlling for reported emotion and suggest that anger may have a stronger impact on satisfaction, while anxiety may have a greater impact on trust.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Anxiety	Anger	Usage Delta	Overall Satisfaction	Overall Satisfaction	Firm Trust	Firm Trust
Surge On	0.484**	0.470**	0.023	-1.483***	-1.165***	-1.319***	-1.125***
	(0.221)	(0.214)	(0.086)	(0.298)	(0.269)	(0.269)	(0.256)
Surge Off	0.267	0.172	-0.069	-0.329	-0.187	-0.645**	-0.552**
	(0.260)	(0.218)	(0.133)	(0.298)	(0.242)	(0.281)	(0.250)
Anger					-0.382		-0.165
					(0.302)		(0.260)
Anxiety					-0.286		-0.241
					(0.174)		(0.168)
Male	-0.065	-0.003	0.057	0.081	0.061	0.199	0.183
	(0.221)	(0.226)	(0.103)	(0.278)	(0.219)	(0.251)	(0.228)
Age	-0.009	-0.001	-0.008*	0.007	0.004	-0.007	-0.009
	(0.011)	(0.008)	(0.004)	(0.010)	(0.009)	(0.012)	(0.011)
Income Level 2	1.262***	0.646**	0.012	-0.590	0.018	-0.437	-0.025
	(0.323)	(0.258)	(0.111)	(0.390)	(0.361)	(0.467)	(0.468)
Income Level 3	1.059***	0.864**	-0.106	-0.598	0.035	-0.669	-0.271
	(0.344)	(0.345)	(0.173)	(0.421)	(0.346)	(0.486)	(0.460)
Income Level 4	0.588**	0.589**	0.012	0.175	0.569**	0.108	0.347
	(0.270)	(0.254)	(0.086)	(0.271)	(0.221)	(0.430)	(0.401)
Income Level 5	0.685*	0.487*	0.036	0.038	0.420*	-0.623	-0.377
	(0.350)	(0.270)	(0.098)	(0.290)	(0.251)	(0.462)	(0.433)
Income Level 6	1.245**	2.546***	0.388	0.450	1.778**	-1.361**	-0.640
	(0.554)	(0.733)	(0.303)	(0.381)	(0.705)	(0.532)	(0.818)
Education Category 2	0.780***	0.459**	-0.155	0.322	0.720*	0.876**	1.140***
	(0.245)	(0.217)	(0.107)	(0.447)	(0.427)	(0.369)	(0.370)
Education Category 3	0.687***	0.385**	-0.088	0.273	0.617	0.440	0.670*
	(0.189)	(0.156)	(0.091)	(0.422)	(0.417)	(0.352)	(0.352)
Education Category 4	0.145	-0.572	-0.219	0.313	0.136	1.270	1.211
	(0.462)	(0.524)	(0.151)	(0.592)	(0.613)	(0.809)	(0.804)
Education Category 5	1.629***	0.895**	-0.209	-0.222	0.585	0.191	0.732
	(0.428)	(0.374)	(0.126)	(0.561)	(0.602)	(0.487)	(0.597)
Constant	-1.364**	-1.194**	0.348*	5.967***	5.121***	5.614***	5.088***
	(0.590)	(0.480)	(0.176)	(0.594)	(0.546)	(0.693)	(0.676)
Observations	118	118	118	118	118	118	118
R-squared	0.201	0.192	0.091	0.272	0.422	0.286	0.351

Table 2.1: Autobiographical recall of surge pricing in an experimental task induces negative emotions and diminishes overall satisfaction and trust in ride sharing services.
All models are estimated with OLS regression and robust standard errors are shown in parentheses. *, **, and *** signify significance at the 10%, 5% and 1% levels respectively.

Mediation Analysis. Although we provide evidence that anger is induced by a surge pricing experience, we home in on the impact of anxiety as the intent of this investigation is to shed light on the influence of this overlooked emotion. Building on our regression results, we use structural equation modelling to conduct a path analysis between the *prospect* of surge pricing and losses to trust through increased anxiety, jointly estimating the equations to control for potential endogeneity. We bootstrap standard errors with 1000 repetitions to alleviate power concerns and avoid normality assumption violations (MacKinnon et al. 2007). Having observed that neither anxiety ratings nor demographics between the two groups that were assigned writing prompts that mention surge pricing differed significantly, we collapse these two groups into one "Surge Mention" treatment group ($N = 74$) for comparison to our control group ($N = 44$).

As shown in **Figure 2.3**, the mention of surge pricing induces anxiety ($\beta = 0.39$, $p < 0.10$) and directly hampers trust in the ride-sharing company ($\beta = -1.03$, $p < 0.01$). Anxiety, in turn, results in losses to firm trust ($\beta = -0.37$, $p < 0.01$). Although the strength of the relationship between surge pricing and trust remains significant, it is reduced ($\beta = -0.88$, $p < 0.01$) indicating a partial mediation that accounts for 14% of the impact to trust. The bias-corrected confidence interval for this indirect pathway from the mention of surge pricing to a reduction in trust through an increase in anxiety levels does not contain zero (95% CI: [-0.45 , -0.00]).

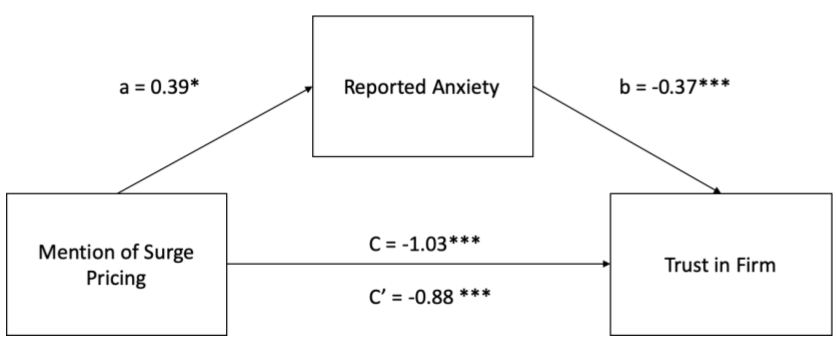

Figure 2.3: Emotional Responses to Surge Pricing Recall Task.
Models control for age, gender, income, education and were estimated with bootstrapped standard errors with 1,000 repetitions. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Although prior literature has identified customer frustrations and perceptions of unfairness as a response to dynamic pricing, this study provides evidence that anxiety may also exert a significant influence – perhaps without customers having to actually transact during variable pricing periods. Our results suggest that the mere prospect of variable pricing may elevate customer anxieties and make them less trusting of service providers. Since it is well established that anxiety and anger exert result in different behaviors in risk environments, we attempt to disentangle these emotional influences using behavioral measures in our next study.

Experiment 2: Anxiety in Dynamic Pricing Environments Increase Risk and Loss Aversion

Having established that surge pricing induces both anger and anxiety, we turn our attention to examining the links between a surge pricing and both risk and loss aversion. Prior studies have shown evidence that anger increases risk-taking while anxiety increases risk aversion (Habib et al. 2015, Lerner and Keltner 2001). Observing effects on commonly used risk and loss aversion measures stemming from our emotion induction should provide evidence that helps us disentangle the presence of anxiety from anger.

3.2.1. Participants. 150 participants were recruited to complete memory recall, risk and loss aversion tasks on the Amazon Mechanical Turk platform in exchange for a $1.00 participation fee with the potential to earn bonuses ranging from $0 to $3.50. 44 observations were dropped where participants failed to comply with the writing instructions for the memory recall task. Another 20 observations were dropped due to inconsistent responses to either the risk or loss aversion task. Our final dataset contained 86 observations for analysis (M_{age} = 34.11, 44.19% Female).

