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Nudging the Digital Pirate: Piracy and the Conversion of Pirates to Paying Customers
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NUDGING THE DIGITAL PIRATE:
PIRACY AND THE CONVERSION OF PIRATES TO PAYING CUSTOMERS

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To my incredible wife Allison and our three dynamic boys,
Matthew Jr., Morgan, and Mason.

Your unconditional love, support, and encouragement, never ceases to amaze me.

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ABSTRACT

Hashim, Matthew J. Ph.D., Purdue University, December 2011. Nudging the Digital Pirate: Piracy and the Conversion of Pirates to Paying Customers. Major Professors: Karthik N. Kannan and Jackie M. Rees Ulmer.

Digital piracy is a significant source of concern facing software developers, music labels, and movie production companies. The current legal and technological strategies for mitigating the piracy problem have been largely unsuccessful, as firms continue to invest in litigation and digital rights management technologies to thwart piracy. Their efforts are quickly defeated by hackers and pirates, motivating the behavioral approach taken in this dissertation. In Chapter 2, we consider the common argument from digital media producers and government entities that there are victims of piracy, whereas pirates may perceive their actions to be victimless. Because of the victimless view, in certain circumstances, perceived moral obligations may become important determinants of piracy behavior. In particular, we theorize that attitudes and social norms could influence perceptions of moral obligation as a consequence of the desire to rationalize unethical behavior. We also identify circumstances under which exogenous nudging from a software company can influence the impact of perceived moral obligations on intentions to pirate. Initial purchase and piracy conversion settings are compared to document when the salient constructs become relevant to the potential pirate.

In Chapter 3, we explore the role of information targeting and its effect on coordination in a multi-threshold public goods game. We consider four treatments, three in which we give feedback about other member's contributions to a subsample of group members, and another treatment in which feedback is not provided at all. Our three information treatments vary in whom receives the information, which can be given randomly, to those whose contributions are below the average of their group,

or to those whose contributions are above the average of their group. Results show improvements in coordination when information targeting is used, leading to an increased contribution to the public good. In contrast, providing information randomly does not improve coordination. Moreover, our random information treatment approximates strategies currently used in practice for educating consumers about business problems such as digital piracy. Thus, our findings provide insights that may be used in practice to enhance education and marketing strategies for reducing the digital piracy problem. The implications of this research may also be employed by management in other contexts where positively or negatively affecting coordination between consumers is of interest.

Consumers receive advice from various sources before making consumption decisions. In Chapter 4, we conduct a laboratory experiment using parents and teenagers as the subject pool, bringing a sample of potential pirates and their parents to the experimental laboratory. Experimental treatments are differentiated by the source of the advice regarding the piracy decision, and subjects make their decisions playing our new experimental game – the piracy game. The results are quite intriguing as subjects do respond to advice, albeit in a temporary fashion. Similar to the results described in Chapter 2, increasing moral saliency assists in mitigating piracy, especially when the source of advice is the subject’s parent.

Overall, this dissertation explores the role of various types of information in impacting purchasing and pirating decisions. We find that pirates may view their actions to be victimless, but this behavior can be mitigated by sending morally-salient information to the pirate. The piracy problem may also be mitigated by carefully targeting information to groups of consumers, rather than taking a blanket approach to informing the population of the piracy problem. Lastly, pirates are receptive to advice about their behavior from sources with whom they have a greater social tie, suggesting the need to carefully consider information delivery channels.

1. INTRODUCTION

The piracy of digital goods impacts many stakeholders in the digital media landscape. Media producers claim to suffer exorbitant losses from rampant piracy, governmental agencies concern themselves with monetary and legal issues, and pirates exhibit a general lack of regard for property ownership. Many technical and legal strategies have been deployed to mitigate the piracy problem, but industry trends and the extensive adoption of peer-to-peer file-sharing suggest that the piracy problem will continue to grow into the future.

This dissertation examines digital piracy from a different perspective than much of the prior literature. The role of information in mitigating the piracy problem using behavioral techniques is examined in this research, allowing us to develop an understanding of the impact of various strategies in affecting piracy. The research presented in this dissertation contributes substantial knowledge to the literature and implements interdisciplinary links between information systems, social psychology, and behavioral economics.

The first study presented in Chapter 2 introduces and tests the notion that digital pirates may consider their acts to be victimless. Digital goods producers of course would disagree with this notion, and in fact claim that there are many victims of this type of crime. We introduce a mediation effect to an existing path model to provide a theoretical contribution to the literature. In our model we show that pirates allow their morals to be influenced by other behavioral factors, providing support for the victimless crime argument. The role of information approach is implemented in this chapter by examining the moderating effect that sending a morally-salient message has on some subjects, mitigating to some extent the influence of other factors on moral obligations.

We introduce experimental economics as a method in studying the role of targeted information in Chapter 3. Many digital goods producers inform their consumers via various communication channels (e.g., press, blogs, etc.) about the rate of piracy that they face in their businesses. Communicating information in this type of random manner to consumers is common among many business contexts in addition to the software, movie, and music industries. In contrast to what is actually used in practice, we show that targeting information to specific groups of consumers is a significantly better strategy in mitigating the type of problems that are faced under contexts such as piracy.

The last study presented in Chapter 4 of this dissertation considers the source of advice in mitigating the piracy problem. Pirates may receive advice about their actions from various sources, and we integrate several of these sources in an experimental framework. In particular, we seek to understand the role of advice when it is received from a strong figure such as a parent, when it is received from a record producer, and when it is received from a third party such as a regulator. We use teens as a novel subject pool to conduct this research, increasing the applicability of the results in developing real strategies to mitigate piracy. Sending advice to pirates about their behavior does have a measurable impact in the experimental setting, especially when the source of the advice has a social tie to the child receiving the advice.

The chapters in this dissertation represent significant contributions to the literature. We extend the existing knowledge in areas of the literature that were previously undeveloped, and introduce novel theoretical implications and actionable insights for the management discipline. The research presented herein also represents the first use of the experimental economics methodology in piracy research that we are aware of, creating a new path for groundbreaking research in the future.

2. A CENTRAL ROLE FOR MORAL OBLIGATIONS IN DETERMINING INTENTIONS TO ENGAGE IN DIGITAL PIRACY

2.1 Introduction

Piracy is widely believed to be on the rise, fueled by the expansion of access to the Internet and increases in piracy sophistication, among other factors. For example, software piracy in 2009 increased worldwide by over three percent compared to the prior year, extending losses in the market to over \$50 billion dollars in unlicensed business software (BSA, 2010). According to industry groups such as the Recording Industry Association of America (RIAA) and the Motion Picture Association of America (MPAA), the increasing rate of piracy can have a domino effect on the respective industries, resulting in job losses, loss of earnings, and loss of tax revenue, to name a few. Smith and Benoit (2010) also report that employees of digital goods producers and other involved parties may suffer. In contrast, Erat and Gneezy (2010) argue that pirates consider piracy to be a white lie (i.e., a small dishonest behavior) and a victimless crime too small to have an impact on the industry or the producer of the digital good. This paper focuses on how these contradicting perceptions can be taken into account for developing behavioral anti-piracy strategies.

In general, anti-piracy organizations and digital goods producers have undertaken several approaches to mitigate piracy: a technology-based approach (e.g., digital rights management (DRM)), a legal approach (e.g., lawsuits), and an educational/nudging approach (e.g., through engagement with their potential customer base). This last approach is becoming increasingly popular not only to limit piracy but also to convert pirates to paying customers (Pyyny, 2003; Stewart-Robertson,

2010). Naturally this approach has to take into account the behavioral aspects of piracy such as perceptions of piracy as a white lie, which is a focus of our paper.

Our motivation to study the last piracy mitigation approach arose from anecdotal evidence provided by the independent software producer 2D Boy. They consciously pursue the educational/nudging approach. The owners speak openly about piracy with the user community and also educate their consumers about piracy through the use of user-generated content such as blog postings and participation in discussion and support forums (2DBoy, 2008). Their approach to anti-piracy appears to limit new consumers from pirating their product while being quite effective at converting former pirates to paying customers (R. Carmel, personal communication, January 13, 2009). Engaging with their customers in this manner is critical because 2D Boy's software is not protected by DRM. Content producers such as 2D Boy may therefore derive benefit from developing a strategy to educate and consequently "nudge" their customers to consider purchasing rather than pirating the digital good (Carroll, 2008; Graft, 2010).

Although the literature on the behavioral aspects of piracy is extensive, to the best of our knowledge, prior literature has not focused on behavioral aspects of nudging (we expand on this technique in the Literature Review Section). Much of the literature has primarily focused on ethical, economic, sampling, or other dimensions in the intent to engage in piracy. They typically treat piracy as a one-shot "pirate vs. purchase" decision and analyze factors leading to piracy. In contrast, we consider multiple stages of the decision involving not only an initial pirate vs. purchase decision but also potential conversion from pirate to paying customer.

Our "staged" approach allows us to develop a positivist framework by distinctively accounting for the influence of perceptions of piracy as a white lie in explaining a potential consumer's purchase or pirate decision. Specifically, we extend the well-known theory of planned behavior (TPB) and validate a new model that accounts for malleability of morals under conditions that facilitate perception of piracy as a "white lie" type of context. Usually, morals are treated as closely held internal beliefs/values

that are not subject to change. However, in white lie contexts such as those involving so-called victimless crime, morals have been shown to be to malleable (Mazar et al., 2008), wherein individuals may justify the white lie. In one such context – the piracy context – we posit mediating effects of perceived moral obligation in accounting for effects of the individual’s attitude and their subjective norms towards the purchase decision. We use this modified theoretical model to generate a normative contribution through practicable insights for nudging potential consumers. In particular, we show how this moral adjustment may be moderated and therefore nudged through individual communications.

The remainder of this paper is organized as follows. Section 2.2 discusses the relevant literature and introduces our extension of the TPB, Section 2.3 outlines our research model and design, the analysis and results are covered in Section 2.4, and Section 2.5 provides the discussion, managerial implications, and conclusion.

2.2 Literature Review

Our paper relates to different streams of research in information systems (IS), social psychology, marketing, ethics, and economics.

2.2.1 Theories Related to Behavioral Aspects of Piracy

The original TPB as proposed by Ajzen (1985, 1991) has been utilized widely in the literature for studying intentions and predicting behavior under various scenarios, as an extension to the theory of reasoned action (TRA; Ajzen and Fishbein (1980)). Along with the TRA, the original TPB suggested that the key predictor of behavior is intentions to engage in the behavior. Also, within each theory, intentions are predicted by individuals’ attitudes toward the behavior (i.e., overall evaluations of the behavior as relatively good or bad) and subjective norms (i.e., perceptions that important others would want the person to behavior in a certain way). The TPB added the notion that perceptions of behavioral control (i.e., ability to enact the

behavior) can influence the intentions as well as determine whether the intentions direct the behavior (for a review, see Armitage and Conner (2001)). In the context of piracy, Chang (1998) demonstrated that the TPB predicts unethical behavior better than the TRA. Consistent with Chang (1998), Peace et al. (2003) used the TPB in conjunction with deterrence and expected utility theories to explain the intention to commit software piracy. Our paper is different from their work both in the focus as well as the model employed. Whereas Peace et al. (2003) mainly focused on factors leading one to commit software piracy; we focus on piracy conversion and the concept of a white lie. From the model standpoint, they employed the original TPB proposed by Ajzen (1985, 1991) whereas we draw upon the extended TPB from Beck and Ajzen (1991), which was specifically developed to account for dishonest actions and is described below. We also develop a new role for moral obligations that differs from that in Beck and Ajzen (1991).

Morals

Gorsuch and Ortberg (1983) found that, for morally charged situations, including a measure for moral obligation in the TRA better predicted behavior than a model without it. Such types of research motivated Beck and Ajzen (1991) to also include moral obligation as a separate predictor in their extension to the TPB for dishonest actions. Perceived moral obligation in the extended TPB includes a measure for guilt, personal principles, and whether or not a particular behavior is considered morally wrong. Accordingly, this subsection surveys prior research on morals related to our piracy context.

Moore and Chang (2006) developed an adaptation of the moral development model (Rest, 1979) and applied it to software piracy. They found that there is a difference in moral judgment varying with age but not with gender. Based on their analysis, they recommended an ethics training program but did not test its effectiveness in deterring piracy. In a similar vein, Tan (2002) also demonstrated the

usefulness of including moral factors (such as moral intensity, moral judgment, and perceived risks) in the piracy context by using an issue-risk-judgment model. Motivated by the aforementioned studies, which demonstrate the salience of morals in the piracy context, we also consider moral obligation in our model. In our paper, we capture morals in our model by following the measures included in the extended TPB by Beck and Ajzen (1991).

In contrast to the aforementioned studies, Logsdon et al. (1994) concluded that piracy is perceived to be of low moral intensity because pirates have a high level of tolerance for deviant behavior and do not feel guilt for their actions. Thong and Yap (1998) made a similar argument regarding the possible inability of pirates to feel guilt, providing evidence that an ethical decision is influenced by factors other than morals. Such contradicting claims regarding the importance of morals in the piracy context, along with anecdotal evidence treating piracy as a victimless crime, suggests the need to develop a model to better explain the moral aspects of piracy behavior. In order to accomplish that, we employ ideas that allow an individual's morals to be influenced.

The Malleability of Moral Obligations

In this paper, we build on consistency theory and cognitive dissonance theory to explain the malleability of morals. Consistency theory (Cialdini, 1993; Freedman and Fraser, 1966; Heider, 1958) states that an individual may repeatedly continue to engage in an action, even if morally objectionable, because of the desire to be consistent. Moreover, prior research has shown that individuals may change their beliefs to align with their past behaviors (Festinger and Carlsmith, 1959). In particular, cognitive dissonance theory (Aronson, 1969; Festinger, 1957) suggests that when a person holds two cognitive elements that are inconsistent, the person is likely to change one of the cognitive elements. For example, in the Festinger and Carlsmith (1959) research, the research participant was induced to tell a lie to another person and, as long as the

lie was not sufficiently justified by monetary payment, the participant shifted related beliefs so that they support the lie. In a piracy context, given the possible discomfort due to cognitive dissonance, a pirate may lessen their internal cognitive friction by casting piracy as a victimless crime. Specifically, digital pirates may allow their moral obligations to “do the right thing” to be influenced by other considerations that support the piracy behavior.

Although we build on both consistency theory and cognitive dissonance theory to explain why piracy might motivate perceptions of a crime as victimless (adjusting one’s moral obligations), we recognize that prior work on piracy has considered other reasons for what may cause morals to be influenced. For example, Higgins (2005) finds that individuals may engage in piracy as a consequence of low self-control. The reduction in self-control generally results from the temptation to engage in piracy and the individual’s inability to recognize the consequences of their actions. Consistent with our morals-based approach, however, Higgins (2005) and Higgins et al. (2008) also found that moral obligation may be influenced by subjective norms. In our framework, we focus on the malleability of morals driven inherently by the individuals themselves. This focus is in contrast to what has been extensively studied in the literature regarding the external factors leading to malleability of morals (e.g., deterrence theory which argues that formal rules and policies lead to malleability of morals).

2.2.2 The Nudging Technique

Companies can also benefit from the consistency of behavior provided they are able to nudge the pirates to engage in purchase actions (that then continue over time). In general, nudging is used in behavioral economics and public policy contexts to push or influence behavior in a socially-positive direction by modifying norms to be more pro-social (John et al., 2009; Kahan, 2000). Anti-piracy organizations have also begun nudging (e.g., by using education) to inform potential consumers about

the negative impacts of piracy on the digital goods industries (Pyyny, 2003; Stewart-Robertson, 2010). Prior researchers, such as Gopal and Sanders (1997), Moores and Chang (2006), and Higgins et al. (2008), recommended that publishers or policymakers may be able to inhibit digital piracy through education. However, to the best of our knowledge, the effectiveness of nudging in the piracy context has not been explicitly examined, nor has the role of perceived moral obligations in the impact of such nudging on purchase intentions. In our research, we study how pirates may be nudged to follow non-deviant behavior. Specifically, we investigate how an anti-piracy messaging strategy, which is one form of educational strategy, can be used to influence the purchase or pirate decision.

2.2.3 Sampling and Pricing Influences on Piracy

Any piracy research must be cognizant of the influences of pricing and sampling, as high prices and desire to sample a product have each led to piracy in previous research. The importance of the cost of the software and the desire to sample in software piracy decisions have been demonstrated both empirically (Bhattacharjee et al., 2003; Cheng et al., 1997) and analytically (Bhattacharjee et al., 2009; Chellappa and Shivendu, 2005; Sundararajan, 2004). Some of these papers also concluded that sampling creates an opportunity for a future purchase (e.g., Chellappa and Shivendu, 2005). We therefore included design features to limit effects of desire to sample and of perceived software costs in our research.

2.3 Research Model and Design

As highlighted earlier, one of the key contributions of our paper is the further extension of the TPB model proposed by Beck and Ajzen (1991) for illegal activities. Although their model included a measure of actual behavior, we did not include it in our setup for practicality reasons. Because digital piracy is an illegal activity, even if we included the measure, it is quite likely to be biased as subjects participating

in the study may alter their behavior in order to avoid being tracked while performing the illegal activity. Furthermore, evidence of actual illegal behavior may expose research participants to a greater amount of risk than is necessary to perform our study. Therefore, we did not implement a longitudinal study to examine piracy over time, and we are unable to measure the causal relation between intention and actual behavior. The use of intention instead of the actual measure of an illegal activity is common in the literature (e.g., Chang, 1998; D’Arcy et al., 2009; Gorsuch and Ortborg, 1983; Peace et al., 2003), both because of these practical constraints and also because there is a strong relation between intention and behavior in many behavioral domains (Armitage and Conner, 2001).

2.3.1 Theoretical Development and Design

As a first step, we consider the Beck and Ajzen (1991) TPB model for predicting dishonest actions. Figure 2.1 illustrates their research model (including age and gender as the relevant piracy controls). Our desire is to develop an enhanced model to explain the moral aspects of piracy behavior. To do so, we introduce a further refinement of the Beck and Ajzen (1991) TPB model.