3.2.2. Design and Procedure. As in our previous study, participants were randomly assigned to a either recall a time when then paid for a ride-share when surge pricing was in effect ("Surge Treatment" , N = 37) or to recall a time when they paid for a ride-share, with no surge pricing prompt given ("Control" , N = 49). Building on the fact that levels of anxiety were induced by the mere mention of surge pricing in our prior study, we drop the Surge Off condition in the interest of parsimony. Once the writing task is complete, we ask participants to rate their levels of anxiety and anger.

Next, we present two lottery preference tasks (Andersson et al. 2016, Holt and Laury 2002) and inform participants that we will randomly choose one of the lotteries from each task and credit them with a bonus payment in accordance with the outcome of the lottery and their indicated preference. We do this in order to align incentives and ensure participant effort on the task. First, we present a risk-aversion lottery task where participants are asked to indicate which of two gambles they would prefer for each of ten rows of paired lotteries. In this task, all lotteries have positive, non-zero potential outcomes. We next present a loss-aversion lottery task where again participants are asked to indicate their preferences across ten lottery pairs. In this case, some lotteries have negative, non-zero potential outcomes.

Once participants have indicated their lottery preferences, we ask that they rate their overall satisfaction and trust in the ride-sharing service provider they wrote about and complete demographic information to end the study. The lottery is conducted outside of the study and participants are credited with bonus payments 48 hours after the study is closed. Because participants are not told the outcome of the lotteries in real time, our study is designed to measure the influence of expected risk and loss aversion as would be the case at the time that customers are seeking to make a decision during a period of dynamic price changes, which allows us to avoid the confounding effects of realized outcomes.

3.2.3. Dependent Measures

Emotion. Following the procedure outlined in Study 1, we measure Anxiety and Anger using the Six-item State-Trait Anxiety Inventory and the five-item Felt Anger Subscale of the State Trait Anger Expression Inventory. Again, we standardize these variables to facilitate comparison and observe a high correlation between the measures ($r(84) = 0.75$, $p < 0.01$) but maintain their separation in our analysis in order to observe their individual effects.

Risk Aversion and Loss Aversion. We adapt the multiple price list structures used in Andersson et al, 2016 where the left-side gambles in each lottery task have constant payoffs and the right-side gambles have increasing expected values. The lotteries are presented as the opportunity to earn points toward a bonus payment, which would be paid at a two points to $0.01 conversion ratio. The probability of each gamble is set to 50% to simplify the procedure as much as possible for participants. As an example, participants are asked to indicate "which of the following two lotteries [they] would prefer, the left or the right? Left: Receive 89 points or 110 points ; Right: Receive 28 points or 110 points" on the risk aversion task which is gain-framed as it only includes positive outcomes. A row on the loss aversion task might read: Left: Receive 35 points or 95 points ; Right: Receive -25 points or 105 points. It should be straightforward that in either case, the left lottery would be preferable as it has a far superior worst case scenario and equivalent or near-equivalent best case scenario, such that its expected value is higher. Since the left lottery is fixed across each array, we measure risk or loss aversion by calculating the point at which the participant indicates a preference for the right lottery. A risk-neutral participant would choose to switch at the point where the expected value of the right lottery is higher than the expected value of the left lottery which occurs at row 6 in both lottery tasks. Participants that switch earlier than row 5 are risk or loss averse ; those that switch at higher values are risk or loss-seeking.

Overall Satisfaction and Trust. Participants were asked to rate their overall satisfaction with the ride-sharing company they wrote about on a seven-point Likert scale. To measure trust, we asked participants to separately rate, on a seven-point Likert scale, the extent to which they agreed with the statements: “I can rely on this ride-sharing company”, “I can trust this ride-sharing company” and “I find this ride-sharing company to be honest” and created a trust variable from the average across these three.

3.2.4. Control Measures. Demographic information (age, gender-identity, education level and income level) recognized as important determinants of risky behavior was collected as control measures. Two-sample independent means comparison tests, pairwise, showed that treatment cells were balanced across each of these measures (all *p-values* > 0.48).

3.2.5. Results

Emotion. In **Figure 2.4**, we again see that a writing task asking participants to recall a time when they paid for a ride-share during surge pricing generated negative emotional responses and that while anger is increased in both groups, the incidence of anxiety is greater. Wilcoxon’s tests confirm that participants in our surge treatment group have significantly higher ratings of anxiety than our control group ($z = -2.58$, $p < 0.01$), while ratings of anger are indistinguishable ($z = -1.40$, p = NS).

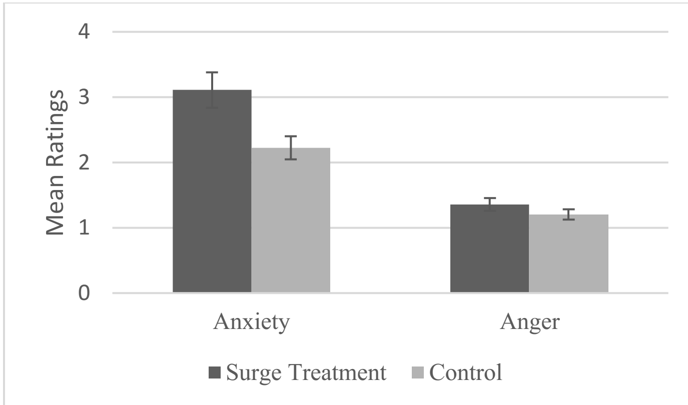

Figure 2.4: Study 2: Emotional Responses to Surge Pricing Recall Task (unstandardized variables)

Regression Estimations. In **Table 2.2,** we conduct controlled OLS regression estimations with robust standard errors to examine the effects of our surge pricing treatment on risk and loss aversion as well as service performance. As shown in Column 1, we see that our treatment resulted in higher levels of anxiety after controlling for demographic variables ($\beta = 0.59$, $p < 0.01$), thus our manipulation worked. In Columns 2 - 4, we examine the drivers of loss aversion. We find that, all else equal, simple recall of a ride-share purchase during surge pricing does not generate higher levels of loss aversion ($\beta = -0.61$, p = NS). and in fact, we see a directionally negative effect indicative of the presence of anger. Although not statistically significant, this result may be explained by two additional factors. First, although we do not include a surge pricing prompt in our control group, a cursory examination of participant responses reveals that many chose to write about a ride share during price surges, resulting in a natural variation in the emotion of our control group. Second, the precision of our standard errors may be affected by the relatively low power of our analysis sample.

Controlling for treatment assignment in Column 3, reveals that greater levels of anxiety drive greater levels of loss aversion ($\beta = 0.92$, $p < 0.05$). When we control for anger ratings in Column 4, we see that directionally, anger reduces loss aversion, and the positive effect of anxiety remains significant ($\beta = 1.02$, $p < 0.10$). In Columns 5 – 7, we can see that the effects on risk aversion slightly differ. Higher levels of reported anxiety lead to higher levels of risk aversion ($\beta = 1.04$, $p < 0.01$). When we control for anger ratings, in Column 7, however, we see that although anxiety appears to exert twice the effect size, both emotions increase risk aversion such that neither rises to the level of significance ($\beta_{anxiety} = 0.77$ vs. $\beta_{anger} = 0.35$, *p's* = NS).