Perceived Moral Obligation as a Mediator

Piracy being a victimless crime is a notion that has been supported by the evidence we presented earlier. This notion is consistent with the theory of self-concept maintenance (Mazar et al., 2008), which discusses how honest people maintain their self-concept (as honest people) even while being engaged in dishonest actions as long as they perceive the negative consequences of their actions to be minimal. For pirates who repeatedly engage in the activity, we contend that they minimize cognitive friction (cognitive dissonance) by shifting their perceptions of moral obligations in the domain (e.g., by viewing piracy as a victimless crime, reducing moral obligations to

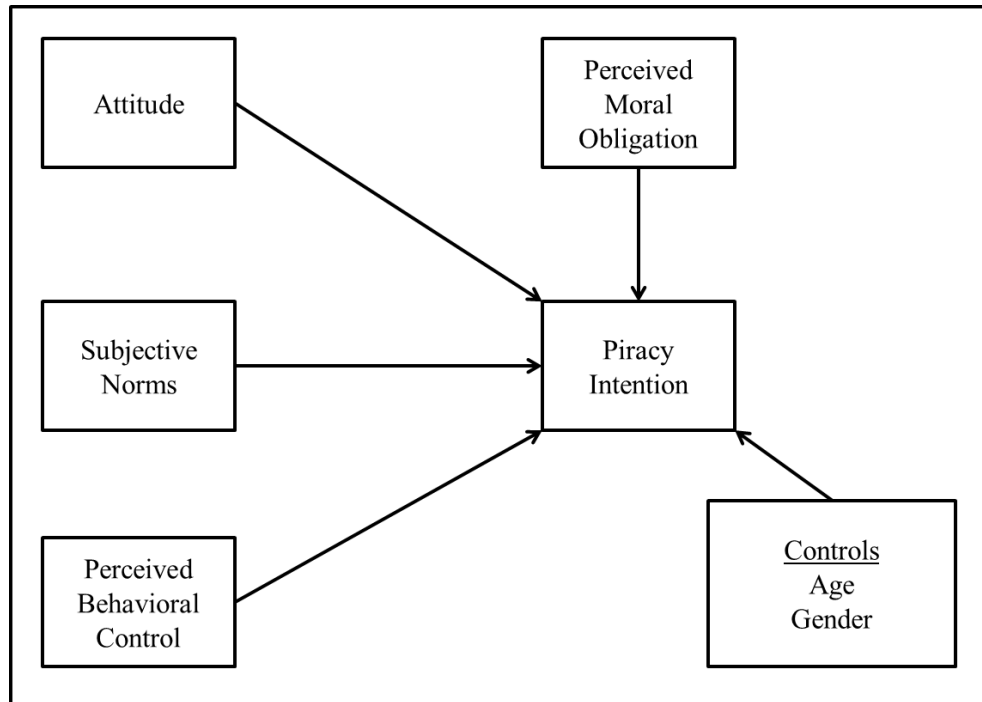


Figure 2.1. The Beck and Ajzen (1991) TPB Model

avoid piracy). Thus, in this context, we believe that morals are not always completely stable and internalized.

Any number of factors may influence morals. Because Beck and Ajzen (1991) have already argued that the constructs within the TPB are the most salient in predicting behavior, we confine the current research to examining how these constructs may influence morals. The theory of self-concept maintenance argues that the temptations to engage in a dishonest action, when they outweigh the potential costs, make the morals malleable. In the TPB, subjective norms and attitudes account for the temptations or reasoning behind the intention to engage in the behavior. However, perceived behavioral control (PBC) does not because that construct is meant to capture the feasibility of whether an individual *can or cannot* engage in the behavior, rather than the reasoning associated with why an individual *should or should not* engage in the behavior.

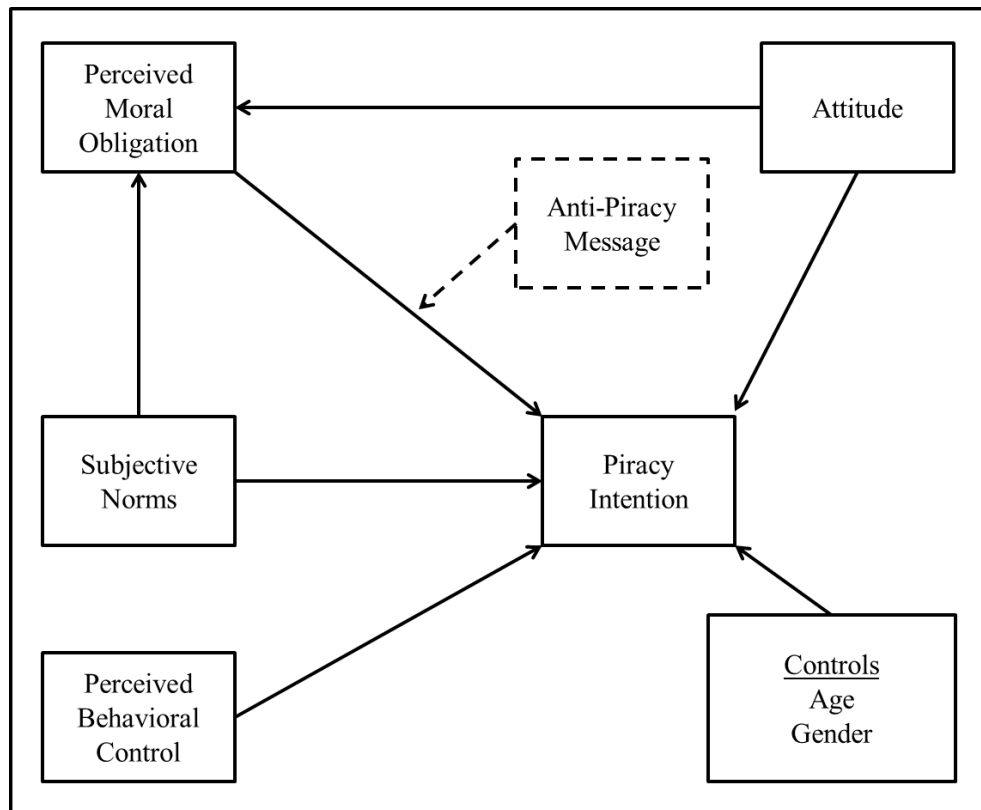


Figure 2.2. Perceived Moral Obligation as a Mediator in our Refined TPB

Hence, we conclude that perceptions of moral obligation in such “victimless crime” contexts should mediate influences of attitudes and subjective norms on behavioral intentions. We, however, continue to maintain perceived behavioral control (PBC) as an independent predictor in the model. In summary, we believe that piracy might be viewed as having fewer negative consequences (and, therefore, as facing weaker moral obligations) when the person’s attitudes and subjective norms support (fail to oppose) piracy. In other words, people who initially feel some moral compunction at pirating software might shift their perceptions of moral obligation to purchase, especially after engaging in piracy and if attitudes, non-moral norms, or both are favorable toward the piracy. Our proposed model illustrating perceived moral obligation as a mediator

is formalized in Figure 2.2. Based on prior literature, we would expect all of the pictured paths from one construct to another to have a positive coefficient.¹

Note that subjects would rationalize unethical behavior primarily if they had previously engaged in unethical behavior. Therefore, we expect to observe the malleability of morals only if they had pirated earlier and not when they had not previously pirated. To address this potential effect, we designed two corresponding scenarios: one where the subjects deal with *an initial purchase decision* and the other where they deal with *a piracy conversion decision*. In the former scenario, the subject is considering pirating a digital good but has not yet engaged in piracy, whereas in the latter scenario, the subject has already pirated and may be a candidate for conversion.

We presented all subjects with both scenarios as the two decisions symbolize the stages of piracy (represented by hypothetical scenarios in our study) in which real consumers may find themselves. We counterbalanced the order in which the scenarios were presented to the subjects, thereby manipulating the standards against which new behaviors are judged. If a subject receives the conversion scenario first, our design integrates the desire for the individual to be consistent with prior piracy behavior, which therefore leads to the desire to adjust their morals to justify their decision. This is a key distinguishing feature of our research in contrast to prior work. Prior literature's focus on piracy has primarily been on the initial pirate or purchase decision, whereas we consider the conversion scenario as well. Because of the design, we can determine if and when the intention to pirate or purchase might change, as well as if and when constructs from the TPB are important to the subject in making their decision. We can also examine potential effects of a desire to remain consistent with prior piracy behavior and the potential mediating role of perceived moral obligations in carrying effects of attitudes and norms to purchase intentions.

¹The only exception is the age control variable as its path should have a negative coefficient.

Nudging in the Piracy Context

In order to study the effect of nudging behavior in the piracy context, we introduced an “anti-piracy” message as a moderator of the role played by moral obligations in the model. The moderator is shown in Figure 2.2 as a dashed path influencing the impact of perceived moral obligations on piracy intentions. As discussed in Section 2.2.2, literature has explored the shifting of morals through nudging. Consistent with that literature, we expected the “anti-piracy” message to moderate the impact of perceived moral obligation on digital piracy intention.

We designed the message to target perceived moral obligation specifically. The wording of the message was aimed to educate subjects about the potential detriments to the company and society from engaging in piracy (BSA, 2010; RIAA, 2010). We examined potential effects of the anti-piracy message on the constructs in our model and on the influences of the constructs on behavioral intentions.² In real life, the message could be delivered by digital goods producers independent of the decisions made by the potential digital pirate. Thus, our design also simulates a realistic yet non-intrusive consumer education technique that represents current efforts by the software and music industry to deter piracy.

2.3.2 Questionnaire Development

We based our measures on previously validated scales and techniques to remain consistent with the literature. We specifically included TPB-related questions modified for the piracy context by Peace et al. (2003) and those measuring perceived moral obligation based on Beck and Ajzen (1991). We used a combination of a between- and within-subject design to study the malleability of morals by employing the two (hypothetical) scenarios (initial purchase and conversion purchase decisions) and the nudging treatment (with versus without an anti-piracy message). Each sub-

²Moderation tests on the impact of other constructs were conducted in the analysis but not presented here. Non-significant moderation of these other influences on piracy intentions is consistent with the message successfully targeting the factor of perceived moral obligation.

ject was provided with a questionnaire having both scenarios and either including the anti-piracy message or not. The sequence of the presented scenarios was randomly alternated to prime the subjects about one particular stage of piracy or the other, as discussed in the prior sub-section.

Throughout the questionnaire, we dealt with scenarios involving the pirating or purchasing of a software application. We believe that the responses will not vary significantly for other digital media contexts, including music, movies, and games, where perceptions of the crime being victimless might be a critical factor.³ Our questionnaire was designed such that, for each of the two scenarios, subjects may or may not observe an anti-piracy message from a fictitious company selling the software. If the subject received a message, it was provided after each scenario and before the intention decision was measured. Because our design was implemented as between-subject, the treatment that did not include the message acted as a control. The anti-piracy (pro-purchase) message stated the following: “Thank you for your interest in XYZ-Soft’s software. Your purchase helps the overall software industry, benefits our employees, increases tax revenue, and reduces job loss. Click here to purchase our software from an authorized retailer.” This latter treatment introduces the “Anti-Piracy Message” construct in our model. By introducing the message, we are interested in determining if management is able to nudge digital pirates to become paying customers.

The two scenarios were different in the following manner. In the piracy conversion scenario, the subject was asked to imagine that s/he had previously pirated and was asked his/her intention to purchase; in the initial purchase scenario, the subject was not told they had pirated previously and was asked his/her intention to purchase. Following the questions for both scenarios, survey respondents were presented with multiple measures from each construct in the TPB (including perceptions of moral obligations to purchase).

³We conducted a pilot study including music and software but did not observe differences between these types of digital content.

The study was designed to control motives to sample and assumptions about pricing by including instructions at the beginning of the survey and within each scenario. The cost of the software was described as being affordable to the subject if they chose to purchase it, making the price relative to each subject.⁴ We also indicated to subjects within each scenario that they did not need to sample before making their purchase decision. The survey was concluded by following prior piracy research and asking participants for their gender and age, as these are considered essential demographic controls for an individual's intention to purchase or pirate (Al-Rafee and Cronan, 2006; D'Arcy et al., 2009; Higgins et al., 2008; Marshall, 2007; Moores and Chang, 2006). All survey questions other than the subjects gender and age were presented as a rating scale between 1 and 7. Please see the appendix for a sample questionnaire.

2.3.3 Sample

We sampled undergraduate students at a large university in the Midwest region of the United States. College students as a target group are representative of the population that tends to engage in digital piracy (Higgins, 2005; Higgins et al., 2008; Limayem et al., 2004; Marshall, 2007). The use of a sample that resembles the population of typical digital pirates (at a large state university including students from across the state, from many other parts of the country, and with a large international student population) also increases the likelihood that this work could be generalized to the population of potential software pirates. Surveys were distributed during the spring and summer 2010 academic semesters to several classrooms, with students representing various concentrations across the management school (e.g., accounting, finance, information systems, organizational behavior, etc). A small number of students from other academic areas such as engineering, liberal arts, or science may also have been included. Prior permission was given to the survey administrator by the

⁴We confirmed our relative cost design by testing the path from expected utility theory to attitude (as proposed by Peace et al. (2003)), and found the path was not significant.

classroom instructor and surveys were completed in about fifteen minutes during the scheduled class time. The directions for completing the survey were read aloud by an administrator, including a definition of what constitutes digital piracy, and voluntary participation was requested but not required. Survey responses were recorded anonymously and confidentially.

Out of 218 surveys distributed, 201 were returned. After further review, three of the surveys were substantially incomplete and/or returned completely blank to the survey administrator, resulting in a total sample of 198 observations. The initial purchase scenario was presented first in 100 of these observations. As mentioned earlier, prior literature has primarily focused on a decision similar to our initial purchase scenario. The other 98 observations took into account our “staged” approach by presenting the piracy conversion scenario first, allowing us to account for consistency of behavior.

2.4 Analysis

We analyzed the survey responses using various methods, including partial least squares (PLS), multiple regression (Baron and Kenny, 1986; Hayes, 2009; Muller et al., 2005), and other multivariate techniques, and found the results to be largely similar. In this section, we primarily present results using PLS path-modeling software SmartPLS 2.0.M3 (Ringle et al., 2005) to be consistent with the prior literature. We recognize that prior work (e.g., Chin, 1998; Goodhue et al., 2006; Marcoulides et al., 2009; Marcoulides and Saunders, 2006) has identified some potential concerns with the implementation of PLS in certain contexts and has proposed guidelines for the use of PLS. In our analysis, we followed those guidelines to ensure the validity of our results. The similarity of the results across analysis techniques also gives us greater confidence in the presented results.

2.4.1 Measurement and Structural Model

All intention responses were scaled between 1 and 7, where 1 referred to lower intention to pirate, and 7 referred to a greater intention to pirate, after adjusting for reverse coding when necessary. Any missing responses were conservatively replaced by using the mean for that particular measure. There were eight such instances across the entire sample, illustrating an extremely low concern for bias created by missing data.

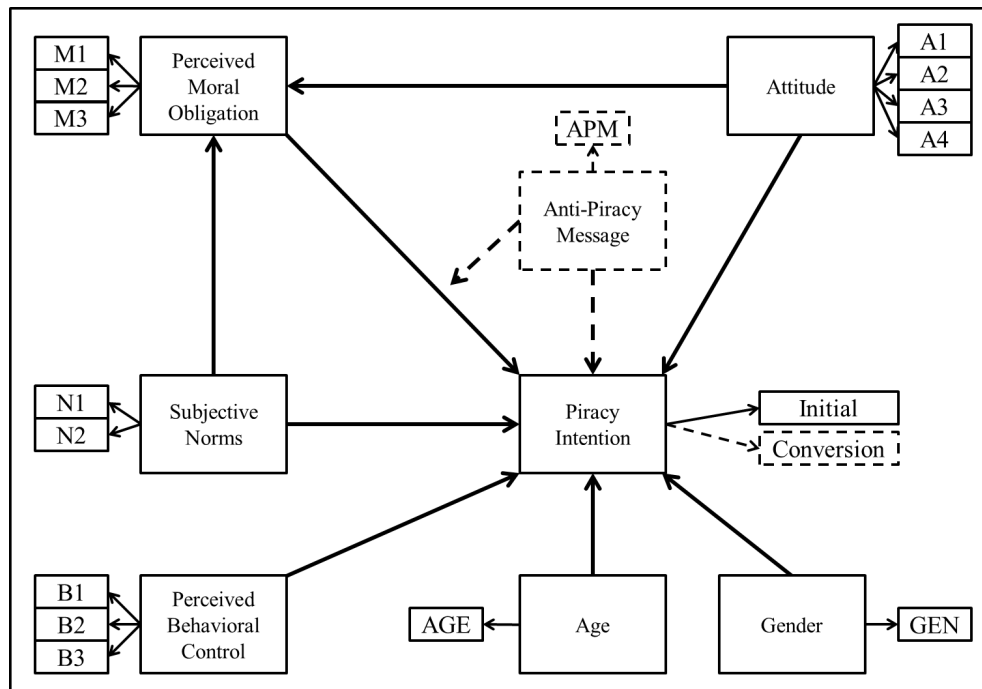


Figure 2.3. Structural Model

We performed multivariate tests for reliability and validity of our measures which are described below. Our examination of the measurement model showed that all of the constructs except subjective norms remained over-identified with three or more highly-interrelated items. The measure for subjective norms, however, had two highly related items, but a third item that did not correlate as expected with the other items. Although the third question (N3) for subjective norms had been tested and validated in prior work, N3 did not correlate as expected in our case, perhaps because that

question was confusing to our subjects.⁵ We believed the problem to be minor and opted to discard N3 from our analysis. The resulting structural model based on Figure 2.2 is shown by Figure 2.3. Note that the constructs and items outlined in dashes will be addressed when nudging is considered in our analysis. Further, we used the same indicators of each construct when examining the model presented in Figure 2.1, so that model is not shown here.

Table 2.1
Descriptive Statistics (n = 198)

Demographics	Count	Mean	Std. Dev.
Male	117	-	-
Female	79	-	-
Gender Unanswered	2	-	-
Age	-	21.072	1.357

Construct	Items	Mean	Std. Dev.
Attitude	A1	3.455	1.195
	A2	3.832	1.216
	A3	3.631	1.344
	A4	3.995	1.462
Subjective Norms	N1	3.954	1.223
	N2	4.753	1.620
Perceived Behavioral Control	B1	4.944	1.746
	B2	5.490	1.630
	B3	4.753	1.553
Perceived Moral Obligation	M1	4.051	1.892
	M2	3.934	1.650
	M3	3.569	1.622
Piracy Intention	Init.	4.188	1.836
	Conv.	5.081	1.743

We conducted several multivariate tests to verify convergent validity, discriminant validity, and internal consistency in our measures before conducting our PLS

⁵The correlation between N3 and the other two items was substantially lower at 0.32 for both, whereas N1 and N2 correlated at 0.52. Moreover, with N3 included in the construct, composite reliability decreased to 0.8194 and average variance extracted (AVE) decreased to 0.6030. When N3 was included in the factor analysis provided in Table B.1 in the appendix, loadings for N3 were 0.455. Cross-loading was not observed with or without N3.

path analyses.⁶ As mentioned earlier, the standard tests for validity and consistency determined that N3 did not correlate well with the other items tapping subjective norms. Hence, for the sake of brevity, we only present here the final set of analyses where N3 is omitted. Descriptive statistics are shown in Table 2.1 and provide the mean and standard deviation for each item in each construct. We generated the results for the final set of analyses using SmartPLS and present them in Tables 2.2 and 2.3. Table 2.2 provides loadings and cross-loadings for the reflective constructs in our model.⁷ Loadings are higher on the theoretically assigned constructs as shown by the bold-faced values, than the cross-loadings on the other constructs. Because the items load on their respective constructs and the t-values for the outer model loadings are significant (t-values > 10), we establish convergent validity in our measures (Gefen and Straub, 2005).

The bold-faced values in Table 2.3 represent the square root of the average variance extracted (AVE). The AVE for each construct is much larger than any correlation among the other constructs. This point from Table 2.3 in addition to the relative lack of cross-loading as shown by Table 2.2, provide sufficient evidence of discriminant validity in a PLS analysis (Gefen and Straub, 2005). Further, the composite reliability in Table 2.3 is higher than the recommended 0.70 threshold (Chin, 1998; Fornell and Larcker, 1981), providing sufficient evidence of internal consistency of the items. In summary, from these test results, our measures appear to be internally consistent, and demonstrate convergent and discriminant reliability.

2.4.2 Results

Note the following regarding the PLS analysis presented in this sub-section. 1) Unless otherwise noted, the dependent variable in all models shown is the subjects

⁶Please refer to the appendix for the equivalent data validity tests using complementary multivariate techniques.