Columns 8 - 11 show that the impacts to satisfaction and trust from recall of a surge pricing experience. We do not include loss or risk aversion in these estimations since these tasks were not contextualized and were thus unrelated to the service ratings. Replicating the pattern we observed in Study 1, we see that participants who recall surge pricing report lower levels of satisfaction ($\beta = -0.80$, $p < 0.05$) and trust in the ride-sharing company ($\beta = -0.62$, $p < 0.05$) in Columns 8 and 10. Although we cannot conclude that reported anxiety mediates the relationship between surge pricing experiences and service performance, the change in magnitude and loss of statistical significance of the coefficient on the treatment variable observed in Columns 9 and 11 suggest the possibility of partial mediation.

In summary, Study 2 provides evidence to suggest that dynamic price environments induce customer anxieties which stimulates both risk and loss aversion and simultaneously hurts service performance. We provide empirical evidence to support assumptions that loss aversion may be induced by dynamic price environments and document the role of anxiety as a potential root cause. Not only do these results imply that there may be short-term demand implications as induced anxieties shift consumer preferences, but there may also be long term implications to service relationships for companies that employ dynamic pricing without accounting for the negative effects of emotion.

	(1) Anxiety	(2) Loss Aversion	(3) Loss Aversion	(4) Loss Aversion	(5) Risk Aversion	(6) Risk Aversion	(7) Risk Aversion	(8) Satisfaction	(9) Satisfaction	(10) Trust	(11) Trust
Anxiety			0.922**	1.022*		1.043***	0.773		-0.440		-0.277
			(0.431)	(0.578)		(0.359)	(0.575)		(0.389)		(0.249)
Anger				-0.131			0.354		0.184		0.041
				(0.564)			(0.526)		(0.321)		(0.256)
Treatment	0.589***	-0.614	-1.157	-1.173	-0.040	-0.654	-0.610	-0.796**	-0.596	-0.616**	-0.466*
	(0.216)	(0.870)	(0.909)	(0.926)	(0.854)	(0.885)	(0.903)	(0.373)	(0.387)	(0.261)	(0.251)
Age	0.007	-0.054	-0.060	-0.061	-0.057	-0.064*	-0.063*	-0.001	0.002	-0.003	-0.002
	(0.012)	(0.040)	(0.039)	(0.039)	(0.039)	(0.035)	(0.036)	(0.022)	(0.020)	(0.011)	(0.011)
Female	0.020	2.905***	2.887***	2.871***	1.548*	1.526*	1.569*	-0.569	-0.541	-0.065	-0.055
	(0.197)	(0.804)	(0.787)	(0.802)	(0.815)	(0.790)	(0.789)	(0.373)	(0.369)	(0.269)	(0.268)
Income Level 2	-0.184	-1.762	-1.592	-1.561	-2.766*	-2.574*	-2.658*	0.976	0.877	2.510***	2.455***
	(0.914)	(1.982)	(1.984)	(2.004)	(1.613)	(1.396)	(1.465)	(1.413)	(1.714)	(0.463)	(0.617)
Income Level 3	0.016	-3.205*	-3.220*	-3.181*	-4.070***	-4.087***	-4.191***	0.148	0.099	1.908***	1.900***
	(0.894)	(1.872)	(1.806)	(1.842)	(1.521)	(1.316)	(1.362)	(1.397)	(1.714)	(0.473)	(0.637)
Income Level 4	-0.517	-0.269	0.208	0.234	-3.107**	-2.567**	-2.637**	0.681	0.489	2.360***	2.225***
	(0.861)	(1.830)	(1.744)	(1.781)	(1.408)	(1.175)	(1.234)	(1.399)	(1.717)	(0.431)	(0.608)
Income Level 5	-0.591	-1.683	-1.138	-1.108	-3.895***	-3.278***	-3.361**	1.223	1.003	3.148***	2.993***
	(0.886)	(2.229)	(2.222)	(2.249)	(1.446)	(1.194)	(1.281)	(1.385)	(1.718)	(0.491)	(0.666)
Income Level 6	-0.043	0.454	0.493	0.506	-2.539	-2.494	-2.528	0.124	0.094	2.420***	2.406***
	(0.922)	(2.767)	(2.709)	(2.710)	(2.342)	(2.303)	(2.376)	(1.777)	(2.075)	(0.709)	(0.841)
Education Category 2	-1.472***	2.934**	4.291***	4.316***	-0.806	0.729	0.664	3.093***	2.617***	1.549	1.180
	(0.382)	(1.242)	(1.373)	(1.357)	(2.614)	(2.960)	(3.151)	(0.405)	(0.515)	(1.076)	(1.067)
Education Category 3	-1.386***	3.118***	4.395***	4.425***	0.493	1.938	1.859	3.021***	2.564***	1.564	1.215
	(0.427)	(1.151)	(1.326)	(1.292)	(2.546)	(2.873)	(3.077)	(0.429)	(0.558)	(1.091)	(1.081)
Education Category 4	-1.036*	1.664	2.620	2.581	-2.165	-1.085	-0.980	2.797***	2.541**	0.596	0.353
	(0.566)	(1.898)	(2.089)	(2.105)	(2.508)	(2.778)	(2.912)	(0.979)	(1.008)	(1.253)	(1.243)
Education Category 5	-0.199	2.884	3.068	3.222	-0.011	0.197	-0.220	2.311*	2.034	1.766	1.669
	(1.175)	(2.511)	(1.858)	(2.050)	(3.383)	(3.089)	(3.324)	(1.186)	(1.337)	(1.156)	(1.235)
Constant	1.139	5.907**	4.857*	4.835*	11.011***	9.823***	9.883***	2.163	2.535	1.886	2.173*
	(1.013)	(2.581)	(2.672)	(2.693)	(3.141)	(3.272)	(3.481)	(1.613)	(1.928)	(1.171)	(1.239)
Observations	86	86	86	86	86	86	86	86	86	86	86
R-squared	0.242	0.314	0.357	0.358	0.181	0.242	0.246	0.201	0.229	0.292	0.318

Table 2.2: Autobiographical recall of surge pricing in an experimental task induces anxiety, increases risk and loss aversion, and diminishes overall satisfaction and trust in ride sharing services.
All models are estimated with OLS regression and robust standard errors are shown in parentheses. *, **, and *** signify significance at the 10%, 5% and 1% levels respectively.

4. Concluding Remarks

This paper contributes to a growing body of research that uses experimental methods to identify and test critical assumptions used in operations management models. The costs and benefits of surge pricing, a form of dynamic pricing, has received attention from popular press and academic study alike, yet the implications of customer emotion has been underexamined. Building on recent work in behavioral operations that explores the role of customer anxiety on decision-making (Shell and Buell 2019), this research project aims to demonstrate that customer emotion, and in particular anxiety, may be a hidden cost to dynamic pricing that companies and academic models have yet to fully consider.

When Coca-Cola attempted to implement variable pricing at vending machines in 1999 and it was revealed that Amazon changed prices based on browsing history, there was public outrage that sparked researchers to examine costly implications of consumer perceptions on dynamic pricing (Bolton et al. 2003, Garbarino and Lee 2003, Haws and Bearden 2006, Xia et al. 2004), yet companies continue to introduce variable pricing policies as scholars demonstrate welfare benefits to companies and consumers alike. Despite recent studies that suggest consumer welfare gains from dynamic pricing strategies (Cachon et al. 2017, Chen and Gallego 2019), customer frustrations with variable prices persist.

Here we demonstrate that customer anxieties about price fluctuations, previously unaccounted for in the dynamic pricing literature, exist alongside customer anger and perhaps present different implications for firm profitability. While anger induced by the experience of surge pricing has an understandably negative effect on satisfaction, anxiety induced by the *potential to* experience surge pricing reduces trust which may have implications for customer engagement (Porter and Donthu

2008) and ultimately aggregate demand. Further, we show that induced anxiety increases both risk and loss aversion, biases that operations scholars previously characterized as consumer types rather than consumer responses in analytical models.

As technologies advance and make it easier for companies to implement dynamic pricing across more everyday settings, consumer sensitivities, and the intensity with which they respond, to price ambiguity could have greater impact on their decisions and service relationships. Our research suggest that transient anxiety induced by price uncertainty may result in demand shifts that scholars ought to incorporate if we are to quantify the true costs and benefits of dynamic pricing policies.

CHAPTER THREE:

ANXIETY AND RISK TOLERANCE

1. Introduction

Across many facets of our lives, we often choose to accept risk exposures that could be easily mitigated. Drivers decline their mechanics' recommendations, students skim their assigned readings taking the chance that they will not be called upon in class, very few households curtail their spending to maintain the 3-6 months of emergency savings that experts advise. At the same time, economists observe that our choices in many service contexts like auto, home, extended warranties, travel and rental car insurance imply inordinately high levels of risk aversion (Cutler and Zeckhauser, 2004; Kunreuther 2013). What else might account for our shifting appetite for risk?

Insurance decisions have long served as a test-bed for the study of decisions under uncertainty (Kahneman and Tversky 1979). Scholars have pointed to misperceptions of risk (Barseghyan et al. 2013), the presence of background risks (Markle and Rottenstreich 2018, Tsetlin and Winkler 2005) and risk vulnerabilities (Beaud and Willinger 2015) that stem from non-focal contexts, as contributing factors to explain the "insurance puzzle" – that our decision to guard against a specific risk is often mismatched to the calculated exposure level - but the role of emotion as a driving force remains unsettled.

Emotions -- whether immediately felt or anticipated -- may influence economic decisions (Loewenstein 2000, Loewenstein and Lerner 2003), and uncertainties -- whether related to the task or not -- in decision environments may stimulate anxieties (Lerner and Keltner 2001). Although the words "fear" and "risk" are closely related in our lexicon (Bhatia 2019), empirical research linking anxiety to risk-taking offers mixed evidence. Distressed participants in laboratory studies have been willing to pay *higher* amounts for a gamble (Mano 1992) and have also been *less* likely to take risks in other settings (Lerner and Keltner 2001, Raghunathan and Pham 1999).

Conventional wisdom links anxiety and self-protection, yet surprisingly little empirical evidence exists to document how, why or under what circumstances anxiety plays a dominant role. Early studies of insurance and extended warranty purchases have noted that consumers may be likely to consult their feelings and use heuristics rather than probability assessments during the decision-making process (Hogarth and Kunreuther 1995) and that the emotional attachment a person feels toward the object to be insured may dominate loss probability assessments (Hsee and Kunreuther 2000). Researchers have theorized that anxiety about future losses or regret about past losses, may explain observed behaviors (Zeckhauser and Cutler 2004) and have provided evidence that heightened worries and feelings of regret *after a salient loss* influences subsequent insurance demand (Kunreuther and Pauly 2014, Schade et al. 2012). We examine the role of coincident anxiety, which may come from a variety of sources, in risk decisions.

Here, we integrate research across disciplines and shed light on a pathway of linkages between anxiety, risk tolerance and insurance take-up. In two laboratory studies, we demonstrate that risk aversion is not a stable trait, but can be significantly influenced by a person's emotional state at the time of assessment. While scholars have suggested that non-focal risks may be incorporated into risky decisions or the pain of loss may drive risk aversion, we offer evidence that situational anxieties – unrelated to the task at hand – can shift our predictions about what risks we would take as well as our willingness to keep pre-existing risks. Further, although the decision to take insurance reduces anxiety, we observe that post-decision anxieties cast a negative pall on decision satisfaction, which may have long-term implications for service relationships (Shell and Buell 2019).

While companies often employ social norm messaging such as “47,257 customers protected their flight in the last 7 days” to influence online insurance uptake, research has shown that peer information may engender or discourage normative behaviors in financial decision-making contexts (Beshears et al. 2015). Building on the notion that the mere presence of others may influence anxious decision-makers (Shell and Buell 2019) in self-service contexts, we included a test of a social information intervention. We find no evidence that this intervention influences decision outcomes or ratings of the experience.

This paper proceeds as follows. In Section 2, we review related literature across economics, marketing and the decision-sciences that might inform our study. Section 3 presents our laboratory experiments and results. We offer brief concluding remarks in Section 4.

2. Literature Review

Studies linking emotion to decision-making have recognized differences in whether the emotion is immediate or anticipated, directly related to the decision task or not , and whether the emotion is a trait or is transient (Cohen et al. 2015, Lerner et al. 2015, Loewenstein et al. 2001, Loewenstein and Lerner 2003, Pham 2007). Research examining how fear and anxiety influences economic decisions are similarly varied. Scholars have shown that people prone to anxiety make pessimistic risk assessments (Lerner and Keltner 2001), that people in anxious moods prefer lower-risk, lower-reward gambles (Raghunathan and Pham 1999), that distress over substantial future losses activate self-protective decision-making (Mano 1994a) and that anxiety’s influence on risk-taking may differ in gain versus loss framed contexts (Habib et al. 2015, Mano 1994a).

Further, the risk elicitation methods used across studies have ranged widely including simple one-shot gambles, multiple price lists, and decision-making tasks, which may or not have had real consequences for participants (Wake et al. 2020). Although fear generally decreases risk-taking, a recent meta-analysis displays the substantial heterogeneity of results -- including findings where anxiety *increases* risk-taking -- in the extant literature, leaving our understanding of how and in what contexts anxiety decreases risk-taking unsettled (Wake et al. 2020).

Economists have observed that insurance behaviors across product types imply extremely high levels of risk aversion that are inconsistent across markets (Barseghyan et al. 2011), theorizing that misperceptions of risk explain insurance behaviors (Barseghyan et al. 2013, Beshears et al. 2018, Zeckhauser and Cutler 2004), but have not identified the mechanisms to explain how these perceptions arise. One study links risky lifestyle behaviors, such as smoking, drinking and seat belt use, as a proxy for risk tolerance to insurance data across five insurance markets, citing that risk preferences – not risk exposures - may explain why people with lower mortality are generally over-insured (Cutler et al. 2008).

While several studies have acknowledged that affect is an important factor in insurance decisions (Hsee and Kunreuther 2000, Johnson et al. 1993, Kunreuther and Pauly 2014), research documenting the influence of emotion at the time of the purchase decision is limited. Loss framing activates strong emotion (De Martino et al. 2006), loss-aversion has been shown to drive extended warranty purchases (Jindal 2015) and loss-framed insurance may command higher willingness to pay than gain-framed gambles (Mano 1994a) so it stands to reason that heightened concern after salient, catastrophic loss would increase demand for insurance (Schade et al. 2012). We submit that incidental anxiety – felt at the time of the decision and perhaps unrelated to financial exposures - may also play a role in shifting people's willingness to take chances and thus influence insurance behaviors. In so doing, these unrelated anxieties negatively affect the way people feel about their choices, which may have long-term implications for providers (Shell and Buell 2019).

Further, we seek to develop insights that help companies design digital environments that neutralize the effects of anxiety and improve service satisfaction. Research suggests that improvements in service quality perceptions can be found by just including the idea of human presence in online settings (Aslanzadeh and Keating 2014). For example, incorporating human images in a shopping website have been found to engender feelings of trust (Cyr et al. 2009) and simply providing anxious decision-makers with the ability to chat with others improved choice satisfaction without them having to use the feature (Shell and Buell 2019).