⁷Please refer to the appendix for a principal axis factor analysis with promax oblique rotation. Results from the factor analysis are consistent with those presented in Table 2.2, with the exception of much lower cross loadings due to the rotation used.

Table 2.2
Loadings and Cross-Loadings

Construct	Items	Attitude	Subj.			Piracy
			Norms	PBC	PMO	Int.
Attitude	A1	0.807	0.308	0.324	0.591	0.329
	A2	0.793	0.376	0.344	0.513	0.308
	A3	0.815	0.339	0.309	0.557	0.293
	A4	0.795	0.401	0.328	0.457	0.314
Subj. Norms	N1	0.464	0.827	0.342	0.404	0.175
	N2	0.327	0.905	0.198	0.395	0.232
PBC	B1	0.370	0.244	0.923	0.361	0.273
	B2	0.323	0.265	0.884	0.296	0.222
	B3	0.365	0.274	0.783	0.380	0.211
PMO	M1	0.637	0.409	0.382	0.909	0.421
	M2	0.571	0.439	0.375	0.910	0.333
	M3	0.554	0.380	0.298	0.871	0.260
Piracy Int.	Init.	0.379	0.193	0.292	0.371	0.897
	Conv.	0.295	0.228	0.181	0.309	0.854

Table 2.3
Reliability and Interconstruct Correlations

Construct	Composite		Subj.			Piracy
	Reliability	Attitude	Norms	PBC	PMO	Int.
Attitude	0.8783	0.8022				
Subj. Norms	0.8579	0.4432	0.8669			
PBC	0.8992	0.4070	0.2984	0.8655		
PMO	0.9249	0.6605	0.4574	0.3982	0.8968	
Piracy Int.	0.8679	0.3883	0.2384	0.2744	0.3901	0.8757

Note: Boldface items are the square root of the average variance extracted

response for the initial purchase intention. 2) We used a dummy coding scheme for the treatment and gender variables. 3) We mean-centered our interacting variables.⁸ 4) Bootstrapping with 500 re-samples of the data were used each time a model was

⁸Mean-centering the multiple regressions we conducted in addition to the PLS analysis allowed us to interpret the resulting main effects in the simultaneous analyses (Aiken and West, 1991; Jaccard and Turrissi, 2003; Jaccard et al., 1990)

tested. 5) We examined standardized coefficients. 6) In order to test the moderating effects, one may use a product indicators or a product sums approach. Henseler and Chin (2010) argue that the product indicator approach ensures the observed interaction effect will be the least biased in comparison to other potential approaches. In contrast, Goodhue et al. (2007) recommend using a product sums approach if there is a concern due to sample size, as might be the case with our dataset. Both of these approaches are equivalent in our case because our moderating variable (Anti-Piracy Message) is a categorical (dichotomous) rather than continuous variable.

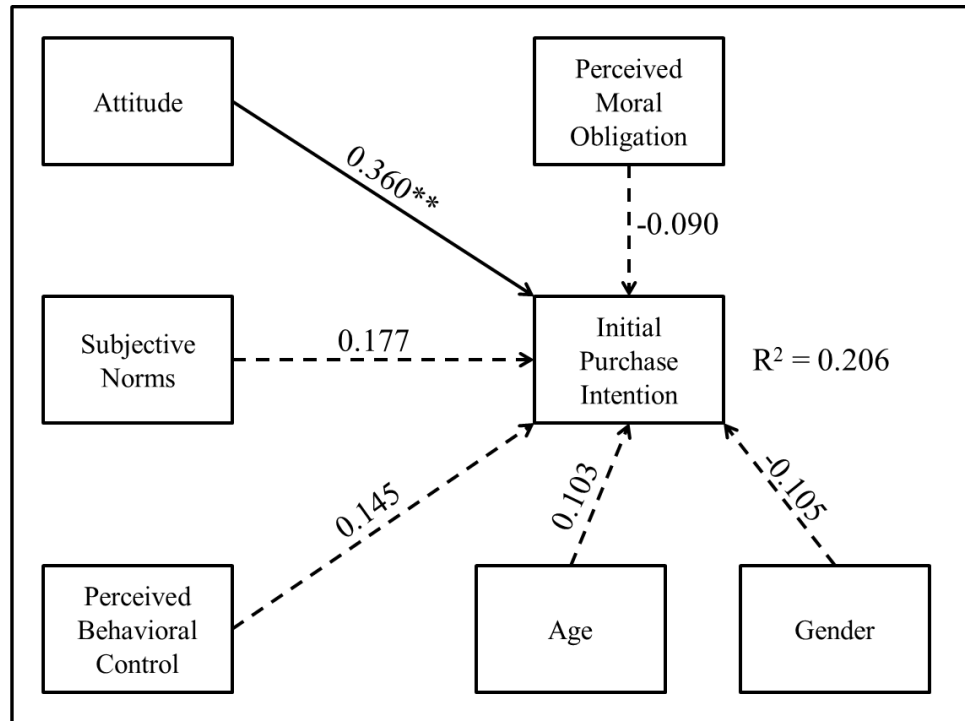
The rest of the sub-section is organized as follows. We present our results by starting with the Beck and Ajzen (1991) TPB model to illustrate the importance of accounting for consistency of behavior after initial piracy. We then introduce our refined TPB model to capture the effects of other constructs on the malleability of morals. We conclude the sub-section by comparing the effectiveness of the anti-piracy message as a moderator in our refined TPB model across the two piracy scenarios.

The Beck and Ajzen (1991) Model for Predicting Dishonest Actions

We initially conducted our analyses using the Beck and Ajzen (1991) model in a manner that is consistent with prior literature on piracy. Specifically, prior work has not analyzed the role of consistency of piracy behavior (across stages). Accordingly, the Beck and Ajzen (1991) model only includes those subjects who received the initial purchase scenario first (n=100). The estimation results are shown in Figure 2.4. From that, we found a positive and significant path predicting purchase intentions only for attitude towards the purchase.⁹ Of note, the construct of perceived moral obligation had minimal impact on the initial intention to purchase. The minimal impact of perceived moral obligation appears consistent with Logsdon et al. (1994) as they

⁹Please refer to the appendix for our mediated model when consistency of behavior is not invoked. Our model is omitted here for brevity as the results are consistent with the Beck and Ajzen (1991) TPB. We expected this model to hold for initial purchase decisions when consistency of behavior is not salient, but expected our model to hold after initial piracy when consistency of piracy behavior is salient.

argue that piracy is of low moral intensity. This pattern of results set the stage for examination of our “staged” approach taking into account settings in which subjects have previously pirated the software.



Note: Paths represented by dashes are not significant ($p > 0.10$). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Figure 2.4. The Beck and Ajzen (1991) TPB: Consistency of Behavior Not Invoked

Presenting the piracy conversion scenario to subjects should put them in the mindset of having previously pirated and wanting to justify prior piracy behavior. Therefore, we believe that this could lead individuals to adjust their morals to justify the prior pirating decision. Consequently, the model in Figure 2.5 examines the original Beck and Ajzen (1991) model for those subjects presented with the piracy conversion scenario first, followed by the initial purchase scenario ($n=98$). Using this model, we found a positive and significant path from perceived moral obligation to the initial purchase intention. When consistency with prior behavior is made salient, the results show that perceived moral obligation is now quite important to the piracy

decision. However, the Beck and Ajzen (1991) model does not capture the underlying factors that might be influencing morals to now be important.

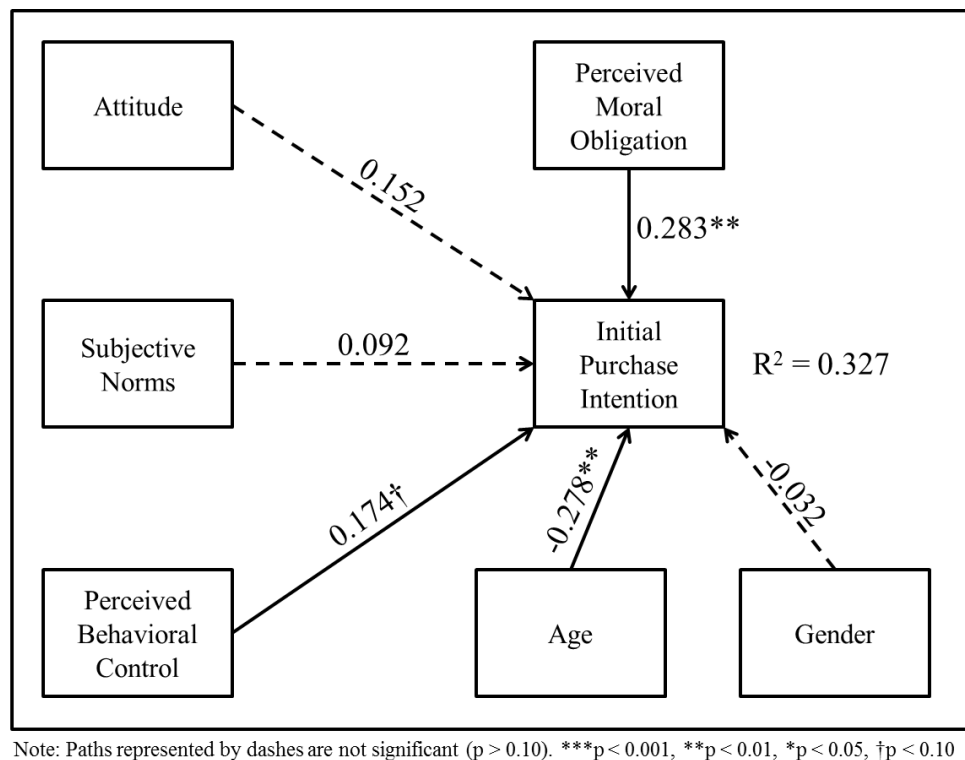


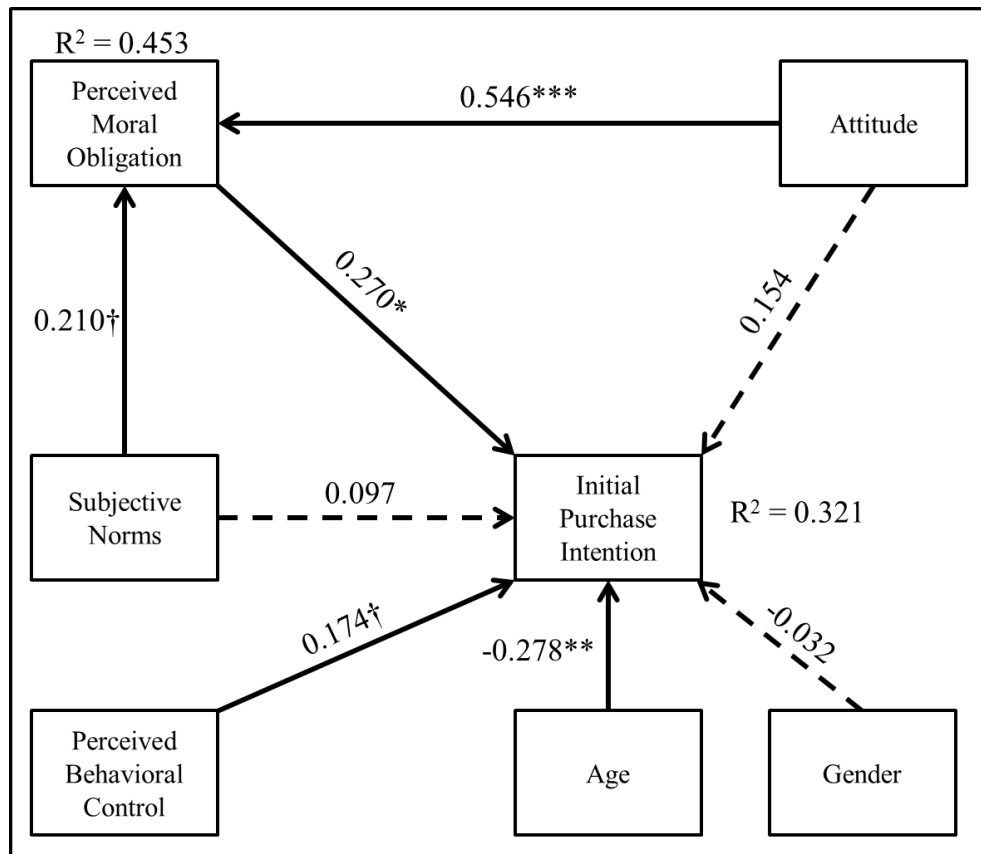
Figure 2.5. The Beck and Ajzen (1991) TPB: Consistency of Behavior Invoked

Perceived Moral Obligation as a Mediator in our Refined TPB

As discussed previously, although perceived moral obligation is often an independent predictor of the intention to perform the behavior, it may not be the case for digital piracy following a previous act of piracy. Recall that Mazar et al. (2008) found that honest individuals may be dishonest sometimes, particularly if engaging in such behavior does not change one's self-perception. Taking that into account, our refined version of the TPB designated perceived moral obligation as a mediator of influences of attitudes and subjective norms on purchase intentions.

Figure 2.6 provides evidence for the primary theoretical contribution of this research. Our results show strong support for perceived moral obligation mediating influences of attitudes and subjective norms on initial purchase intention. These significant paths indicate that morals are malleable and are influenced by other constructs. Individuals may be choosing to rationalize their unethical “white lie” behavior, thereby allowing their morals to be influenced. We also found strong support for the path from perceived moral obligation to initial purchase intention. We therefore provided evidence of the desire for the individual to remain consistent with prior unethical behavior. Perhaps the past piracy behavior makes individuals look for bases for rationalizing the behavior, thereby increasing the relevance of attitudes and norms for perceptions of moral obligation. Otherwise, morals would have not been affected by the other constructs in the model.

Although our primary goal was to provide strong statistical support for perceived moral obligation as a mediator in the TPB, we also provide evidence of improved model fit compared to the Beck and Ajzen (1991) model. The model fit indices that may be used in PLS analyses to provide a measure of model quality are: average path coefficient (APC), average R-squared (ARS), and average variance inflation factor (AVIF). The indices for our model shown in Figure 2.6 are: APC=0.222, ARS=0.389, and AVIF=1.437. The indices for the Beck and Ajzen (1991) model shown in Figure 2.5 are: APC=0.170, ARS=0.327, and AVIF=1.452. In addition to our model providing the ability to show perceived moral obligation as a mediator, it also has a better fit across all three indices. Thus, when focusing on parameter estimation or on model fit, the data provide support for perceived moral obligation as a mediator of influences of attitudes and subjective norms on piracy intentions in this “victimless crime” context.



Note: Paths represented by dashes are not significant ($p > 0.10$). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Figure 2.6. Perceived Moral Obligation as a Mediator in our Refined TPB: Consistency of Behavior Invoked

Nudging in our Refined TPB

We now consider the implementation of a nudging strategy to mitigate rationalization of pirating, thus combating piracy. In particular, our design includes a morally-salient anti-piracy (pro-purchase) message that we expect to moderate (and therefore mitigate) effects of perceived moral obligation on purchase intentions. This mitigation pattern would be evidenced by a negative coefficient for the interaction between the presence of the anti-pirating message and the impact of perceptions of moral obligation on purchase intention.

The results in Figure 2.7 show a negative and significant moderating effect of the anti-piracy message on the impact of perceived moral obligation on initial purchase intention. The moderating effect may be classified as medium to small as the Cohen's f^2 for this effect¹⁰ is 0.1074 (Chin et al., 2003; Cohen, 1988).¹¹ The ΔR^2 when the moderating effect is included in the initial purchase scenario model is 0.071. The direct effect from the anti-piracy message is marginally significant and of relatively small magnitude. Because we show evidence of a moderating effect due to the anti-piracy message on effects of perceived moral obligation in Figure 2.8 it is likely that management would benefit from knowing when this type of moderating strategy is most useful. Therefore, Figure 2.8 provides a comparison to the initial purchase intention by including the piracy conversion decision under our refined TPB model.

Unlike the initial purchase case shown in Figure 2.7, the anti-piracy message does not have a significant moderating effect on perceived moral obligation in the conversion case as shown in Figure 2.8. Although, the coefficient for the moderator is not statistically significant, we still observe a potentially meaningful value of -0.201.¹² Otherwise, the paths are quite similar to those in Figure 2.7. These results indicate that the anti-piracy message does not mitigate effects of perceived moral obligation to the same degree when a pirate is considering conversion to a paying customer. However, the message is generally mitigating the (justifying) impact of perceived moral obligations on intentions, so inclusion of the anti-piracy message does not appear to make piracy worse, even when the messages impact is not as strong (in conversion contexts).

¹⁰Cohen's $f^2 = [R^2 \text{ (interaction model)} - R^2 \text{ (main effects model)}] / [1 - R^2 \text{ (main effects model)}]$

¹¹Although not presented for brevity, to provide a direct comparison to the interaction model presented, we add the main effect for the moderator to our refined TPB and use that $R^2 : f^2 = (0.410 - 0.339) / (1 - 0.339)$

¹²Chin (1998) suggests that standardized coefficients greater than 0.20 are potentially of meaningful magnitude.