Interventions that provide information about peer decisions have been shown to affect decision-making, but the results have been mixed (Schultz et al. 2007, 2018). In financial matters, social information may backfire – using peer information as a benchmark for what people ought to do may have a different effect than simply providing information on what peers decided (Greenberg and Hershfield 2018). In a field experiment, for example, Beshears et al. (2015) show that providing information about how much peers save for retirement may have discouraged non-savers from beginning to save. Scholars recognize that the underlying mechanisms driving these diverging outcomes are not well understood and suggest that the context within which social norm interventions are tested may explain the divergent outcomes (Hauser et al. 2018). Building on the observed use of social norms messaging in the online distribution of add-on insurance products like travel insurance, car rental insurance and extended warranties, we include an exploratory test of the influence of social information in a high-anxiety choice environment.

3. Presentation of Experiments

3.1 Experiment 1: Anxiety and Risk Attitudes

In our initial study, we show that exogenously-induced anxieties can influence attitudes toward financial risks. In a between-subjects design, we randomly assign participants to watch a short video designed to manipulate emotion before completing a risk tolerance questionnaire that is much like risk profile questionnaires that are used in practice.

3.1.1. Participants. 102 participants were recruited on Amazon MTurk to watch a video and complete a short decision-making study in exchange for a $0.10 participation fee with a bonus drawing opportunity for payments ranging from $0 to $3.50. The target sample size was chosen with the goal of capturing at least 30 observations per condition after exclusions. To maximize our emotion induction, we exclude participants in the lowest quartile of video watch time since we did not force participants to watch the videos. We apply this quartile-based exclusion criteria to both treatment and control groups. Our final dataset consisted of 77 observations (M_{age} = 31.80 ; Female = 38.61%).

3.1.2.Design and procedure. Participants were randomly assigned to one of two conditions: anxiety or neutral. In the anxiety condition (N = 36), participants watched a 3 ½ minute clip of the opening scene from the movie Vertical Limit (Brooks and Schweitzer 2011), where a family is faced with an intense moral dilemma after a mountain climbing accident. In the neutral condition (N = 43), which serves as our control group, participants watched a video clip of equal length from a National Geographic documentary about the Indian Ocean. Participants are next asked to write a few sentences that describe the video that they watched in detail. This serves as both an attention check and a way to reinforce the emotion induction.

After rating their levels of anxiety and calm, participants complete a risk tolerance questionnaire which asks them to indicate how they would respond to a series of hypothetical financial scenarios. For example, an item asks participants whether they would invest in stocks, bonds or cash if they unexpectedly received $20,000 to invest. Participants are paid a completion bonus to ensure effort.

3.1.3.Manipulation check. The six-item Short-Term Spielberger State-Trait Anxiety Inventory ("STAI") (Marteau and Bekker 1992) was used to measure whether self-reported levels of anxiety were higher in our treatment group than in our control group. Ratings of "calm", "content" and "relaxed" are reverse-coded, averaged and rescaled and then added to the average rating of "worried", "tense" and "upset" so that the average rating of anxiety ranges from 1 (low) to 7 (high). **Figure 3.1** shows that participants in the anxiety condition reported feeling almost twice as much anxiety than those in the control condition ($M_T = 4.01$, $SD = 1.43$ vs. $M_C = 2.14$, $SD = 1.03$; $t(77) = -6.76$, $p < 0.01$).

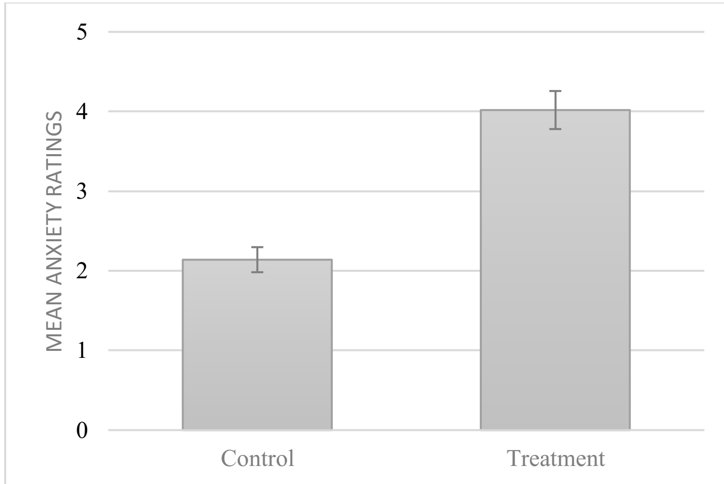

Figure 3.1: Manipulation Check

3.1.4.Dependent measures. We measure risk attitudes using the thirteen-item Grable and Lytton Risk Tolerance Questionnaire (Grable 1999). Like assessment tools commonly used in the financial services industry, this questionnaire uses easy-to-understand scenario-based questions to assess three dimensions of general risk-taking: 1) investment risk, 2) risk comfort and experience and 3) speculative risk.

3.1.5.Control measures. We control for demographic variables: age, gender, income and education levels that might affect risk attitudes (Cochran et al. 2011). Means comparison tests show that our treatment and control groups were balanced across these characteristics (*p's* > 0.29) with the exception of gender, which was had a marginally significant difference (p = 0.10). For this reason, coupled with the fact that gender has been a widely investigated determinant of risk attitudes (Filippin and Crosetto 2016), we only report the results of controlled estimations.

3.1.6.Results. A controlled OLS regression estimate with robust standard errors in **Table 3.1** shows that our treatment, watching an anxiety-inducing video clip, caused participants to become more conservative in their attitudes toward economic risks (β= -2.20 , p <0.05). This demonstrates that background anxieties, such as those that might arise from wading through complex options in an isolated self-service environment, may be intense enough to affect the way that people respond to questionnaires that providers often use to determine comprehensive investment advice. Next, we investigate whether this link between situational anxiety and risk perspectives carries through to choices with real consequences.

	Risk Tolerance
Treatment	-2.202**
	(0.983)
	Includes Control Variables
Constant	26.994***
	(2.461)
Observations	77
R-squared	0.223

Table 3.1: Unrelated anxiety manipulation lowers financial risk tolerance.
Model controls for age, gender, income, education, and was estimated with robust standard errors. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

3.2. Experiment 2: Risk Tolerance, Social Presence and Insurance Take-Up

Building on this initial study showing that induced anxiety lowers risk tolerance, we show that the change in risk tolerance, measured by a hypothetical questionnaire, extends to risk avoidance when faced with real consequences, and we test whether a simple social norm intervention, often used in practice, exerts any influence.

3.2.1. Participants. 150 participants were recruited on Amazon Mechanical Turk to participate in an academic study about online assessments in exchange for a \$1.00 participation fee and entry into a 50/50 drawing for a \$0.50 bonus. Participants that failed our attention checks were dropped, leaving us with a sample of 142 participants for analysis (M_{age} = 35.97 , 47.89% Female).

3.2.2. Design and Procedure. Building on the design of our initial study, we designed a 2X2 laboratory experiment in order to first test whether anxiety's effect on risk tolerance extends to risk-taking and then to determine whether and how social information exerts an influence.

After an instruction screen which informs them about the bonus payment, participants were randomly assigned to watch an anxiety-inducing video clip (*N* = 70) or a neutral video clip (*N* = 72). Immediately after the video ends, participants answered a risk tolerance questionnaire. Emotion was measured and then participants were randomly assigned to one of two versions of a bonus offer. In the "No Social Presence" condition (*N* = 78), participants were asked whether they would be interested in foregoing the drawing in favor of a fixed payment. Because the gamble and fixed payment have an equivalent expected value, participants that accepted the trade would be exhibiting risk-seeking behavior. Participants assigned to the Social Presence treatment (*N* = 64) received the same bonus offer with additional text that says "Over 97 people like you will have considered this opportunity today" **(Figure 3.2).** After they made their decision, we again measured emotion. Finally, participants completed an exit survey where they were asked about decision satisfaction and they submitted demographic information before the drawing is conducted and they received final confirmation of their bonus payment.