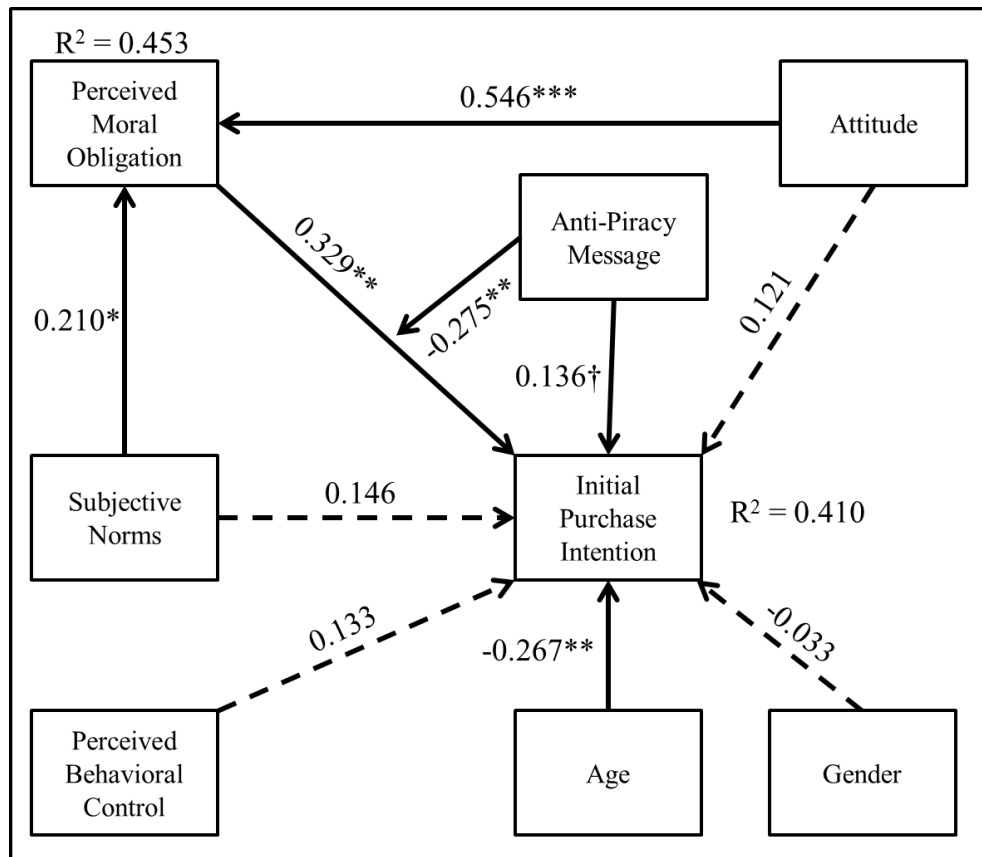
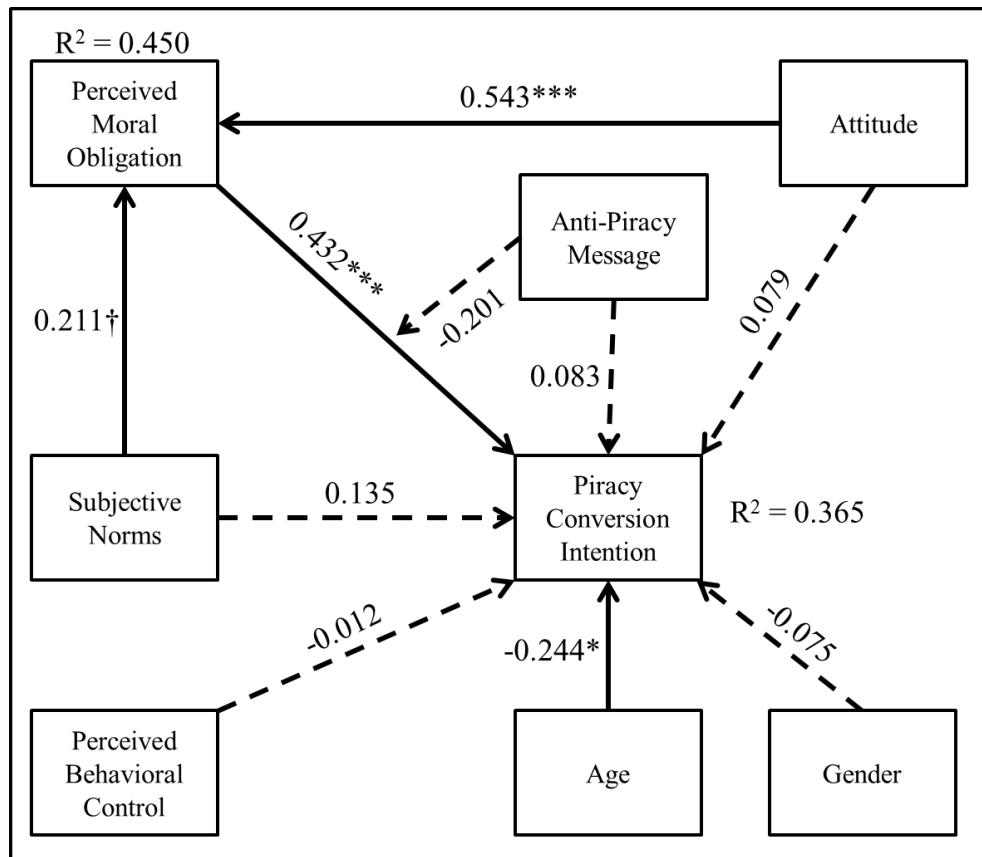


Figure 2.7. Nudging in our Refined TPB: Consistency of Behavior Invoked

2.4.3 Tests for Potential Sources of Bias in Our Results

We discuss two potential sources of bias in our results in the sub-sections that follow. First, we address the potential for bias due to common method variance (CMV) because our subjects completed the survey questions at one time. CMV may be an issue because our measurement is at the individual level and therefore the subject may bias their responses due to the common method being used. Second, we address concerns about using cost as a control. As with any human research study, our sample consists of subjects of varying financial capacity. Therefore, we designed cost controls into the survey instructions to purposely reduce the possibility for misinterpretation, and accordingly diminish the potential for bias in our results.



Note: Paths represented by dashes are not significant ($p > 0.10$). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Figure 2.8. Nudging under the Conversion Scenario in our Refined TPB: Consistency of Behavior Invoked

Common Method Variance

We used two techniques to ensure that CMV is not a source of bias with our data.¹³ The first technique we used is Harman's single-factor test by including the reflective indicators in a principal components analysis without rotation (Malhotra et al., 2006; Podsakoff et al., 2003). The first factor in the resulting output explains approximately 35% of the variance, providing reassurance that our data do not indicate substantial CMV. Second, our correlation matrix shown in Table 2.2 as well as in the appendix

¹³Because the primary contribution of this research is perceived moral obligation as a mediator when the past-piracy scenario is first, we focus on that particular subsample of our data for these tests.

(Table B.3) does not indicate any highly correlated constructs (Pavlou et al., 2007). Overall, we conclude that our data do not suffer from strong bias due to CMV.

Cost as a Control

Prior work hypothesized that expected utility theory should cause changes in the attitude of the digital pirate (Peace et al., 2003). We originally included this construct in our survey instrument but dropped it from our final analysis. Its inclusion did not change any of the coefficients or path significance in any of our models as expected due to our survey instructions designed to minimize consideration of software price.

2.5 Discussion and Conclusion

Digital piracy is a growing and serious problem that affects individuals, businesses, and governmental entities. Our study is motivated by a real-world setting and provides both positivist and normative contributions to the literature.

This research develops positivist insights into why pirates perceive their actions as victimless crimes, allowing for greater understanding of the underlying purchase or pirate decision by extending existing theory. We utilized both the Beck and Ajzen (1991) TPB for predicting dishonest actions and our refinement to the TPB model for examining purchase intentions in the piracy context. Because our model included perceived moral obligation as a mediator, we empirically reinforced our theoretical assertion that perceived moral obligation may be influenced by both attitude and subject norms. We believe that the mediation effect of perceptions of moral obligation results from motives to justify past unethical behavior when considering past piracy. This malleability of morals may be an important path through which people are able to continue past behaviors, even in situations like piracy where a moral dilemma can be made salient to the individual.

In addition to our theoretical refinement to the TPB, we also provide a normative contribution by showing that it is possible to encourage changes in piracy inten-

tion through exogenous manipulation. Management can use our findings to improve current forms of communication, thereby contributing to mitigation strategies by countering the threat of piracy by potential consumers. We tested an anti-piracy educational message in this study, but the message can be tailored to the specific needs of the firm and adjusted for the characteristics of their customer base. A message can then be quickly disseminated through social networking, peer-to-peer networks, online discussion forums, and opinion pieces and interviews. We anticipate that similar principles would apply to other commonly used mediums such as e-mail, phone, and postal mail as well. Further, the existence of one-to-one marketing and widespread use of online discussion forums and blogs makes using this type of strategy quite tenable and realistic for firms to utilize.

We expected that there would be changes due to the moderating effect of the anti-piracy message on links between perceived moral obligation and intentions to purchase or pirate, and observed a slight increase in likelihood to purchase when the message was received. The moderation of the link between morals (justification) and intentions suggests that future messages could be designed that would have stronger impact on intentions. We found that the moderating effect can be reasonably large in magnitude (greater than 0.20), especially for an initial purchase decision. Because the message did not increase the likelihood to pirate for people making an initial purchase decision, it may be reasonable to convey a message to all potential consumers regardless of whether or not their past behavior is known. We did not identify a significant direct effect from subjective norms to piracy intention regardless of the model tested. Perhaps this is a nuance of our particular sample but we do not believe it to be cause for concern. We did find support for indirect effects of subjective norms through the mediator of perceived moral obligation. In regards to the control variables, we did find that older subjects tend to have a lower piracy intention than younger individuals. We did not identify a measurable effect for gender, and we did have reasonable representation of both males ($\approx 60\%$) and females ($\approx 40\%$).

2.5.1 Managerial Implications

The primary implication that management might glean from this research is a normative approach for piracy mitigation due to the possibility to exogenously nudge potential consumers away from piracy. In particular, a strategy of communicating to customers about the negative effects of piracy can be useful, especially when past piracy is salient to the consumer. This approach does not appear to increase the likelihood to pirate for those subjects who are not susceptible to nudging, but it should be mentioned that the message we tested was quite benign in its wording. The message we sent our subjects was not confrontational. For example, some music producers (e.g., Madonna) have poisoned peer-to-peer networks with music that has been modified with a confrontational message about piracy. Instead of this approach, perhaps music producers should poison the network with informative yet benign messages appended to the end of the music rather than the beginning. Our results would suggest that this latter approach would not make piracy worse. In fact, receiving an anti-piracy message may lead to a lessened effect of rationalized perceptions of moral obligation on a purchase or pirate decision.

We should note that although we include a morally-salient message in our paper, a message could certainly be adjusted as needed by the firm according to their understanding of their customer base. In particular, management should perform additional analyses of their customers and what is important to them, and then tailor their message in a way that invokes constructs that fit the characteristics of the customers. This is especially true for those firms that engage in active data collection and analysis about their target audience.

2.5.2 Future Research

Although our focus was on the use of a morally-salient message to intervene in a purchase decision, future research could address all types of other interventions. In particular, the dissonance approach of communicating with a consumer that they

purchased a previous product in order to encourage them to purchase a future product has yet to have been explored. This consistency in behavior across time (or motives to rationalize past potentially unethical behavior) should receive greater attention in future research on digital piracy.

3. INFORMATION TARGETING AND COORDINATION: AN EXPERIMENTAL STUDY

3.1 Introduction

Many critical business and social contexts have the unfortunate potential to suffer from an *everybody else is doing it, so I should do it too* mentality. A few mainstream examples that are not exempted from the effects of this mentality include individuals taking liar loans during the sub-prime housing bubble (Nocera, 2011), the social pressure involved with teen drinking, and the rampant prevalence of digital piracy. These types of behaviors may in fact be reinforced and compounded by the manner in which they are addressed, resulting in further undesirable consequences. We focus on digital piracy as a motivation for this study due to the inherent ability to model this type of behavior in an experimental setting.

Other than the use of technological solutions such as digital rights management (DRM), firms specifically engage in educational strategies (2DBoy, 2008; Graft, 2010; RIAA, 2010) to combat the piracy threat. One interesting aspect of these educational strategies is the *delivery of information pointing to high piracy rates* observed for digital goods (Smith and Benoit, 2010).¹ Does informing consumers about high piracy rates further this *everybody else is doing it* attitude towards piracy? Or does this type of information mitigate the behavior?

In this paper we investigate the impact of information feedback on a consumer's contribution behavior through the implementation of coordination strategies. Understanding the effects from coordination strategies is critical, especially given that consumer preferences for goods are not necessarily homogeneous regarding purchas-

¹Educational strategies may also present evidence of the economic implications of piracy on firms, jobs, and the consumers themselves.

ing, or in our case, pirating behavior. Should all types of consumers be targeted for information equally? For example, following the logic presented by the *everybody else is doing it* attitude, if we inform contributing consumers of a high rate of non-contribution, does the high rate embolden them to discontinue contributing as well? Does observing a high rate on non-contribution justify the decisions of those that always fail to contribute? Or does it encourage them to adopt the social norm and convert to a contributing consumer? Answers to these questions provide us with practicable insights that may be used to deliver informative strategies to many business contexts to avert the *everybody else is doing it* attitude.

We address these questions from a behavioral economics perspective through the use of a controlled laboratory environment. Specifically, we design a modified version of a threshold public good and implement the game in an abstract frame.² The experimental framework is highly suitable in this case, especially due to our desire to extend these coordination mechanisms to the piracy context. On one hand, since piracy is an illegal behavior, naturally occurring data is hard to obtain and not reliable. On the other hand, randomization into treatments allows us to tightly control possible confounding and selection effects that are typical with naturally occurring data (e.g. firms may only get a selective sample of consumers when providing information about piracy rates).

We compare behavior among subjects by developing a no feedback treatment, a random feedback treatment, and targeted (above / below) feedback treatments. We develop several thresholds distinguished by the quality of good that a firm delivers to the group of consumers, dependent on the rate of contribution to the good. The use of several thresholds allows our setup to determine which feedback treatment leads to the most efficient provision of quality for the good, resulting in implications for information targeting strategies. This approach is quite realistic as the threat of

²Abbinck and Hennig-Schmidt (2006) find that careful experimental design yields consistent results across context-specific and abstract framing of laboratory experiments. Rather than implement a loaded context, we implement an abstract frame in our design due to our desire to focus entirely on the role of targeted information across any context.

piracy may deter firms from investing in additional product development, increasing product quality, investing in support, and other product utility related consequences. Overall, we find that targeted information feedback results in the greatest level of coordination among subjects, whereas randomly providing information to subjects is as ineffective as providing no information at all. Between the two targeted treatments, sending information to those that are contributing more to the good on average, provides the best level of coordination among the subjects.

The remainder of this paper is organized as follows. We review the literature in Section 3.2. Section 3.3 introduces our multi-provision point public good game, followed by our experimental setup and predictions in Section 3.4, and experimental procedures in Section 3.5. Results are provided in Section 3.6, followed by a discussion and conclusion in Section 3.7.

3.2 Literature Review

Our paper relates to various streams of research on coordination in public goods games. We review the literature relevant to building our experimental framework in the following sub-sections.

3.2.1 Coordination Mechanisms in Public Goods Games

In the most general case, the provision of a public good³ relies on contributions from some consumers, but not necessarily all of them. This results in a Pareto optimal equilibrium of voluntary contributors and free-riders (Marwell and Ames, 1979, 1981; Sugden, 1984).⁴ Given the inherent threat of free-riding in public goods games, the study of mechanisms that affect coordination among subject contributions have been of great interest to researchers and practitioners alike.

³Public goods may be described as being non-rival and non-exclusive, and therefore cannot be diminished by individual consumption.

⁴The dominant strategy in a public goods game is to free-ride, potentially resulting in the loss of the public good in the future due to lack of funding from voluntary contribution.

Coordination mechanisms in public goods games generally include, but are not limited to: communication, threat of punishment, anonymity vs. identifiability (e.g. a type of reputation), and information. The implications of the first three types of mechanisms are briefly summarized as follows: communication amongst subjects improves group optimality, whereas no communication increases free-riding because subjects will play the Nash equilibrium (Isaac and Walker, 1988). In a similar vein, Fehr and Gächter (2000) show that maintaining a high level of contributions under the threat of punishment is possible and mitigates the free-riding problem. Croson and Marks (1998) explore the role of anonymous and identifiable information on contribution to a threshold public good and find that contributions are higher when individual subjects can be identified (vs. anonymous contributions having a lack of subject reputation). The last coordination mechanism, information, is of the greatest importance to our study and follows in the next sub-section.

3.2.2 The Role of Information on Coordination

The role of information about contributions to a public good and its affect on coordination were explored in detail by Sell and Wilson (1991), and Weimann (1994). Both studies find that being informed about contribution levels does not seem to matter, suggesting that aggregate level information may not necessarily be the cure for the free-rider problem. At the same time, Weimann (1994) documents the existence of heterogeneous subject types, with the average subjects behaving as a “weak free rider” type. Following these initial works, Marks and Croson (1999) illustrate that whether or not a particular type of information is complete or incomplete does not matter (such as heterogeneous valuations or endowments), rather the critical piece is the fact that some level of useful information is made available to the subjects.

These studies led to further exploration and understanding of the role of information about other’s contributions enabling *conditional cooperation* as a coordination mechanism (Fischbacher et al., 2001; Croson, 2001; Croson et al., 2005; Croson, 2007,

among others). In general, 50% of subjects vary their contributions according to the average group contribution when contribution information is made available to them. Contributions are largely reciprocal in manner, defining one's cooperation as being *conditional upon* their belief that others are contributing in a similar manner. There are various types of cooperators, ranging from selfish, to reciprocal, and finally to altruistic (Fischbacher and Gächter, 2010; Croson, 2007), with each type usually classified by comparing elicited beliefs with actual contribution decisions. Conditional cooperation is greater when the subjects know they are matched as partners rather than strangers (Keser and van Winden, 2000), which is likely due to reputation effects. As we would expect, the strangers play Nash while the partners coordinate to higher contributions, generally matching the contributions of the other players (Croson et al., 2005).

Conditional cooperation is observed in the field in addition to the laboratory (Frey and Meier, 2004), extending the validity of utilizing information to produce pro-social outcomes in a real world environment. These findings parallel what we might expect to observe under piracy if subjects are aware of other consumer's behavior through some type of communication from a firm, the press, or other industry source, with increased interest on the targeting information to particular recipients. The use of information as a coordination mechanism has also been shown to invoke pro-social outcomes in a dictator game (Krupka and Weber, 2009). This is important to note as the prior literature focuses primarily on public goods or minimal effort games that do not have the pro-social element concern for the subjects.

Our paper is novel when compared to the prior literature because we focus on the role of *targeted information* as a coordination mechanism in a public goods context. To the best of our knowledge, the study of targeted information has not been explored in the literature. Our approach also fits with the desire to test the role of information on piracy decision-making, especially if the targeted information reaches various types of conditional cooperators. Given the opportunity to coordinate through information sent to particular types of subjects, it may be possible for the firm to provide a high

quality good while extracting the necessary rate of contribution from the consumers.⁵ The threat of defecting to the low-quality good if contributions fall below a certain threshold represents a credible threat to the consumers, and may result in the ability to maintain a Pareto optimal strategy for the firm and consumers.

Overall, because producers of digital goods are generally motivated and sustained by sales revenue, a lack or substantial loss of sales revenue certainly results in failure and delivery of a lower quality good (if delivery of the good occurs at all). We therefore draw upon the threshold public goods (and to a lesser extent, common-pool resources) literature by extending the idea that a firm that cannot cover its development costs and other investments may develop a product of poor quality if subjected to a high level of piracy.

3.2.3 Threshold Public Goods

Experimental evidence suggests that games designed with a given safe threshold eventually result in destruction of the resource (Walker and Gardner, 1992) (or lack of provision of the good). This result parallels the free-riding strategy dominant in typical public goods games. If the firm is able to survive by providing a basic level of functionality when faced with high piracy, might the firm introduce a higher quality good if they are likely to be compensated for their efforts under low piracy? Consider the case where a firm is willing to invest in comprehensive support solutions or other efforts that a consumer would derive utility from. This situation is quite similar to the provision of a threshold public good.

The presence of uncertainty about the provision of a public good (or high quality good), results in lower contributions to the public good (Dickinson, 1998; Isaac et al., 1989). If the threshold is too difficult for the consumers to reach, provision of the public good again fails (Cadsby and Maynes, 1999). However, if the step return defining the payoffs associated with a particular threshold is relatively high, it is pos-

⁵We assume that the firm can forecast an expected rate of sales and an expected rate of piracy when determining the quality of product to provide.

sible to maintain equilibrium at the threshold (Croson and Marks, 2000). Success in finding the equilibrium at the threshold is not always guaranteed, but the probability of success strictly increases as payoffs increase. Although a threshold may be an efficient Nash equilibrium, the lack of a coordination mechanism may result in inefficient allocation amongst group members to the public good. We therefore employ targeted information as a coordination mechanism under a multiple threshold public good in our paper to explore potential coordinating effects using this mechanism.

3.3 The Multi-Provision Point Threshold Public Good

Our setting considers a modified version of a threshold public good. Specifically, we use a multi-provision point mechanism with different step returns in the thresholds to elicit the quality of a public good. In our game there are n homogenous consumers, each of them endowed with an amount E_i which can either be used to buy a private good or a public good. The public good can be of different qualities, $Q \in \{Poor, Medium, Good, Very Good, Excellent\}$ provided in a threshold setting with cost \underline{X}^Q . If at least \underline{X}^Q units of the private good are contributed, then one unit of the public good is provided with quality Q . Costs are increasing in quality, $\underline{X}^{Q+1} - \underline{X}^Q = c^Q$ with $c > 0$ and \underline{X}^{Q+1} the next quality level as compared to Q . Our setting does not contemplate refunds or rebates. More specifically, contributions are not returned to their contributors when the provision point is not met. Also, contributions are not returned when they exceed a certain threshold but are still insufficient to provide the next quality level.

Consumers submit simultaneous and independent contributions. Call the contribution by consumer i for the public good x_i . The price of the private good is normalized to 1. The individual's earnings from the consumption of the private good are $E_i - x_i$. The individual earnings from consumption of the public good are dependent upon the quality which is delivered based on the quality threshold reached. Consumers always prefer a high-quality good to a low-quality good. Individuals care

only about the total public and private provision level. The utility function of consumer i is linear and given by:

$$U_i(v_i^Q, x_i) = E_i - x_i + v_i^Q \quad \text{if} \quad \underline{X}^Q \leq \sum_{i=1}^n x_i < \underline{X}^{Q+1} \quad (3.1)$$

where v_i^Q refers to the strictly positive value derived by consuming a good characterized by quality level Q . Utility derived for each quality level increases in Q , with $v_i^{Q+1} > v_i^Q \geq 0$.

In equilibrium, the individual decision on how much to contribute to the public good depends on how much her contribution is crucial for the provision of a certain quality level. Denote by X_{-i} the sum of all individuals' contributions except the one of individual i . Given X_{-i} , individual i 's contribution is crucial if and only if $\underline{X} - E_i \leq X_{-i} \leq \underline{X}^Q$. Being crucial is a necessary but not sufficient condition for contributing. No individual contributes more to a certain quality public good than her individual gain from extra quality, i.e., the individual rationality constraint, $x_i \leq v_i^Q - v_i^{Q-1}$ has to hold. It follows that the decision rule for each individual i is:

$$x_i = \begin{cases} \underline{X}^Q - X_{-i} & \text{if } \underline{X}^Q - E_i \leq X_{-i} \leq \underline{X}^Q \quad \text{and} \quad X_{-i} \geq \underline{X}^Q - (v_i^Q - v_i^{Q-1}) \\ 0 & \text{otherwise} \end{cases} \quad (3.2)$$

There is a continuum of pure Nash equilibria⁶ consisting of all possible situations where quality thresholds are met. In particular these equilibria consist of all vectors of x_i satisfying the efficiency constraint: $\sum x_i = \underline{X}^Q$ and the individual rationality constraint: $x_i \leq v_i^Q - v_i^{Q-1}$. These equilibria can be symmetric and asymmetric depending on the cost-sharing rule. In a symmetric equilibrium $x_i = x_j, \forall i, j$, in an asymmetric equilibrium at least $\exists x_i \neq x_j$. In the multi-provision point threshold public good the symmetric equilibria are not necessarily payoff equivalent. Consider

⁶In this game there are both pure and mixed equilibria. Our theoretical predictions focus exclusively on pure Nash equilibrium.

the step return which gives the ratio of an individual's value of a certain quality public good to their share of the cost $SR = \frac{nv^Q}{\underline{X}^Q} > 1$. The Pareto-efficient symmetric equilibria maximizes the step return.

3.4 Experimental Setup and Predictions

3.4.1 Experimental Design and Parameters

The experimental design implements our multi-provision point mechanism with 5 symmetric players⁷ randomly re-matched every period. This reassignment minimizes direct reciprocity and reputation effects,⁸ and is also most appropriate for capturing a one-shot equilibrium (Andreoni and Croson, 2008; Croson, 1996). We first elicit an expectation about the average contribution the subject believes the other participants will contribute to the public good. The subjects then decide how much they would like to contribute to the public good, with the knowledge that the combined group contributions will dictate a particular quality level of the good provided. After submitting their decision, each subject learns the quality level attained and the profit earned for the period.

The individual contribution level depends on her subjective probability of being crucial in providing a certain quality level for the public good. Therefore, information about the contribution behavior of others in the group may affect individual's contribution decision. As such, we consider four information treatments. In three of our four treatments, a subset of subjects in the group is informed about the average contribution of their actual group members before they make their individual contribution decisions. The average contribution of their actual group is computed

⁷Public good experiments generally consider between four to ten subjects per group (see for example Croson (2007)), with coordination being more difficult as the number of subjects increases (Engelmann and Norman, 2010; Knez and Camerer, 1994).

⁸Even in randomly matched settings, information feedback can work as a reputation building device. In a repeated random-matching prisoner's dilemma game information on the current partner's past actions can theoretically be enough to sustain any level of cooperation (Takahashi, 2010). However, reputation through information seems less likely in our setting as we have a five-player game and individual behavior counts for $\frac{1}{5}$ of the information.

using individual allocation decisions from the previous round. We implement three information treatments that vary with respect to whom receives information: In the *random feedback treatment* (random info) $m < n$ randomly selected consumers receive information; in the *target below feedback treatment* (target below) consumers whose contribution in the previous round is below the average contribution of their actual group receive information; and in the *target above feedback treatment* (target above) consumers whose contribution in the previous round is above the average contribution receive information. Our fourth treatment considers the *no feedback treatment* (no info) that implements our multi-provision point mechanism with no feedback.⁹

Each of our treatments consists of three blocks of 15 rounds each, with the exception of the first block which has 16 rounds (46 total rounds across all three blocks). The first block contains one extra round to allow for the same number of rounds *with information* as the second and third blocks. Table 3.1 shows the four different lineups of our treatments. In treatments B, C, and D subjects play one of the three information treatments for the first 16 rounds. From round 17 until 30 they play the no info treatment. After round 31 until the end of the experiment, subjects play the information treatment they had played in the first 16 rounds. In treatment A subjects start with the no info treatment, then play the random info treatment followed by the no info treatment again. Therefore, each subject only plays two treatments, one of the information treatments, and the no information treatment.

Our design allows us to analyze the impact of information both within- and between-subjects. Our primary interest is in contrasting the feedback treatment effects on coordination, for which a between-subject analysis is preferred for avoiding learning effects. Further, the within-subject aspect allows us to infer whether the effect of receiving information about others contributions as well as targeting the receivers has an effect that lasts even when information ceases to be received. The last block of rounds for treatments B, C, D, when one of the info treatments is played

⁹In our experiment subjects are never informed about their group members' contribution for the public good after making their decision. They are informed about their earnings based upon reaching a particular threshold after each round.

Table 3.1
Experimental Treatments

	Rounds 1-16	Rounds 17-31	Rounds 32-46
A	No Info	Random Info	No Info
B	Random Info	No Info	Random Info
C	Target Below	No Info	Target Below
D	Target Above	No Info	Target Above

again, allows us to compare the impact of giving information for the first time with the impact of re-implementing it. Comparing with the 17-31 rounds of no info we can somehow infer about the marginal returns of information.

In our setting, each of the five players receives an endowment of 50 tokens every period¹⁰ which they can allocate to the purchase of a private good and a public good. Each token allocated to a private good earns 1 token. Subjects may choose any integer between $[0, 50]$ to allocate to the public good. If less than 50 tokens are invested in the public good the quality provided will be poor; If at least 50 tokens, but less than 100 are invested in the public good the quality provided will be medium; If at least 100 tokens, but less than 150 the quality provided will be good; If at least 150 tokens, but less than 200 are invested the quality provided will be very good; If more than 200 tokens are invested in the public good the quality provided will be excellent. Table 3.2 provides a summary of the parameters.

We utilize an increasing step return and an increasing percentage of the threshold for the subject to be interested in contributing to the public good. These parameters require each subject to expect that the other subjects are providing a greater allocation towards the group account in order to meet the next higher threshold.

¹⁰The purpose for providing the endowment each period is to avoid exposure to potential risk due to the subject's prior performance, as well as maintain the non-repeated design in our game.

Table 3.2
Experimental Parameters

Quality	\underline{X}^Q (% of endowment)	Group payoff(v_i^Q) for the good	Step return	% of threshold to be able to contribute
Poor	0 (0%)	0 (0)	Indeterminate	0%
Medium	50 (20%)	92.5 (18.5)	1.850	63.0%
Good	100 (40%)	227.5 (45.5)	2.275	73.0%
Very Good	150 (60%)	405 (81)	2.700	76.3%
Excellent	200 (80%)	625 (125)	3.125	78.0%

3.4.2 Discussion of Behavioral Predictions

Recall that our game has a continuum of pure Nash equilibria consisting of all possible situations where quality thresholds are met. These equilibria can be symmetric and asymmetric depending on the cost-sharing rule. The Pareto-efficient symmetric equilibrium is the one that maximizes the step return (see Figure 3.1). As in any coordination game played in the lab, subjects may experience difficulty in playing a Nash Equilibrium, which is true in our game as well. In our setting no refund is given for over-funded or under-funded contributions, therefore an individual is only willing to contribute if the probability that her contribution is crucial for reaching a certain quality level is sufficiently large. More specifically, if an individual believes that other's contributions are enough such that jointly with her own contribution a certain quality level is provided, the individual is willing to contribute with the remaining amount to reach the threshold (assuming that the rationality constraint is satisfied). As beliefs about other's contributions may not be correct and as consumers are randomly re-matched after each round, the scope for coordination is limited and the convergence towards a more efficient Nash equilibrium may not happen over time.

If subjects receive information and use it to correctly update their beliefs about other's contributions, we expect that they will coordinate to a higher quality level

with minimal costs. However, we do not expect that targeting information to those either below or above the average contribution of others in their group will make a difference in the individual's ability to coordinate to a more efficient equilibrium, as compared to what may happen in the random information treatment.

The above predictions are derived assuming individuals are homogenous and purely money maximizers. However, consumers are likely to be heterogeneous regarding their social preferences. For instance, they may have outcome-oriented social preferences, considering not only their own payoff but other's payoffs as well. Or, consumers may have preferences for conformity and decide to follow others in their choices. In any of these cases, not only would information play a role, but targeted information can influence subject's decisions differently.

Let us consider that individual consumers are influenced by inequity aversion and care about an equitable outcome between themselves and another.¹¹ A consumer may experience disutility if their own outcome is not equitable compared to the average outcome for the other consumers (Bolton and Ockenfels, 2000). This is the appropriate model of inequity aversion for our game since the players will receive feedback based upon an average contribution.¹² Consider the n -player motivation function that illustrates the inequity aversion caused by differences between player i and the mean payoff of the other players (i.e. consumers). The utility function is characterized by $U_i(m) = U_i(m_i, \frac{m_i}{\sum_{j=1}^n m_j})$ where player i desires for their own payoff to equal the average payoff for the group. As before, if a player is concerned about inequity aversion, the player will adjust their decisions one way or the other to equalize their own share with the average share from the group.

It is quite realistic to utilize this model of inequity aversion for studying coordination between consumers because they may have some expectation or information

¹¹The same predictions are obtained in case individuals do have a preference for conformity.

¹²The Fehr and Schmidt (1999) model will give the same predictions but it assumes that players know the payoff of each other player in the game, such that a one-to-one comparison is possible. Given that in our setting players receive information concerning the average contribution rate, the Bolton and Ockenfels (2000) model is easy to apply with no need for extra assumptions about a player's behavior.

about how they are doing in comparison with their peers. Further, comparison of inequity among other consumers may increase feelings of guilt or fairness if the particular consumer has a lower than average contribution rate. In contrast, if the contribution rate is higher than another player's contribution, the consumer may feel emboldened by the group's behavior, resulting in a decrease in contribution rate. Therefore, given the Bolton and Ockenfels (2000) motivation function, we expect the manipulation of contribution information to influence consumer decisions.

Figure 3.1 illustrates the reaction function for subject i based upon the experimental parameters provided in Table 3.2. The solid black lines refer to the equilibria where the combined allocation of tokens for the group account exactly satisfies a given threshold. If the subject is inequity averse in any way, the subject strives to meet the symmetric equilibria where all subjects receive the same utility. If for example, as the Bolton and Ockenfels (2000) model predicts, the subject dislikes being behind the average utility for the group, the subject allocates tokens at or below the symmetric equilibria for a given threshold. Regardless of type, subject i should never allocate more than 44 tokens to the group account, otherwise the threshold for the Excellent quality level will be exceeded, resulting in an inefficient outcome.

Because our focus is on targeted information, we expect the targeted feedback treatments to result in a different level of coordination in comparison to the random feedback treatment. If a consumer observes a low average contribution rate in the random feedback treatment, the consumer may encounter disutility from other consumers doing better than they are, resulting in a decrease in their own contribution rate. In contrast, if a consumer observes a high average contribution rate in the random feedback treatment, the consumer may encounter disutility from other consumers doing worse than they are, resulting in an increase in their own contribution rate. Overall, we expect subjects in the random information treatment to converge at symmetric contribution levels since adjustments will be simultaneously made up and down by the players. Given this prediction, it is not clear that feedback will help consumers to coordinate on a more efficient equilibrium.

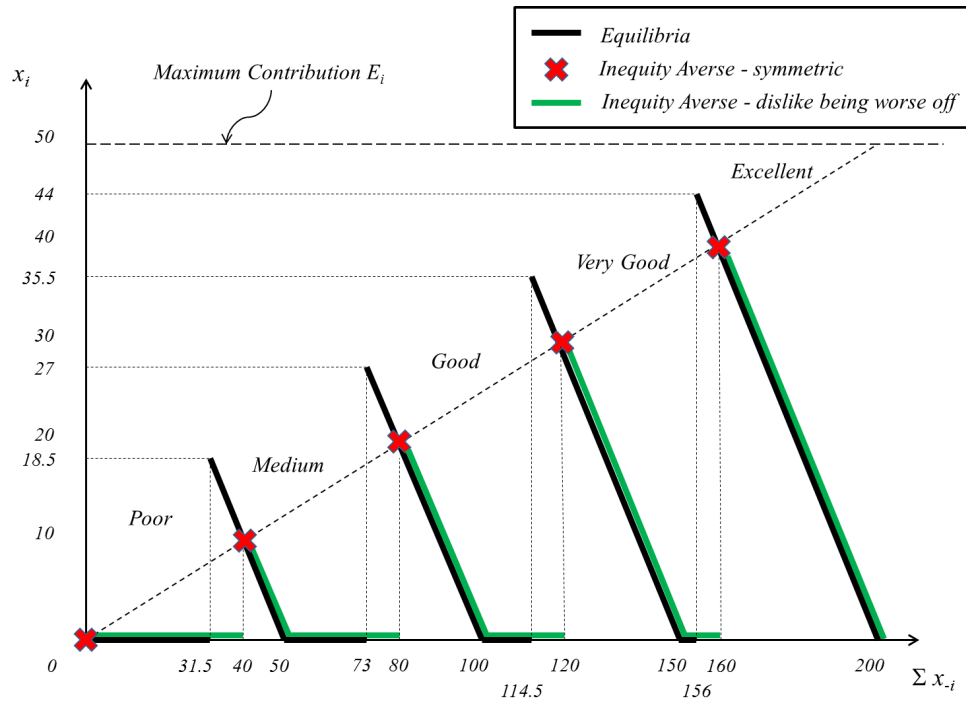


Figure 3.1. Graph of the Reaction Function for Subject i

In contrast, we believe the targeted feedback treatments will reach more efficient equilibria. Consider the targeted below treatment where only those subjects that contribute below the average will receive feedback. In this case, these subjects contributing below the average will move along the solid black threshold lines shown in Figure 3.1 to a more asymmetric rate of contribution. This will eventually lead to the below average subjects contributing more than the above average subjects, resulting in a change of roles between the below and above average contributors. As this process continues, we expect to see continual increases in contributions because there will not be feedback that will drive the contribution rate down as in the prior prediction for random feedback. We expect the opposite result for the targeted above treatment.

The random feedback treatment may increase coordination amongst the players towards the symmetric equilibrium. This is due to subjects being targeted with below / above information about the average contribution of the players in the group, poten-

tially driving their contributions upwards and downwards simultaneously. We expect the no feedback information treatment to have more difficulty with coordination and in fact expect to see a failure of coordination towards lower thresholds, if not complete free-riding by all subjects.¹³ All of these predictions of course rely to some extent on the homogeneity of social preferences, as a heterogeneous preference towards selfish (or altruistic) behavior will certainly increase the difficulty of coordination amongst the subjects.

3.5 Experimental Procedures and Implementation

We conducted the experiment at the Vernon Smith Experimental Economics Laboratory (VSEEL) at Purdue University in February of 2010.¹⁴ Subjects were recruited by email using the laboratory's online recruitment system, and subject participation was limited to a single session. The computerized experimental environment was implemented using the z-Tree v.3.3.6 software package (Fischbacher, 2007). Subjects were randomly assigned to individual computers and communication was not allowed during the session. Copies of the experiment instructions were provided to each subject and were read aloud by the experiment administrator. A copy of the instructions used to conduct the experiment is available in Appendix D. Completion of control questions was required to ensure each subject understands the experimental procedures prior to starting the actual experiment. Any subject that fails to answer the control questions after three attempts was personally assisted by the experiment administrator.

¹³In a linear public goods game, we would expect results to be similar when comparing a no information feedback condition to a random (or aggregate) information condition (Sell and Wilson, 1991; Weimann, 1994). However, because we implement our design with multiple thresholds, it is unclear if this previously observed result will hold. This is especially the case if subjects are able to coordinate in a symmetric manner as mentioned prior.

¹⁴VSEEL contains 28 computers with flat-panel displays on partitioned desks for the subjects, and one administrator server computer. The partitioned layout makes it quite difficult for subjects to coordinate by glancing at another screen or otherwise discussing the experiment. Further, an observation room with one-way glass is used to monitor subject behavior throughout the experiment.

A \$5 US dollars show-up fee was paid to the subjects that were randomly excused from the experiment if more than 25 subjects arrived at each session. To avoid wealth effects, we randomly choose three of the forty-six periods for payment, and pay each subject their total profit over these periods at conversion rate of 20 tokens per dollar. The experiment lasted on average 1 hour and subjects were compensated between \$8.25 and \$16.75, with the average subject earning \$12.60. All subjects were paid in cash privately and individually at the conclusion of the experiment after completing a short demographic questionnaire.

Each period the subjects were re-matched using a random draw by the computer and assigned to a new group for that period. It is possible but not likely that subjects may be in the same group each period, but this information is never communicated to them. Subjects were never informed of who is in their group or the specific decisions that other subjects make during the experiment. At the beginning of each round subjects were first asked about their beliefs about the average contribution in their group. We do not incentivize beliefs since we would prefer to not have the elicitation result in behavioral changes by the subjects (Gächter and Renner, 2010). Then subjects had to type their individual contribution into a text box. Input was validated by the computer and subjects were shown a warning message if they attempted to violate the interval provided. Validation also includes entering a negative integer or non-integer value. After submitting their decision, the quality level attained and the profit earned for the period is displayed to each subject.

Subjects were explicitly notified of a restart when the experiment moves to the next block of the experiment (e.g. change in the information treatment). They did not know *ex ante* if or when a restart would occur. The restart included the distribution of supplemental instructions on-screen and read aloud by the experimenter. The subjects were never informed about the random vs. targeted information treatments. In the information treatments, some subjects are presented with a stock of information that includes the average token allocation rate for the subjects that are in the group for the current period. The allocation rate is obtained from the prior period for each

subject. This feedback allows some subjects to obtain some information about what they might expect their group members to do in the current period. Subjects are also reminded of their own allocation rate from the prior period.