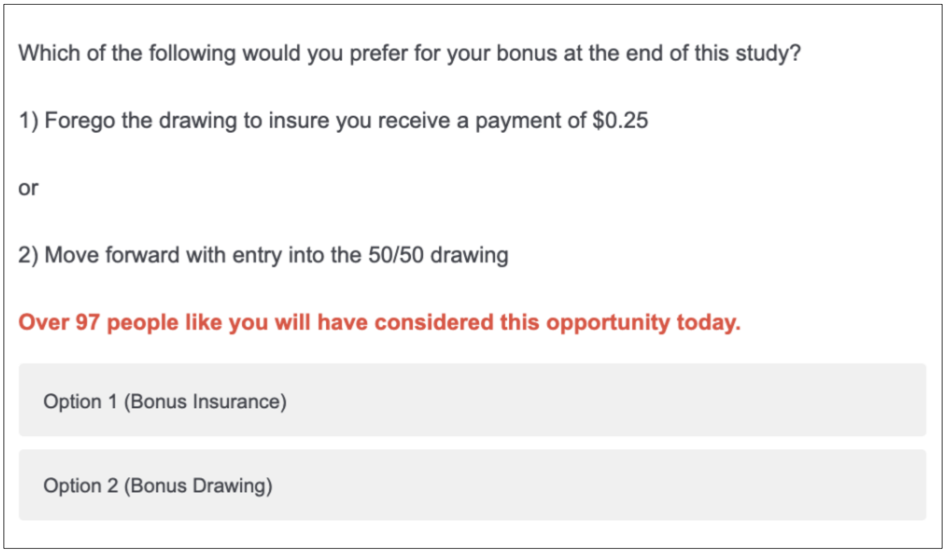

Figure 3.2: Social Presence Manipulation

3.2.3. Manipulation Check. The six-item Short-form Spielberger State-Trait Anxiety Inventory ("STAI") (Marteau and Bekker 1992) instrument was used to measure anxiety and as a manipulation check to ensure that feelings of anxiety were indeed more prevalent in the anxiety condition. Ratings of "tense", "worried" and "upset" were averaged and added to averaged and reverse-coded ratings of "calm" relaxed" and "content". When administered as a manipulation check, participants are asked to report how they feel right at that moment whereas when administered as a dependent measure, participants are asked to report their feelings "as they reflect on the decision you just made". The choices are randomized each time the questionnaire is presented.

3.2.4. Dependent Measures.

Risk Tolerance. As in Study 1, we use the Grable and Lytton Risk Tolerance (Grable 1999) to measure financial risk tolerance, but for the sake of parsimony, we only ask six of the original thirteen questions, two from each of the three components of risk.

Insurance Decision. Participants are asked to choose which option they prefer, "Forego the drawing to insure you receive a payment of $0.25" or "Move forward with entry into the 50/50 drawing". In contrast to many studies of risky decisions, we contextualize the decision by specifically label the choices as an "insurance" option and a "drawing" option in order to make an insurance framing salient. An indicator variable reflects whether participants choose the insurance option.

Choice Satisfaction. Participants are asked, on a 1 (Extremely Dissatisfied) to 7 (Extremely Satisfied) scale to report "how satisfied are you with your bonus choice?"

3.2.5. Control Measures. In addition to asking about demographic information that is commonly associated with risk-taking (age, gender, income level and education level), we also ask about factors that have been shown to influence risk tolerance and insurance in the field: a categorical variable for marital status and a binary variable to indicate the presence of dependent children in the household (Chew et al. 2018, Roussanov and Savor 2014). Age is assessed by open-response and an indicator variable is used for female. Income and Education are assessed with categorical variables. Means comparison testing reveals that there is a statistically significant gender difference between two of the six treatment cells ($p < 0.01$), so we only report results of controlled regression estimations.

3.2.6. Results. Using OLS regression estimations with robust standard errors, we begin our analysis by checking that our anxiety manipulation indeed elevated participant anxiety. In **Table 3.2**, Column 1, we see that our manipulation worked. Participants that were randomly assigned to our anxiety treatment video reported higher levels of anxiety ($\beta = 0.45$, $p < 0.05$). Column 2 shows that the effect holds after controlling for risk tolerance, which is assessed before anxiety is measured ($\beta = 0.49$, $p < 0.05$).

	(1) Pre-Decision Average Anxiety	(2) Pre-Decision Average Anxiety
Risk Tolerance Score		0.019
		(0.039)
Anxiety Treatment	0.453**	0.491**
	(0.226)	(0.227)
	---- Includes Control Variables ----	
Constant	3.673***	3.354***
	(0.690)	(0.936)
Observations	142	141
R-squared	0.166	0.169

Table 3.2: Manipulation check succeeds after controlling for risk tolerance.
Model controls for age, gender, income, education, and was estimated with robust standard errors. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

In **Table 3.3**, we replicate and extend our results from Study 1. Column 1 shows that our anxiety treatment of having participants watch a video clip about a mountain climbing accident, results in lower financial risk tolerance scores ($\beta = -1.19$, $p < 0.05$). The result of a logit regression in Column 2 shows that risk tolerance and the likelihood of accepting the insurance offer have a negative relationship ($\beta = -0.13$, $p < 0.05$). In other words, a lower risk tolerance score increases the likelihood that a participant would choose to forego the status quo gamble and take our offer of bonus insurance. Controlling for the level of anxiety reported, in Column 3, we see the risk tolerance remains the primary driver of the decision ($\beta = -0.14$, $p < 0.05$). Finally, when we look at how participants felt about their decision to insure payment or accept risk, we see that those that took insurance, and thereby reduce uncertainty, were marginally more likely to be satisfied with their choice ($\beta = 0.41$, $p < 0.10$) in Column 4. A means comparison test confirms that those that take insurance experience a significantly larger reduction in anxiety than those that did not (M_{Insure} = -0.37 vs. M_{Gamble} = -0.01 ; $t(140) = 2.51$, $p < 0.05$) owing to uncertainty reduction. In Column 5, we see that the decision to accept the insurance offer continues to have a positive effect on choice satisfaction even after controlling for the significant effect of remaining anxieties ($\beta = 0.36$, $p < 0.10$). We also corroborate evidence of a significant negative link between anxiety and choice satisfaction ($\beta = -0.32$, $p < 0.01$) that has been observed in other studies (Shell and Buell 2019).

In **Table 3.4**, we see that the pathway of interest that we observed in Table 3.3 is unaffected by the social presence manipulation. Columns 1 and 2 show the impact of social presence on the likelihood of accepting the insurance offer without ($\beta = -0.36$, p = NS), and with including ($\beta = -0.39$, p = NS) the interaction with our anxiety treatment, which has a negligible effect ($\beta = 0.05$, p = NS). Column 3 shows that the main effect of social presence on choice satisfaction is insignificant and minimal ($\beta = 0.04$, p = NS). Column 4 controls for the interaction of social presence and our anxiety treatment ($\beta = -0.52$, p = NS). Because of the strength of the relationship between choice satisfaction and post-decision anxiety observed in Table 3.3, we estimate the determinants of post-decision anxiety in Columns 5, observing that pre-decision anxiety ($\beta = 0.76$, $p < 0.01$) and the decision to accept the insurance offer ($\beta = -0.27$, $p < 0.05$) were the strongest influences. Column 6 shows that post-decision anxiety was not driven by our manipulations.