In order to achieve the same amount of information each period, we use the same algorithm for determining how many subjects in each group will receive the information. This technique allows for direct comparison of results between the information treatments. In the targeted rounds the specific below or above average subjects receive information. We use this algorithm for determining the number of participants that will receive information in the non-targeted rounds. More specifically, we count the number of subjects that would have been targeted, and then randomly select the same number of subjects for the “randomly given” information.

3.6 Experimental Results

A total of 90 subjects participated in our experiments (treatment A: $n=20$, treatment B: $n=25$, treatment C: $n=25$, treatment D: $n=20$). Unless specifically noted (e.g., Section 3.6.5), results presented are for the first block of rounds (2 – 16), providing the clearest interpretation of subject behavior without exposing subjects to changes in information treatments.

We first present the aggregate data for all four treatments. Graphical views of the aggregate data provide initial insight into overall patterns and discrepancies that will be disentangled as our deeper analysis unfolds. Mean allocations for all subjects in each treatment are provided in Figure 3.2 and mean quality levels for all subjects are provided in Figure 3.3. As expected, the mean allocations in the first round for all sessions follow the stylized fact that subjects allocate approximately half of their endowment to the public good in the beginning rounds (Ledyard, 1995). These initial allocations of course begin to change as subjects develop expectations by learning about the game, as well as the consequences / rewards of their actions during successive rounds of play. However, as described in Section 3.4.1, our design ensures

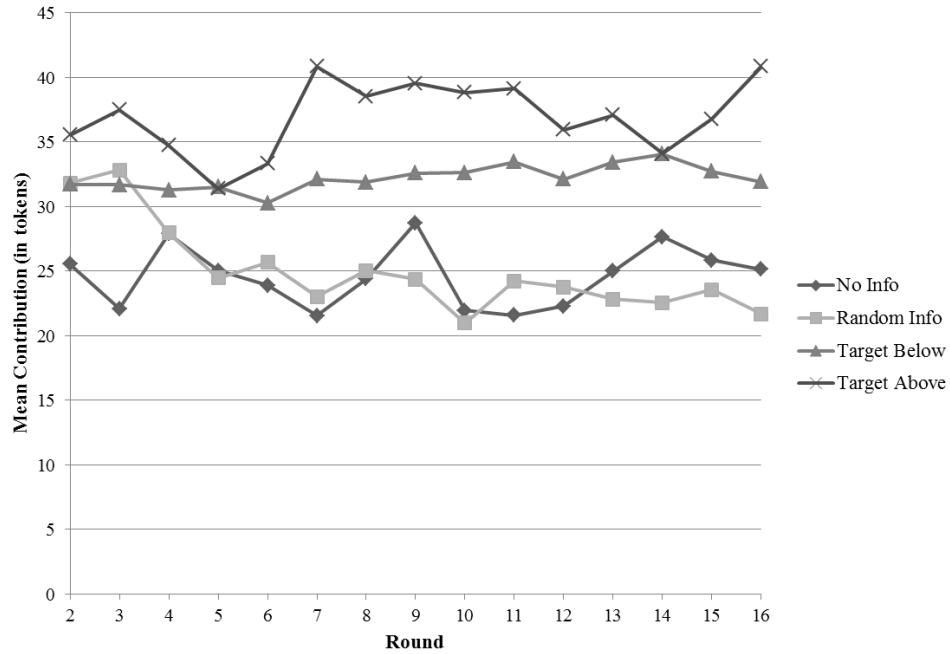


Figure 3.2. Mean Contribution per Round

direct reciprocity and reputation effects are kept to a minimum because each round is played as a one-shot game due to our random re-matching of subjects (Andreoni and Croson, 2008; Croson, 1996).

In regards to mean contribution at an aggregate level (Figure 3.2), subjects in both of the targeted treatments appear to coordinate to higher thresholds across all periods in comparison to the no information and random information treatments.¹⁵ In contrast, the treatments beginning with the no information or random information feedback treatments are not able to coordinate as effectively as the targeted treatments.

Similar patterns are observed for the mean quality at an aggregate level (Figure 3.3). The targeted above feedback treatment appears to enable and maintain coordination around the *Very Good* threshold, whereas the targeted below feedback

¹⁵Although not presented in a figure here, coordination appears to remain stable in the targeted treatments when moving to the second block of rounds (i.e., rounds 17-31) when subjects are restarted with the no information treatment.

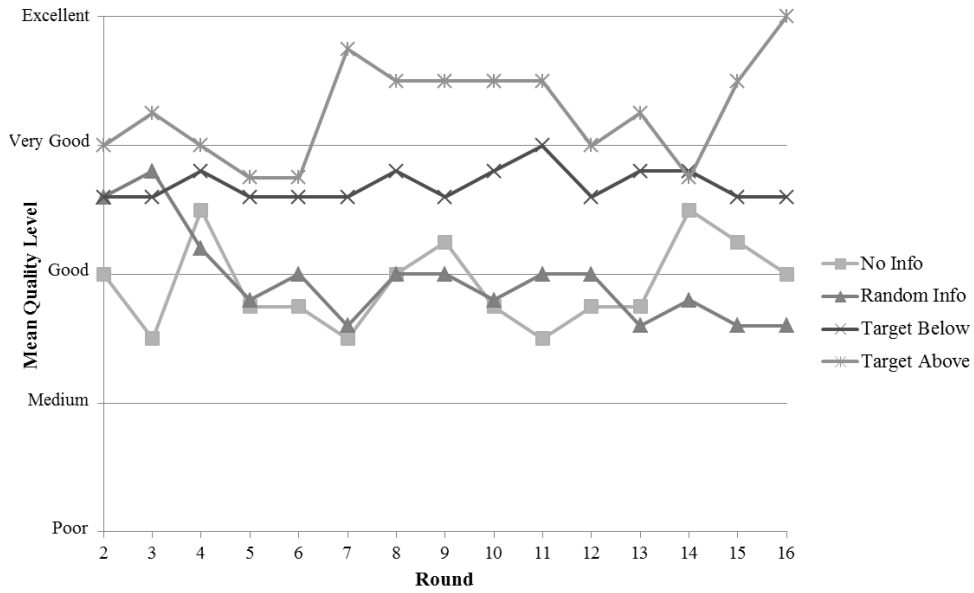


Figure 3.3. Mean Quality Level per Round

treatment is less efficient yet still well above the *Good* threshold. There is considerable noise for the no information treatment, with mean quality ranging between *Medium* and *Good* across rounds. The mean quality for the random information treatment appears to consistently degrade over time.¹⁶ Another view of these results is shown by Figure 3.4, providing additional insight into the actual proportions of groups that receive a discrete quality level.¹⁷ In that regard, Figure 3.4 is quite useful in drawing conclusions about which treatments are likely to be better at coordinating at higher or lower levels of quality. In particular, we see that the no information and random information treatments are nearly identical in the distribution of quality levels, whereas the targeted treatments are able to coordinate a greater proportion of groups at higher qualities.

Given the aggregate patterns of contributions just described for each of the treatments, we now desire to carefully analyze and compare feedback treatments using

¹⁶Eventually to a free-riding state in later rounds.

¹⁷Groups are explicitly classified each round at a particular quality level, then summed giving us a proportion. This is in contrast and complementary to just merely looking at mean quality values.

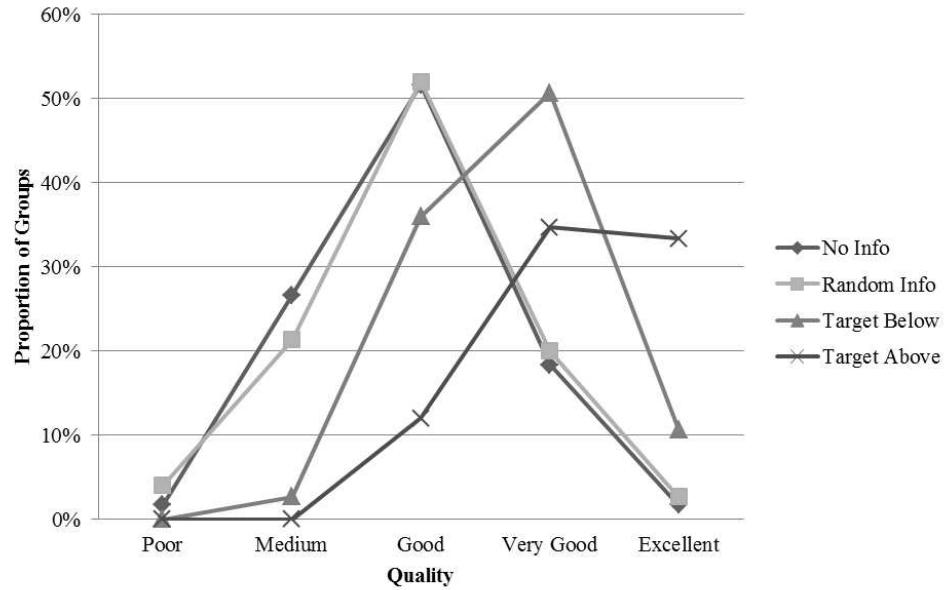


Figure 3.4. Proportion of Groups Reaching Specific Quality Levels by Treatment

both non-parametric and parametric techniques. We can then determine if there are significant differences in the ability for subjects to coordinate amongst the various information treatments, providing insight into the most effective approach that could be used in practice.

3.6.1 No Information vs. Random Information

The no information feedback treatment represents a baseline which is consistent with the prior literature. We therefore conduct our initial comparisons between the baseline (no information) and the random information feedback treatment. The random information treatment is our representation of complete information (although clearly incomplete in our case), which is typically the information approach used by the literature.¹⁸ Once this comparison is made, we may then compare the targeted feedback treatments to the random feedback treatments.

¹⁸Complete information is often referred to as ‘aggregate’ information.

Table 3.3
Contribution to the Group Account: No Information vs. Random Information

Treatment	n	Mean Contribution	Std. Err.	Mean Quality	Std. Err.
No Info.	300	24.58	0.92	2.92	0.04
Random Info.	375	24.99	0.78	2.96	0.04

Table 3.3 includes the mean contribution and mean quality levels for the first block of 15 rounds (2 – 16) in the No Information and Random Information treatments. We begin our analysis of the mean contribution and quality level by using the non-parametric Mann-Whitney U test for between-subject analysis. When we compare the mean contribution rates between the first block of rounds for these first two treatments, we do not find a significant difference between the no information treatment (24.58) and the random information treatment (24.99) (Mann-Whitney U test, $z = 0.44$). The same pattern holds true for the mean quality level as well (Mann-Whitney U test, $z = 0.92$). Given the results of these non-parametric tests, and considering the aggregated figures presented prior, providing random information is no better or worse in enabling coordination than not providing information at all.

3.6.2 Random Information vs. Targeted Information

Because we have concluded that random information is for all intents and purposes, equally effective as no information using non-parametric tests, we can step into the comparisons of the feedback treatments. Comparing the targeted treatments to the random information treatment is the most appropriate approach because we desire to compare similar levels of information stock between treatments. As described in Section 3.5, we use the same algorithm for determining how many subjects receive information in the random and targeted information treatments. Therefore, the information stocks are expected to be comparable, allowing direct comparisons to be made.

Table 3.4
Contribution to the Group Account: Random Information vs. Targeted Information

Treatment	n	Mean Contribution	Std. Err.	Mean Quality	Std. Err.
Random Info.	375	24.99	0.78	2.96	0.04
Target Below	375	32.23	0.70	3.69	0.04
Target Above	300	36.95	0.59	4.27	0.04

Table 3.4 shows the mean contribution and quality levels for the information treatments in our experiment. There is a significant difference between the mean contribution for the targeted below information treatment (32.23) and the random information treatment (24.99), with the targeted below information treatment reaching a higher level of mean contribution (Mann-Whitney U test, $z = 6.67$, $p < 0.001$). As with the targeted below information treatment, there is also a significant difference between the means for the targeted above information treatment and the random information treatment (24.99) (Mann-Whitney U test, $z = 10.47$, $p < 0.001$). Further, the targeted above information treatment also reaches a mean contribution (36.95) that is significantly higher than that of the below information treatment (32.23) (Mann-Whitney U test, $z = 4.31$, $p < 0.001$).

We also observe measurable differences between the mean quality level attained by each treatment in Table 3.4. The mean quality for targeted below (3.69) is significantly different than the random information treatment (2.96) (Mann-Whitney U test, $z = 12.03$, $p < 0.001$). The mean quality for the targeted above (4.27) is also significantly different than the random information treatment (Mann-Whitney U test, $z = 17.10$, $p < 0.001$). Lastly, there is a significant difference between mean quality levels reached by the targeted below and targeted above information treatments (Mann-Whitney U test, $z = 9.77$, $p < 0.001$).

Because the results in Table 3.3 and Table 3.4 rely upon the mean contribution and mean quality across all 15 rounds in the first block of rounds, a round-by-round

Table 3.5
Comparison of Contributions by Round to the Random Information Treatment

	3	7	8	9	10	11	12	13	14	15	16
No Info.	2.57	0.39	0.21	0.99	0.13	0.64	0.25	0.42	1.02	0.49	0.70
Target Below	0.34	2.17	1.76	1.89	2.96	2.29	1.78	2.26	2.39	2.05	2.40
Target Above	0.94	4.00	3.05	3.55	4.32	3.49	2.49	2.69	2.53	2.79	3.84

Mann-Whitney U test. Bold-faced z -scores > 1.96 are statistically significant.

comparison of contributions is also be useful in discerning when measurable differences occur, and whether or not they are sustained. Table 3.5 compares each of the treatments against the random information treatment for the first block of rounds. Z -scores generated by conducting Mann-Whitney U tests are displayed in each cell, with statistically significant coefficients shown in bold. Rounds 2 and 4-6 did not produce significant differences between contributions, and are thus omitted for brevity. Regarding the no information treatment, only round 3 is significantly different than random information, perhaps due to a noisy coincidence. Both target below and target above provide many rounds that are significantly different than the random information treatment, which is not surprising given the results presented earlier in this sub-section. Overall, the target above treatment has the greatest number of rounds that are significantly different than the random information treatment.

A measure of efficiency for each of the treatments is given by a calculation of coordination waste in Table 3.6, or the inefficiency created by the combined contributions over and above meeting a particular threshold. In our design, these excess tokens are simply wasted. As we might expect given the results thus far, the target above treatment is significantly less wasteful in comparison with the random information treatment (Mann-Whitney U test, $z = 2.09$, $p < 0.05$). The other treatments are equally wasteful in comparison to the random information treatment, a result that is also shown by Figure 3.3 presented earlier. We did not anticipate this result because subjects receiving information in the target above treatment should decrease their contributions if motivated by inequity version. Decreasing contributions should oc-

Table 3.6
Coordination Waste

	Mean Waste	vs. Random Info.		
No Info.	27.07	$z = 0.11$		
Random Info.	26.96			
Target Below	26.49		$z = 0.26$	
Target Above	21.43			$z = 2.09$

Mann-Whitney U test. z -scores > 1.96 are statistically significant.

cur at an asymmetric rate, continually cascading in a downward fashion, rather than stabilizing at a particular threshold. Perhaps in this case the subjects are able to update their beliefs in a clearer manner than the other treatments, resulting in the ability to truly understand how critical their contribution is to meeting a threshold.

Given the results presented thus far, it is apparent that the targeted above information treatment reaches the highest mean contribution level, followed by the targeted below information treatment, with the no information and random information treatments performing similarly. These results do not suggest inequity aversion as the only mechanism for coordination amongst the subjects, as otherwise the targeted below information treatment would perform better than the targeted above information treatment. Instead, it appears that another behavioral mechanism may be affecting the decisions made by the subjects in our experiment instead of, or in conjunction with, inequity aversion. The heterogeneity of subjects would certainly lead to the failure of our behavioral predictions discussed in Section 3.4.2, as our predictions using the Bolton and Ockenfels (2000) model are based upon the assumption of homogeneous types. An intuitive explanation of why target above is the best coordination mechanism in our free-riding context is due the influence of altruistic and optimistic types receiving the targeted information. These types of subjects do not draw down towards a lower level of contribution due to inequity aversion, and in contrast, may be optimistic about reaching the next higher equilibrium, rather than reducing their contributions.

3.6.3 Impact of Contribution Tendencies on Coordination

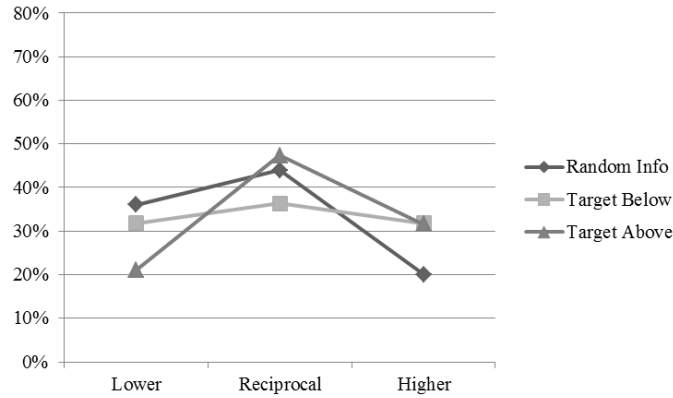
Recall that the subjects in our experiment observe the following independent steps per each round: (1) belief elicitation, (2) information provided about average group member contributions (depends on the information treatment and whether or not the subject receives information in the current round), and (3) the subject makes a contribution decision for the current round. Our approach allows us to capture any discrepancies between the subject's beliefs – which are based upon learning the outcomes from previous rounds – and the use of the information to update beliefs. Therefore, the receipt of information by the subject has the potential effect of influencing their contribution decision in the current round.¹⁹

Figure 3.5 illustrates the effect of the specific information treatments on the subject's ability to update their beliefs.²⁰ Specifically, the tendency of the subjects to increase, decrease, or remain at a reciprocal level after receiving information absolutely influences the ability to coordinate in the game. Comparing these directional tendencies therefore provides an underlying explanation – rooted in the ideas of inequity aversion and conditional cooperation – about why targeted information is the best coordination mechanism in our free-riding context.

We measure directional tendencies by determining the relationship between beliefs and contributions for every subject receiving information in our sample. If the relationship between beliefs and contributions is around 1, then the subject is acting using reciprocal tendencies (i.e., contributing about the same as what she originally believes others are contributing). If the relationship is generally below 1, then the subject is acting using a lower tendency (i.e., contributing less than what she originally believes others are contributing). Lastly, if the relationship is generally above 1, then the subject is acting using a higher tendency (i.e., contributing more than what she originally believes others are contributing). Note, each of these tendencies draws

¹⁹Although the subjects learn about group contributions over time, there is no reason *ex ante* why the new group would be better, worse, or otherwise different than a prior group.

²⁰We do not collect beliefs using the strategy method. We therefore cannot *ex ante* classify subjects by cooperation type (Fischbacher and Gächter, 2010).



(a) Comparison Across Information Treatments

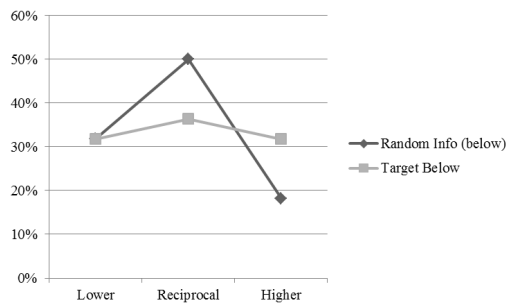
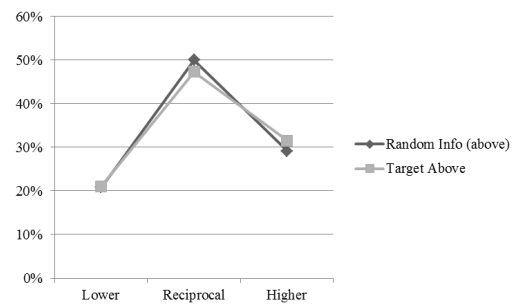
(b) Target Below vs. Random *Below*(c) Target Above vs. Random *Above*

Figure 3.5. Contribution Tendencies of Subjects Receiving Information

upon ideas from conditional cooperation, such as selfishness, altruism, and reciprocity, but only to see if inequity aversion as modeled by Bolton and Ockenfels (2000) and discussed in Section 3.4.2 is a reality in our game. We then calculate quartiles from the coefficients generated from the relationship between beliefs and contributions for each subject and bucket the tendencies by treatment. Specifically, if the coefficient for the relationship is less than the value for the first quartile, we consider the subject to have a lower contribution tendency. If the coefficient is greater than the third quartile, we consider the subject to have a higher contribution tendency. We consider the subjects falling into the middle two quartiles as having a reciprocal tendency.²¹

²¹The coefficient value for the 2nd quartile in our data was 1, or perfectly reciprocal. The pattern remains consistent using other bucketing techniques, such as thirds.

As shown by Panel (a) in Figure 3.5, the random information treatment has a greater percentage of lower and reciprocal tendencies when compared to the other two treatments. Target below is relatively flat amongst the three tendencies, whereas target above has a greater percentage of reciprocal and higher tendencies. The most interesting result from this figure is for the random information treatment because it has a greater proportion of both lower and reciprocal tendencies than target below, while having a lower proportion of higher tendencies than the other two treatments. We believe the reason for this result is explained by Panels (b) and (c) in Figure 3.5. These panels compare target below and target above to the random information treatment *as if* the subject was being targeted when the information was sent to them. Here we see the discrepancy in proportions in the target below panel, where the random information treatment has a greater proportion of reciprocal tendencies but a small proportion of higher tendencies. The target above panel is virtually identical to random above in comparison.

The explanation for this result is quite straightforward and is in support of Bolton and Ockenfels (2000). Across the spectrum of heterogeneous subjects, there are inequity averse types that given an opportunity to learn about other's actions, will update their beliefs and lower their contributions accordingly. These subjects may initially be above or below the mean contribution level, depending on the other subjects they are matched with that round, and their initial contribution strategy. Therefore, those subjects that are more likely to have lower or reciprocal contribution tendencies due to inequity aversion, will have an opportunity to receive information and update their beliefs if they are randomly targeted. In other words, the random information treatment is the "perfect storm" of information strategies because inequity averse types from both ends of the spectrum may at some time receive information, and accordingly act in a manner that reduces contributions. In contrast, the targeted treatments do not allow this *doubling up* of inequity averse subjects to occur (i.e., from below *and* above), unless of course the subjects are playing a completely random contribution strategy. Targeted strategies are the preferred approach when subjects

may be heterogeneous in their type, with target above having the greatest chance of altruistic and optimistic subjects, leading to the best opportunity to maintain coordination in the contributions.

3.6.4 Parametric Analysis Across Treatments

We also conduct parametric regressions to provide insight into how the availability of information specifically is affecting the subject's decisions. The regressions for the first block of rounds are shown in Table 3.7 and Table 3.8. As before, we focus on the first block of rounds in both of these regressions because we wish to compare decisions between treatments, without allowing history to affect future decisions (e.g., the restarting of information treatments when switching to a new block of rounds). All models are tested using random effects GLS regressions, with random effects for each subject and the round (period of the game) to control for any learning or other characteristics that may occur over time. The dependent variable is contribution to the public good for all models.

Table 3.7 contains three models differentiated by the subject's beliefs about other's contributions. Model (3) in particular contains an interaction between beliefs and the existence of information in a particular round. Observations are pooled amongst all of the treatments, with the no information treatment as the base case. The first three variables (treatment name) are dummies assigned a value of 1 if the subject is in a particular treatment; 0 otherwise. The next three variables (existence of information) are dummies assigned a value of 1 if the subject received information in a particular round; 0 otherwise. The last two (beliefs) are continuous variables representing the subject's beliefs about contributions of others.

The results from Table 3.7 parallel those of the non-parametric tests discussed earlier. The targeted information treatments have positive and significant coefficients across all three models. As expected, the target above treatment has the largest magnitude coefficient in comparison to the other treatments. Interestingly, the existence

Table 3.7
Random Effects GLS Regression: Pooled Data

DV: Contribution	(1)	(2)	(3)
Random Info.	0.867 (2.512)	2.530 (2.263)	2.624 (2.276)
Target Below	9.125*** (2.544)	5.634* (2.298)	5.326* (2.318)
Target Above	12.938*** (2.695)	9.352*** (2.434)	9.192*** (2.449)
Info. (Random)	-1.016 (1.063)	-1.350 (0.959)	1.102 (1.793)
Info. (Below)	-3.211* (1.359)	-1.607 (1.229)	1.522 (2.281)
Info. (Above)	-1.040 (1.308)	-1.877 (1.180)	1.539 (2.425)
Beliefs		0.544*** (0.031)	0.577*** (0.037)
Beliefs * Info.			-0.094 (0.058)
Constant	24.580*** (1.838)	8.936*** (1.878)	7.988*** (1.976)
Observations	1350	1350	1350
R^2	0.143	0.337	0.337
Wald X^2	40.99***	363.44***	363.44***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Note: The Information dummy variable represents the existence of information sent to a subject in a particular treatment in a particular round.

of information does not appear to influence contributions to the public good, as indicated by the information (random / below / above) dummies. If we recall Figure 3.5, it becomes clearer as to why this might be the case. Each group of subjects in each treatment have their share of variance in contribution tendencies after receiving information. We therefore tease out the existence and consequences of these tendencies by using a non-pooled regression where each treatment is looked at independently.

Table 3.8 is a simpler version of the regressions presented in the pooled models (Table 3.7). The first variable listed is a dummy that is assigned a 1 if the particular

Table 3.8
Random Effects GLS regression: Non-Pooled Data

DV: Contribution	Random Info.	Target Below	Target Above
Info.	-1.422 (1.034)	-3.051** (1.038)	2.644* (1.154)
Beliefs	0.645*** (0.053)	0.422*** (0.061)	0.408*** (0.082)
Constant	8.873*** (2.094)	19.347*** (2.412)	20.754*** (2.913)
Observations	375	375	300
R^2	0.350	0.380	0.115
Wald X^2	151.21***	68.05***	38.59***

*** p < 0.001, ** p < 0.01, * p < 0.05

subject received information in a particular round; 0 otherwise. The second variable captures the beliefs that are elicited from each subject prior to any information being provided. As we expected, the coefficient on the information dummy reflects the non-parametric results provided in Table 3.4 and Figure 3.5. The signs on these coefficients are consistent with the contribution pattern for each of these information treatments, with the random and targeted below treatments having lower contributions than the target above treatment. As before, targeting above the mean allows us the greatest opportunity to inform altruistic and optimistic subjects, maintaining an increase in contributions when information is received.

3.6.5 Sustaining Coordination over Blocks of Rounds

The last set of results that we present consider the blocks of rounds that subjects experienced *before* and *after* a restart at rounds 17 and 32. Specifically, we would like to determine if subjects are able to sustain their level of coordination over time and over treatment restarts. Mean contributions across all three blocks of rounds are presented in Table 3.9. For the first treatment (no information / random information / no information), there is not a significant difference between the first and second

Table 3.9
Sustaining Coordination: Mean Contributions

Treatment	Block of Rounds		
	2 – 16	17 – 31	32 – 46
No Info. / Random / No Info.	24.58	23.67	21.21
Random / No Info. / Random	24.99	19.42	11.81
Target Below / No Info. / Target Below	32.23	31.05	28.79
Target Above / No Info. / Target Above	36.95	38.80	36.92

blocks of rounds. Although the mean is slightly smaller in the second block (23.67) compared to the first block (24.58), subjects generally appear to be maintaining the same level of contributions after moving to the random information treatment. However, when we compare the first block to the third block, we do find a statistical difference between the means (two-sided Wilcoxon signed-rank, $z = 2.48$, $p < 0.05$). This result suggests that the subjects are having difficulty maintaining the same level of coordination in the third block of rounds, in comparison to the first two blocks of rounds. We would expect this result because the subjects are not receiving any information about the average contribution to the good, therefore the subjects will converge to a lower threshold (in this case, approximately 20 tokens), or perhaps ultimately to a free-riding equilibrium.

For the second treatment (random information / no information / random information), we find the subjects degrade quite rapidly in their ability to coordinate. This is an unexpected result as the results for this treatment should parallel those of the prior one. We observe significant differences between the means from the first block (24.99) to the second block (19.42) (two-sided Wilcoxon signed-rank, $z = 6.41$, $p < 0.001$), as well as the first block to the third block (11.81) (two-sided Wilcoxon signed-rank, $z = 12.66$, $p < 0.001$). We observe in this treatment a quick degradation in coordination during the random feedback treatments, whereas the second block (no information treatment) provides evidence of some ability to maintain a threshold around 20 tokens. Clearly there is a discrepancy in contribution behavior between

those subjects that receive information above and below the mean contribution rate from the prior round (as discussed in Section 3.6.3, thereby driving the mean contribution rate downwards.

If we compare the no information treatment in the first block to the no information treatment in the second block (19.42), we do observe a significant difference between the means (Mann-Whitney U test, $z = 3.98$, $p < 0.001$). The same result does not hold true for comparing the random feedback treatments between the first two treatments (Mann-Whitney U test, $z = 1.09$). These results suggest that history matters to the subjects, particularly if they received random information prior to the no information treatment. However, if the subjects never received information about the mean contribution in the first block of rounds, the subjects did not degrade significantly in their ability to coordinate around a stable threshold.

Next we consider the means for the targeted information treatments in the third and fourth row in Table 3.9 to each other as well as the random information treatment. In regards to the target below treatment, there is a significant difference between the first block (32.23) and the second block (31.05) (two-sided Wilcoxon signed-rank, $z = 2.61$, $p < 0.01$), as well as the first block and the third block (28.79) (two-sided Wilcoxon signed-rank, $z = 5.41$, $p < 0.001$). The mean contribution is degrading slightly over time and changes of information in this treatment. The subjects approach the equilibrium at 30 tokens in the first two blocks. In the latter rounds in the third block the subjects fail to maintain the threshold at 30 tokens and instead degrade into the next lower threshold level. Although the contributions decrease over time, the subjects are still able to maintain contribution levels at or above 30 tokens. This is in stark contrast to the random information treatment.

In regards to the targeted above information treatment, there is a significant difference between the first (36.95) and second block (38.80) of rounds (two-sided Wilcoxon signed-rank, $z = 3.14$, $p < 0.01$), however there is not a significant difference between the first and third block (36.92) of rounds. Therefore, the target above information treatment appears to be able to recover from a slight degradation in

coordination during the middle block of rounds (no information treatment), to the prior level of coordination (target above treatment).

To summarize the non-parametric, sustainability of coordination results just discussed, it is clear that the targeted information treatments allow subjects to coordinate at higher allocation levels than when compared to the random information treatment. The targeted information treatments also appear to maintain a stable rate of contributions over time and restarts, whereas the random information treatment degrades rapidly towards free-riding. The random information treatment and the no information treatment perform similarly, at least in the initial blocks of rounds.

3.7 Discussion and Conclusion

The overall goal of this research is to understand the role of information targeting as a coordination mechanism. We motivate our study using the phenomenon of the *everybody else is doing it, so I should do it too* mentality, with a specific focus on digital piracy. We focus on piracy because information goods suffer from extensive free-riding and have the characteristics of a public good, and design and implement an abstract framework of a multiple-threshold public good game. We develop information treatments based upon strategies used in the real-world for informing consumers of piracy rates faced by digital goods producers, allowing us to provide a significant contribution to the coordination literature.

Consistent with prior research, we find that randomly providing consumers with information about the contribution rate results in the same level of coordination as not providing any information at all, particularly over the short-term. Providing information in a random manner allows subjects from across the spectrum of contributions to update their beliefs, resulting in a decline in the ability to maintain coordination. The decline in coordination is due to the underlying characteristics driving inequity aversion and conditional cooperation among subjects. In contrast, the ability to target information to specific consumer groups increases the ability for

coordination to occur amongst subjects. Informing those consumers who are currently above the average contribution to the public good encourages them to continue their good behavior, and at the minimum remain reciprocal with others, thus maintaining a high level of quality for the good. Similarly, informing those consumers who are currently contributing below the average amount to the public good allows subjects to maintain reciprocity while not drawing down the inequity averse types that are currently above the average.

Our research provides new insights into the role of targeted information as a coordination mechanism in a public goods setting, allowing for useful implications to mitigate the free-riding problem in practice. Employing targeting strategies plays to the strengths of conditional cooperation, while simultaneously not allowing inequity aversion to draw down overall contribution levels. Unlike other coordination mechanisms such as communication, punishment, and identifiability, targeting strategies are certainly more feasible to deploy in a real setting, among real consumers.

4. DIGITAL PIRACY, TEENS, AND THE SOURCE OF ADVICE: AN EXPERIMENTAL STUDY

4.1 Introduction

“While downloading one song may not feel that serious of a crime, the accumulative impact of millions of songs downloaded illegally – and without any compensation to all the people who helped to create that song and bring it to fans – is devastating.” –RIAA (2011b)

The ubiquity and ease of access to peer-to-peer networks and torrents has made it quite trivial for all but the most novice of pirates to obtain copyrighted content illegally. Due to the threat of digital piracy, many methods have been developed and used to combat the behavior (e.g., technology, legal, and educational), each having their own strengths and weaknesses. The advice given to prospective music pirates above from the RIAA represents an example of an educational approach to mitigate piracy, advising the pirate about the perils of piracy, while simultaneously informing them of others who are suffering from engaging in that behavior. Several other stakeholders¹ to the piracy problem have also attempted to deliver advice to potential pirates about engaging in the behavior, but it is unclear which source of advice is the most effective at mitigating piracy.

The two leading bodies for the movie and music industries, the Motion Picture Association of America (MPAA) and the RIAA, have been active in exploring the delivery of advice through their websites and direct communication channels, as well as through *other sources* such as university administrators, teachers, and parents (Anderson, 2009; Stewart-Robertson, 2010; RIAA, 2009, 2011a). Popular recording

¹Software producers, record labels, movie studios, governmental regulators, as well as those figures that are personally close to the pirate (e.g., parents, friends, teachers).

artists such as Metallica (Jones, 2000), and software developers such as 2DBoy (2008), have taken the onus upon themselves to deliver advice about piracy to their fans. Results among the sources have been mixed, sometimes resulting in backlash (in the case of Metallica), or acknowledgment of the problem (in the case of 2DBoy), from consumers about engaging in piracy. Ultimately, the communication of anti-piracy advice has been a controversial topic for the last decade as the industry has tried – and is still trying – to understand the best approach for addressing the problem.

The sharing of anti-piracy advice with those that are likely to pirate is a sound, but unexplored approach by the literature. Evidence from the software industry shows us that the educational strategy has exhibited some success, as digital pirates sometimes reconsider their illegal behavior (2DBoy, 2008). Both 2DBoy and the RIAA provide some information about the extent of the problem, reinforcing the fact that piracy is not without a victim. We have also documented evidence of this phenomenon in prior research using theories from social psychology and behavioral economics (Hashim et al., 2011a, 2011b), by showing that pirates may believe their actions to be victimless, while also being influenced by information that is given to them.

Summarized another way, digital pirates may be receptive to information given to them about piracy, leading to the modification of their illegal behavior. Our research questions follow by integrating the educational strategy of sending information about the extent of piracy, and varying the *source of advice* for the information. In particular, does sending informative advice matter in a framed piracy context? Who is the best source of advice for the message to come from? Does it matter if the source of advice has a stake in the outcome of the piracy decision?

We implement a laboratory experiment in this paper – using parents and their teenagers as the subject pool – to determine if there are observable differences in real consumer behavior when varying the source of advice about piracy.² Our experimental treatments vary in the *source of advice* that is sent to the music consumers at various

²Unless otherwise noted, most laboratory experiments utilize a *standard* subject pool of university students. Our experiment uses a *non-standard* subject pool of parents and their teenagers, increasing both the novelty and the applicability of our treatment design to reality.

points during the game. Although there are many possibilities for the source of advice, our design focuses on those that we believe accurately represent reality, while having the potential to provide for meaningful managerial insights. Each treatment varies in not only the source, but whether or not the source has a direct stake in the outcome of the decisions made by the music consumers. Advice in our game consists of the average profit in tokens the record producer is making per round, and also the average number of songs the group is pirating per round. The text of the advice sent to the subjects is identical for every treatment, and *only* varies in the source.

Our approach is novel and significantly contributes to the literature because we draw upon the real population of potential pirates, and we introduce a new game – *The Piracy Game* – for studying piracy. The results presented provide evidence that the source of advice about piracy does in fact matter. Advice coming from a source with a greater social tie is more important than advice coming from an unrelated 3rd party. Further, following the advice is most effective when there is a stake for the advisor in influencing the pirate’s purchase or pirate decision. Given these results, record producers and industry regulators can develop approaches at disseminating advice about piracy through more effective channels.

The rest of this paper is organized as follows. We review the relevant literature in Section 4.2, and introduce the piracy game in Section 4.3. The experimental setup and procedures are described in Section 4.4. We discuss our preliminary analysis and results in Section 4.5, and conclude in Section 4.6.

4.2 Literature Review

Our paper primarily relates to the public goods and economics of advice literatures. We review the key literature relevant to building our experimental framework in this section.

4.2.1 Public Goods and The Piracy Game

We base our piracy game on the characteristics inherent to information goods. Digital goods subject to piracy are in fact information goods, and have the following two fundamental features. First, making a pirated copy of a digital good does not diminish the availability or utility that other consumers may obtain from the good. Second, the absence of “perfect” copy protection technology ensures that a pirated digital good is non-exclusive. Stated simply, consuming an information good (e.g., music, software, video, e-books) is both non-rival and non-exclusive. We therefore adopt Varian’s (1998) assertion that information goods share the key characteristics of public goods, and build our experimental setup in Section 4.3 from that perspective.³ Our approach allows us to utilize the extensive theoretical foundation in public goods for our experiment.

We develop our piracy game as an extension to the public goods game modified by Goeree et al. (2002). In their model, players receive a different internal and external return depending on what each player contributes to the game. In this way, Goeree et al. (2002) differentiates between altruism and warm-glow contribution behaviors by varying the differences between returns. Although we follow the same premise of differentiating between internal and external returns, our piracy game differs significantly from Goeree et al. (2002) in several key ways. In our piracy game, we use the internal return to represent the utility derived from purchasing an information good, whereas the external return represents the utility derived from pirating an information good. In our game, players do not pirate an information good and receive the external return unless they choose to do so. Unlike most linear voluntary contribution mechanisms (VCM), including Goeree et al. (2002), our game is therefore non-binding in consumption. Another key factor differentiating our game is we include private provisioning of the public good by the information goods producer.