	(1) Risk Tolerance	(2) Likely to Accept Insurance	(3) Likely to Accept Insurance	(4) Choice Satisfaction	(5) Choice Satisfaction
Pre-decision Anxiety			0.160		0.020
			(0.152)		(0.112)
Post-decision Anxiety					-0.317***
					(0.116)
Risk Tolerance		-0.131**	-0.136**	-0.045	-0.038
		(0.065)	(0.066)	(0.034)	(0.034)
Accept Insurance				0.406*	0.357*
				(0.209)	(0.200)
Anxiety Treatment	-1.191**	-0.435	-0.520	-0.014	0.121
	(0.583)	(0.392)	(0.402)	(0.204)	(0.208)
Age	-0.032	0.009	0.009	-0.006	-0.008
	(0.028)	(0.019)	(0.020)	(0.010)	(0.009)
Income Level 2	0.679	0.599	0.694	1.242***	1.078***
	(1.110)	(0.784)	(0.781)	(0.343)	(0.393)
Income Level 3	0.583	-0.186	-0.043	1.077***	0.824**
	(1.112)	(0.799)	(0.797)	(0.319)	(0.363)
Income Level 4	0.385	2.942**	3.272***	1.528***	1.004*
	(1.257)	(1.175)	(1.219)	(0.478)	(0.523)
Income Level 5	0.530	1.067	1.200	0.801*	0.347
	(1.239)	(1.065)	(1.036)	(0.453)	(0.498)
Income Level 6	-3.042	0.000	0.000	1.336***	1.391*
	(2.729)	(0.000)	(0.000)	(0.494)	(0.663)
Education Category 2	0.779	-0.953	-0.951	-0.567	-0.518
	(0.939)	(0.696)	(0.695)	(0.358)	(0.314)
Education Category 3	0.896	-0.062	-0.137	-0.113	0.153
	(0.788)	(0.524)	(0.526)	(0.222)	(0.199)
Education Category 4	-1.187	0.107	-0.006	-0.536	-0.327
	(0.934)	(0.724)	(0.718)	(0.359)	(0.350)
Female	-1.566***	-0.637	-0.675*	-0.031	-0.030
	(0.583)	(0.405)	(0.408)	(0.202)	(0.191)
Dependent Children	-0.111	0.442	0.482	0.255	0.162
	(0.683)	(0.510)	(0.518)	(0.250)	(0.239)
Marital Status Category 2	-1.028	-1.715	-1.712	-0.414	-0.605*
	(1.220)	(1.300)	(1.326)	(0.393)	(0.342)
Marital Status Category 3	-1.254*	0.065	0.136	-0.218	-0.366
	(0.697)	(0.500)	(0.508)	(0.245)	(0.229)
Constant	14.642***	1.264	0.782	5.240***	6.220***
	(1.372)	(1.453)	(1.514)	(0.685)	(0.781)
Observations	141	139	139	141	141
R-squared	0.148			0.190	0.280

Table 3.3: A series of OLS and Logit regressions sheds light on a pathway of influence from incidental anxiety to choice satisfaction through shifted financial risk tolerance.
Regressions estimated with robust standard errors. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

	(1) Likely to Accept Insurance	(2) Likely to Accept Insurance	(3) Choice Satisfaction	(4) Choice Satisfaction	(5) Post-Decision Anxiety	(6) Post-Decision Anxiety
Social Presence	-0.364	-0.386	0.039	0.296	0.198	0.023
	(0.397)	(0.587)	(0.208)	(0.299)	(0.140)	(0.173)
Anxiety Treatment	-0.520	-0.541	0.121	0.370	0.085	-0.084
	(0.403)	(0.540)	(0.208)	(0.303)	(0.140)	(0.191)
Anxiety X Social Presence		0.045		-0.517		0.350
		(0.834)		(0.398)		(0.280)
Accept Insurance			0.359*	0.367*	-0.272**	-0.274**
			(0.200)	(0.199)	(0.130)	(0.129)
Pre-Decision Anxiety	0.159	0.160	0.023	0.005	0.755***	0.758***
	(0.153)	(0.152)	(0.113)	(0.115)	(0.054)	(0.052)
Post-Decision Anxiety			-0.321***	-0.304**		
			(0.122)	(0.125)		
Risk Tolerance	-0.135**	-0.135**	-0.039	-0.036		
	(0.066)	(0.066)	(0.034)	(0.034)		
	--- Includes Control Variables ---					
Constant	0.993	1.003	6.202***	6.039***	0.748*	0.825*
	(1.585)	(1.611)	(0.755)	(0.730)	(0.429)	(0.446)
Observations	139	139	141	141	142	142
R-squared			0.280	0.290	0.703	0.707

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: The social presence manipulation did not affect our main pathway of interest.
OLS and Logit regressions estimated with robust standard errors. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

4. Concluding Remarks

This paper builds upon prior research on the role of negative emotion in economic decisions to shed light on a causal pathway examining links between incidental anxiety and risk-aversion, contributing to our understanding of inconsistency in risk decisions. We show that anxiety does not have to be related to the future loss or focal risk in order to influence economic decisions. Anxiety from any source may activate risk avoidant choices in a financial domain – with deleterious effects on service satisfaction if left unabated. Although companies often use social norms in an attempt to persuade customers to purchase a variety of insurance-related products, we find no evidence that they are effective in influencing either choices or affect.

Understanding the various influences that drive people to accept or to hedge known risk exposures may inform the design of choice environments. One obvious application is to insurance distribution, which is currently experiencing massive investment in digitalization (Catlin and Lorenz 2017). More broadly, this research offers insight to employers considering ways to encourage higher levels of retirement savings or public health advocates aiming to increase vaccination uptake, among others. Background emotion, whether related to the decision or not, may spillover to shift our willingness to accept risks -- and may have lasting effects.

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APPENDICES

A1: Instructions for the Expert Role

You may cut and paste from the information provided below as necessary to answer participant questions.

Click on the tabs on the header bar of the application to move through the tool.

Your Portfolio Tab

Here you are given information about your current balance, how the balance is divided among the investment choices and how the funds – as well as your overall portfolio – performed in the prior periods.

We provide investment commentary explaining what happened in the economy to affect the investment performance of each fund in the immediately preceding round.

Research Tab

You can learn about the characteristics of each investment choice by clicking on the Research tab, but are not required to do so in any round.

With each round, the historical performance and performance characteristics of stocks, bonds, and cash are updated.

Definition of Terms

Average Annual Return – If you put $1 into the fund 20 years ago and held it since, your $1 invested would be worth some amount now. We use that growth to determine the average annual return. Even though the fund return for any individual year within the history may be positive or negative, over the entire time period, the gains outweigh the losses to result in an average annual return over time.

Standard Deviation – Standard deviation is a measure of how spread out the annual returns for a fund are from its long term average. A higher standard deviation means that the return history is more widely spread from the average, while a lower standard deviation means that the returns are more narrowly spread.

Best / Worst Returns – Looking across the prior 20 years, the highest and lowest annual return for the fund.

Percentage of up periods – Looking across the prior 20 years, this shows the percentage of years with a positive, non-zero return.

Take Action Tab

On the Take Action Tab, you enter your investment decisions. You may choose to allocate any percentage of their portfolio from 0 to 100% to each of the investment choices. You do not have to make an allocation to all investments. In other words, you could allocate 0% to one or two funds, but the allocation decisions across the three funds must total 100%.

Once you submit your choices for a given round, your results are locked in for that round. Each investment will generate a return, which may be positive, negative or zero in that round.

After each round, the tool will take you back to the *Your Portfolio* tab where you will see the results of your previous choices.

This begins a new round, where you have the opportunity to change your allocations if desired. If you do not wish to make any changes, you may simply click the “Submit Allocation” button. Note that any allocation changes will apply to future rounds only and do not affect previous performance.

A2: Predictors of Chat Feature Use

As described in Section 3.2.6, a logistic regression modelling the choice to pursue human contact, if offered, as a function of the full panel of control variables used in Study 2 showed that the greatest and only statistically significant predictor of whether a participant would take advantage of the option to chat was how anxious he or she felt before beginning the investment simulation ($\beta = 0.74$, $p < 0.01$). This result, which is shown in **Table A.1**, dovetails with the earlier finding that access to human contact is beneficial to customers who are experiencing low levels of anxiety associated with the service task itself – hinting at the potential for a broad array of firms to improve customer experiences through the integration of human access in their self-service offerings.

	Attempted Chat
Pre-Treatment Anxiety	0.743***
	(0.281)
Pre-Treatment Calm	0.127
	(0.151)
Age	-0.127
	(0.140)
Income Level	-0.128
	(0.106)
Education Level	0.096
	(0.468)
Female Indicator	-1.042
	(0.780)
Relative Underperformance	-3.165
	(3.570)
Constant	-3.162
	(3.272)
Observations	144
Pseudo R-squared	0.193

Table A. 1: The likelihood that a participant would take advantage of the chat feature if offered is best predicted by the extent to which he or she reported pre-existing anxiety (Experiment 2).
All models are estimated with logistic regression, and robust standard errors are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

A3: Ex-Post Study of Effects of Transparency on Anxiety

Although one may reasonably expect to have their creditworthiness evaluated when applying for a loan, we hypothesize that making participants aware of the fact that they were being evaluated at the time that the evaluation was occurring may have amplified the anxiety customers experienced during the loan application process we studied in Experiment 3 (Zeidner and Matthews 2005). Since we could not practically administer a manipulation check during our field experiment without substantively impacting customer experiences, we designed an ex-post experiment to replicate the emotional experience of being transparently evaluated on a consequential task. Participants completed a three-part financial literacy quiz used in prior academic studies (Lusardi and Mitchell 2017, van Rooij et al. 2011). Between modules, those in the treatment cell and were made aware that their answers were being evaluated, while those in the control cell were simply asked to wait for the next set of questions to load.

A.3.1 Participants. 224 participants (M_{age} = 36, 43% Female) were recruited on Amazon Mechanical Turk to complete the financial literacy test and answer questions about their experience. To insure incentive compatibility, participants were paid \$1.00 for their participation and a \$0.50 cash bonus for scores of 75% or higher.

A.

B.

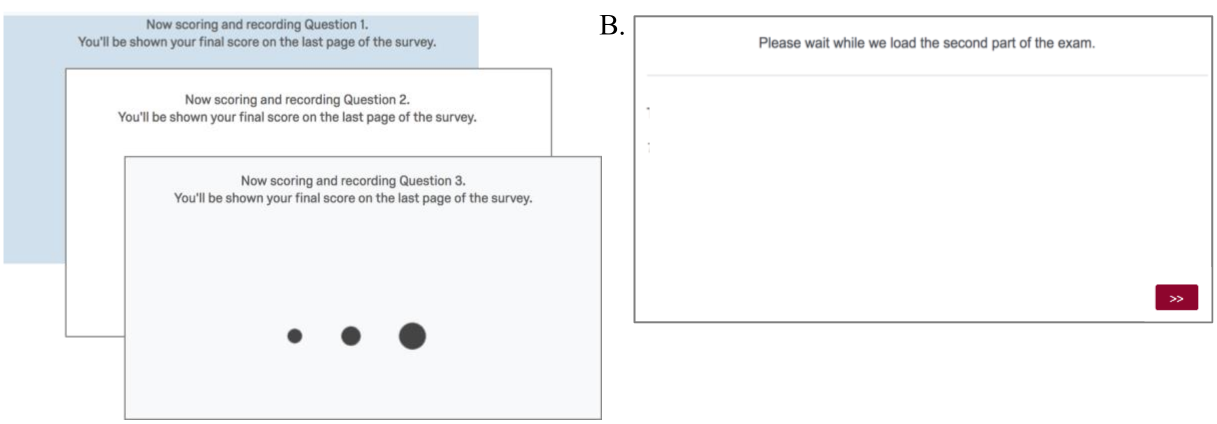

Figure A. 1: Screenshots of the participant experience.
Panel A depicts “Scoring Process Transparency”. Panel B shows the wait screen shown to our control group.

A.3.2 Design and Procedure. We primed participants to expect a high rate of failure on the test by reporting that "Studies have shown that many Americans are poorly educated about important financial topics", that "only half of Americans over the age of 50 can correctly answer two simple questions about compounding interest and inflation" and " less than one-their of those under 30 understand these topics" (van Rooij et al. 2011). **Figure A.1** shows our anxiety manipulation. In our treatment condition, ("Scoring Process Transparency") we reminded participants that we were evaluating their test performance and recording their scores. In our control version, we simply asked participants to wait while the next module of the exam was loaded. We designed the flow so that the treatment and control groups experienced the same wait duration between modules. In both cases, test scores were revealed at the end of the survey.

A.3.3 Dependent Measure. As in our previous laboratory studies, we administered the STAI to measure participant anxiety. Since *Reported Anxiety* was our primary outcome of interest for this study, we measure anxiety levels once, at the end of the experiment but before revealing final test scores.

A.3.4 Control Variables. We included demographic controls (age, income, gender, education), as in our previous lab studies, and controlled for *test score* in order to avoid any confounding effects that may have arisen from participants' test performance expectations.

A.3.5 Analysis and Results. In **Table A.2**, we model Reported Anxiety as a function of our treatment condition as well as a vector of controls, as described above. Column 1 demonstrates that our manipulation was effective in stimulating participant anxiety ($\beta = 1.47$, $p < 0.01$). Column 2 shows that the effect remains significant ($\beta = 1.46$, $p < 0.01$), after controlling for test score, which was also a significant predictor of anxiety ($\beta = -0.24$, $p < 0.01$) in that higher scoring participants were less anxious. Finally, in the fully-specified model in Column 3, we see that the size and significance of scoring process transparency remains ($\beta = 1.44$, $p < 0.01$).

	(1) Reported Anxiety	(2) Reported Anxiety	(3) Reported Anxiety
Scoring Transparency	1.473*** -0.487	1.456*** -0.479	1.440*** -0.487
Test Score		-0.240*** -0.073	-0.203** -0.087
Age			-0.015 -0.024
Female Indicator			-0.485 -0.505
Income Level			-0.009 -0.116
Education Level			-0.098 -0.271
Constant	-5.509*** -0.305	-2.618*** -0.936	-1.773 -1.351
Observations	224	224	224
R-squared	0.04	0.078	0.084

Table A. 2: Scoring transparency induces anxiety (Ex-post Manipulation Test for Experiment 3).
All models are estimated with OLS regression and robust standard errors are shown in parentheses. *, **, and ***, signify significance at the 10%, 5%, and 1% levels respectively.

Taken together, these findings suggest that customers using the self-service loan application process, who received transparent updates as their loan application was evaluated and considered, likely felt elevated levels of anxiety, consistent with the experiences of participants in the investment simulation utilized in Experiments 1 and 2. Considered in that light, the result that increasing access to human contact led to a significant increase in loan acceptance by customers whose applications were approved provides converging evidence of our intervention's capacity to enhance customer experiences and service relationships in high-anxiety service settings.