³We do not assert that a digital good *should be* a public good. Rather, it is clear that digital goods retain the key characteristics of public goods, allowing us to adapt existing robust models to our piracy context.

These fundamental differences in our game compared to Goeree et al. (2002) allow us to cleanly develop experimental treatments founded in the economics of advice literature as discussed in the following subsection.

4.2.2 The Economics of Advice

There are many mechanisms for influencing an individual's decision-making processes. One such mechanism that appears absolutely critical to the piracy context – but has yet to have been explored – is the role that the source of advice has in piracy-related decision-making. The source of advice is fundamental to piracy because in practice, firms, law enforcement, and parents (or guardians) can all be impacted by piracy behavior.⁴ Although advice coming from these various sources might be identical in every way, the fact that the advice is coming from a *different* source may have a different magnitude in effect on behavior.

One of the earlier works related to the economics of advice was by Crawford and Sobel (1982). They model information transmission between a sender and receiver, where the sender knows of private information that may enable the receiver to decide upon an optimal outcome. An interesting implication of this work to our study is the importance of receiving advice from senders that *may or may not* have a stake in the outcome, as their work focused on senders whose utility was expressly tied to the receiver's decision. Even though we do not use a Sender-Receiver game, the receiver can make a decision to impact not only the sender, but also other parties in our paper.

In other economics of advice work, Che and Kartik (2009) find that a difference of opinions between advisors and advisees leads to an increased incentive for the advisor to convince others to reach a collective understanding. Their result is intriguing to our context, especially because we vary the source of advice. Each source in our experiment have different underlying incentives to convince the advisee, whereas Che

⁴Several examples have been documented in the press of a child's piracy leading to legal action against a parent or guardian, see e.g., Purvis (2005) among others.

and Kartik (2009) do not consider the issue. In a similar vein, Healy (2009) finds that advice received from heterogeneous sources impacts decision making. However, their work only considers differences between nationalities of those giving advice, not the actual role or stake that the advisor has in the outcome of the experiment. In addition, Schotter (2003); Chaudhuri et al. (2006) show that inter-generational advice (i.e., advice based upon prior experience), has a significant impact on the decision-making made by those receiving the advice. The finding is especially important when common advice is given to all of the subjects in the experiment.⁵ Chaudhuri et al. (2006) specifically recommends that increasing the degree of social connectedness will result in greater contributions to the public good. As a result and of importance to our study, a source of advice about piracy that has a greater stake in the outcome, social connectedness, as well as difference of opinion about the decision, should be able to provide a more meaningful influence on the decision made by the pirate. Our work considers these aspects across our source of advice treatments, whereas the prior work does not integrate them. Our current work therefore addresses significant gaps in the literature, adding the novel strategy of implementing a laboratory experiment using a non-standard subject pool in the piracy context.

4.2.3 Related Piracy Literature

Much of the existing literature that specifically addresses the piracy context is based in the Information Systems (IS) field. The existing IS research has focused primarily on behavioral and analytical approaches to understanding the problem. To complement and significantly expand upon the prior work in the IS field, we approach the piracy problem using experimental economics as our methodology. We can eliminate the potential confounds that have been identified in the piracy literature by using a careful experimental setup and design, focusing entirely on utility derived by consumption.

⁵Although unknown to the subjects, our design utilizes common advice.

IS researchers have shown that the relative cost of a digital good has the potential to play an important role in pirate vs. purchase decisions (Chellappa and Shivendu 2005; Gopal and Sanders 1997). Pricing concerns between pirating and purchasing are integrated into the utility function of the game, addressing the problem uniformly among all players. Other analytical models have explored when technology protection strategies and bundling of goods should be implemented to reduce piracy (Bhattacharjee et al. 2003; Bhattacharjee et al. 2009; Chellappa and Shivendu 2005; Sundararajan 2004). Although we do not address bundling in our game, we do incorporate the inability of firms to adequately protect their digital goods with technology by assuming the good may be shared publicly without restriction. From the behavioral perspective, strategies have been suggested to enhance customer retention by addressing their intentions to use legal software (Hashim et al., 2011; Peace et al., 2003). These strategies include pricing, communication, and legal, among others (Chiu et al., 2008; Moores and Chang, 2006). In our work we experimentally test advice as an educational strategy, moving beyond conjecture in the prior literature. Our approach is especially useful given our experimental treatments that are designed to tease apart implications based upon the source of advice.

Overall, the ability to address the confounds discussed in the prior literature, with the strong parallel between piracy and free-riding in public goods, presents an appropriate foundation for the development and introduction of our *Piracy Game*.

4.3 The Piracy Game

Our piracy game is modeled as an extension of the linear VCM game with differing marginal returns, similar as in Goeree et al. (2002). We adapt the Goeree et al. (2002) game to our specific context of music piracy⁶ and model a different rate of return between choosing to *pirate songs* from other players, and choosing to *purchase*

⁶There is not anything in particular that limits our model to the music piracy context. However, the simplicity and believability of parameterizing our model with \$1 purchases makes music a great candidate context.

songs from a record producer instead. Because of our piracy context, we have two primary types of agents in our game: the record producer, and the music consumer. We introduce the novel *record producer* entity to our game because the purchase (i.e., contribution) decision by the consumer generates profit for the record producer. We therefore implement private provision of a public good in our game.

The *Piracy Game* defines n music consumers, where consumer i decides how many songs s_i they would like to purchase from the record producer (r), or pirate (p) from a shared resource. The profit of the record producer is dependent upon the purchasing behavior of the consumer, where $\pi_r = \sum_{i=1}^n s_i$. Every music consumer contributes to the “music sharing” network (e.g., peer-to-peer network, torrent network, casual piracy among friends) the songs they are endowed with, and the songs that they purchase from the record producer. The utility function 4.1 of music consumer i is linear and given by:

$$U_i(s_i, k_i) = (E_i - s_i) + \alpha_r s_i + \alpha_p k_i \quad (4.1)$$

In our game, E_i refers to the initial endowment of tokens, less the number of songs purchased s_i . Purchasing a song from the record producer yields a return of α_r per song, whereas pirating $k_i \leq s_{-i}$ songs shared by other players yields a return of α_p per song. The net returns generated by our α parameters assumes $\alpha_p > \alpha_r > 0$. Tokens held privately yield a return normalized to 1. If $\alpha_r > 1$, then it is socially optimal to contribute songs to the public good by purchasing songs from the record producer. In equilibrium, because $\alpha_p > \alpha_r$, the rational player will always prefer to download (pirate) as much as possible, and only purchase when there are no more shared songs left to download.⁷ Pirating from the public good in excess of contributing songs to the public good implements the dominant strategy of free-riding in a linear VCM.⁸

⁷We assume the return from purchasing a song generates more utility than just keeping the endowment for a private investment.

⁸As we would expect in a VCM game, we set marginal values to maximize payoffs when following a pirating strategy.

Compared to the *Piracy Game*, Goeree et al. (2002) prescribe returns generated from contributions to the public good that are different for ‘internal’ (i.e., oneself) and ‘external’ (i.e., other) players. Individuals contribute a portion of their endowed tokens to the public good, yielding an internal return. The sum of tokens contributed by other players yields an external return. In their game, as in most VCM games, “consumption” of the public good is binding.

In summary, please note the following fundamental features of our *Piracy Game*. Only the music consumer has choices (s_i, k_i) to make. All other players in the model only exist to mimic the real world environment in the game. Further, although the songs in our *Piracy Game* are privately provisioned, because the music consumers “share” their songs with others, the songs become a public good. Compared to Goeree et al. (2002), the following critical elements differentiate our *Piracy Game* characterized by the utility function 4.1, from Goeree et al. (2002) and other similar linear VCMs. 1) Private provision of a public good by the record producer. 2) Consumption of the “public good” is non-binding – consumers must decide to pirate, rather than receive utility automatically.

4.4 Experimental Setup

4.4.1 Experimental Design and Parameters

We implement our treatment design based primarily upon the Sender-Receiver game described theoretically by Crawford and Sobel (1982). In their game, the receiver accepts a message from a sender where the receiver has the power to implement outcomes. The sender in Crawford and Sobel (1982) has no direct stake in the outcome, resulting in the message being sent being viewed largely as “cheap talk” in the game. Our design departs from the theory by implementing treatments that retain the “cheap talk” perspective, while also introducing social ties in the source of advice. Because we emphasize the *source of advice*, our design focuses on the sender, rather than the receiver, as having the power to implement outcomes in the game. The ex-

Table 4.1
Experimental Treatments

Advisor Type	Stake in the Game
Parent – Punishment (PP)	Music downloads decrease profit
Parent – No Punishment (PNP)	No direct stake
Regulator (REG)	No direct stake
Record Producer (RP)	Music sales increase profit

isting theory is silent on the both varying the source of advice, as well as integrating social ties to the treatment design, and only cares about the receiver’s decision to implement outcomes. Table 4.1 details the differences between treatments which are distinguished by the source of advice (including the implied social tie), and the stake in the game.

In the *Record Producer* treatment, the advice comes from the record producer who has a stake in the game. Additional purchases of songs results in additional revenues for the record producer. In reality, the treatment represents the marketing efforts and publicity surrounding record labels and musicians announcing their loss of sales due to piracy. The *Regulator* treatment is similar to the record producer treatment, except for the fact that the regulator has no direct stake in the game. The experimental administrator plays the role of the regulator, who in reality could be considered an organization such as the Recording Industry Association of America (RIAA), or a governmental agency, resulting in advice that is entirely “cheap talk” in this treatment. The *Parent* treatments have the advice coming from the parent of the student. The two treatments vary in whether or not the parent has a stake in the game, making the parent treatments equivalent with the record producer (stake) and regulator (no stake) treatments. Consider the parent suffering a punishment as a result of their child’s downloading behavior. In reality, the punishment could be the risk of litigation associated with being caught for downloading music illegally. Because the parent may have a social tie with their child, it may be possible for the

parent treatments to be more efficient in changing their child's behavior in comparison with those treatments not having a social tie.

We design our piracy game with 9 players grouped as partners for every round. The makeup of the group is as follows: 4 music consumers (students), 4 non-consumers (parents of the students), and 1 record producer (senior graduate student). Each round of the game the music consumers determine whether or not they would like to download music for free from the Internet, purchase music from the record producer, or do nothing. The individual decision by the music consumer depends on whether or not there are songs available for download from the Internet, and whether or not there are songs available for purchase from the record producer. At the beginning of each round, every music consumer is endowed with 8 tokens to spend on music, and 2 songs to be shared on the Internet. Our music sharing mechanism is based upon the reality of peer-to-peer music sharing networks, where each consumer allows other consumers to download from their stock of music. If a music consumer purchases a song from the record producer, their stock of songs available for download increases by 1. The cost of each song to the music consumer is 8 tokens. Given a group of 4 music consumers having 8 tokens each at the beginning of each round, the record producer thus has 32 songs available for sale each round. If the music consumer instead chooses to download from the Internet, their stock of songs available for download does not change.⁹

Table 4.2 provides an outline of the game's parameters. The music consumer earns 0.5 tokens in utility for each song downloaded for free from the Internet. If the music consumer instead chooses to purchase a song from the record producer, 1 token is spent for the song, earning 1.1 tokens in utility. The net gain to the music consumer is therefore 0.1 tokens per purchased song, ensuring the music consumers do not suffer negative utility if they choose to purchase instead of pirate. The record producer earns 1 token for each song sold, and also receives utility of 0.1 tokens per unsold song left

⁹Each song owned via initial endowment or purchase is considered unique. A download only makes a copy of another's song, therefore it is not unique and not added to the stock of music available for download from the Internet.

Table 4.2
Experimental Parameters

Subject Type	Endowed		Net Utility Earned		
	Tokens	Songs	Download	Purchase	Unsold
Music Consumer	8	2	0.5	0.1	–
Record Producer	0	32	0	1	0.1
Parent (punishment)	12	–	-0.6	0	–
Parent (no punishment)	12	–	0	0	–

in their inventory. We limit each round to 20 decisions, creating a 0 token floor of earnings for the parent in the PP treatment assuming their child downloads 20 songs from the Internet that round. Each round contains multiple decisions to allow us to capture the order that the decisions were made by the subjects, lending our design the potential to infer *why* and *when* music consumers decide to purchase or pirate.

4.4.2 Predictions

The advice given to a subject prior to making a decision is nothing more than an information stock. Given that rational players always seek to maximize their utility, the standard prediction in our *Piracy Game* is the source of advice will have no impact on the subject’s behavior. Selfish / self-centered subjects will always maximize their utility by pirating as much music as possible, purchasing additional music only when there are no more songs to be pirated.

The prospect of harming another’s utility could compel them to behave in a more social way if we consider factors that are not incorporated in the standard prediction discussed above and in Section 4.3. Assuming subjects are aware of, and not underestimating the losses of utility by others, models of social preferences (i.e., Fehr and Schmidt (1999); Bolton and Ockenfels (2000)), cannot explain the impact of advice on decision-making in our game. Heterogeneity of social preferences (e.g., fairness and altruism) may surface in behavior (see e.g., Croson (2007); Fehr and Schmidt

Table 4.3
Impact to the Music Consumer's Utility due to Social Tie

	No Stake in the Game	Stake in the Game
Parent	No Punishment (PNP)	Punishment (PP)
	no impact	$-(\eta_{pp}k_i)$
3rd Party	Regulator (REG)	Record Producer (RP)
	no impact	$+(\eta_{rp}s_i)$

(1999); Goeree et al. (2002), among others) and would be consistent throughout the game, but not change after receiving advice. The only way to explain the impact of the source of advice on subject behavior is the presence of a social tie (van Dijk et al., 2002), and / or morality issues stemming from feeling obliged to follow the advice. Specifically, the parent is expected to have a social relationship of greater strength with the child, in comparison to the record producer or regulator. The strength of the tie may result in the child being less willing to see the parent suffer than the 3rd party player.

Table 4.3 presents an alternate view of the treatments in Table 4.1, by outlining a 2x2 matrix contrasting whether or not the parent or a 3rd party is involved (column), and whether or not the source has a stake in the game (row). Let us first consider the 'No Stake in the Game' column in Table 4.3. There is no *ex ante* reason to expect a difference in behavior between whether or not the advice comes from the parent, or the regulator. The purchase or pirate decisions made by the subject have absolutely no effect on the utility of these two parties. Advice would only have an effect on the subject if the social tie in conjunction with feeling of obligation to follow the advice is incurred by the subject in the parent treatment.

In contrast, if we delve into the 'Stake in the Game' column in Table 4.3, explicit incentives to modify their behavior may have a more effective impact on the decisions made by the subjects in the presence of social ties. Consider the row where the parent receives a punishment for the pirating behavior of their child. Upon receiving

the advice, the child may feel a compunction to incorporate an intrinsic reduction to their utility $\eta_{pp} = 0$ by pirating k_i songs, based upon the social tie and moral obligation to follow the advice. An obligation to follow the advice may also have an impact on the decision to purchase songs from the record producer, as the child may intrinsically increase their utility by $\eta_{rp} = 0$ for the songs s_i they purchase compared to when advice is not received. In both cases where social ties and morality may influence behavior, having $\eta = 0$ is the same as the standard prediction.

To summarize, standard predictions suggest that subjects behave the same across all four cells because information in the form of advice should not have an impact on the behavior. The advice is merely “cheap talk” and we should not observe different reactions among the sources. However, the source of advice might matter to the subject in terms of accepting the “cheap talk” if they care more about the source, or are intrinsically more obliged to follow their advice, as discussed in the prior paragraphs. The most notable exception to the standard prediction is the PP cell, as it clearly combines explicit incentives to modify the behavior (i.e., punishment), with social ties (i.e., advice from a parent).¹⁰ Overall, the combination of the source of advice with the inclusion of social ties and morality in the treatment design, makes our research unique in the literature.

4.4.3 Experimental Procedures and Implementation

We conducted the experiment at the Vernon Smith Experimental Economics Laboratory (VSEEL) at Purdue University during June and August of 2011.¹¹ Subjects were recruited by our visiting of freshman orientation sessions, making a verbal announcement to the audience, and asking for voluntary participation. Subject participation was limited to a single session. The experiment was computerized, imple-

¹⁰An additional outcome that we did not directly discuss in this section is the possibility for the record producer to decrease the intrinsic motivation for the subject to purchase by sending advice (e.g., negative sentiment towards Metallica (Jones, 2000)).

¹¹VSEEL is constructed with partitioned desks for each subject, and has 28 computers with flat-panel displays, plus one administrator server computer. There is an observation room with one-way glass adjacent to the laboratory and is used to monitor subject behavior throughout the experiment.

mented using the z-Tree v.3.3.6 software package (Fischbacher, 2007). Upon entering the laboratory, subjects were randomly assigned to individual computers and communication was never allowed during the session. Experiment instructions were provided to each subject and were read aloud by the experiment administrator. A copy of the instructions is available in Appendix G.

A \$5 US dollars show-up fee was paid to the subjects that were randomly excused from the experiment. If we did not have at least 18 subjects at each session, the session was canceled (8 students, 8 parents, and 2 senior students, were the minimum number of required participants).¹² We randomly choose three of the twenty periods for payment, and pay each subject their total profit over these periods at conversion rate of 0.8 tokens per dollar. Using this approach avoids wealth effects because the earnings from each round are valued independently of each other, reducing the ability for wealth to encourage manipulation of later rounds. The experiment lasted on average 1 hour and subjects were compensated \$11.95 on average. We concluded each session with a short demographic questionnaire, and all subjects were paid in cash privately and individually.

Each subject is assigned to a group at the start of the session, but the subjects are never informed of who is in their group or the specific decisions that other subjects make during the experiment. At the beginning of each round subjects were given 25 seconds to make as many *purchase / pirate / do nothing* decisions they would like to make. 25 seconds was chosen as our per round interval after several test sessions as the time limit to make up to 20 decisions. The intent of having a time limit is to encourage subjects to make as many decisions as possible, without allowing them time to establish any explicit or implied strategies with any of their peers in the room. After the conclusion of 25 seconds, the profit earned for the round is displayed to each subject.

¹²Pilot data for the regulator and record producer treatments was collected *without* parents due to the difficulty in recruiting these types of subjects. Parents have no stake or involvement in these treatments.

Advice was sent to the subjects twice during the 20 rounds of play. The first piece of advice was given after the 8th round, and the second piece of advice was given after the 14th round. The first group of rounds includes 2 extra rounds in comparison with the other groups – this allows each subject 2 rounds to learn how to play the game and develop their own strategy going forward. They did not know *ex ante* when they would receive advice. If the treatment involved advice from the student’s parent, the advice was written by hand on paper, given to the experiment administrator, and then given to the student. If the advice was to be received from the record producer or experiment administrator, the advice was sent via the computer screen. Although handwriting the advice from the parent creates additional time spent and organizational challenges, using this approach reinforced the belief that the advice was truthfully from the parent, rather than computer-generated.

4.5 Experimental Results

We present our experimental results in this section, based upon the recruitment of 48 test subjects across 5 sessions. Each treatment was run at least once with a minimum of 8 students, with the parent without punishment treatment being run twice.¹³

Figures 4.1 and 4.2 plot the mean downloads and purchases respectively for each treatment. Recall that advice is given between rounds 8-9, and rounds 14-15. We can observe from the figures that subjects follow a similar pattern of downloading and purchasing, but there are several notable differences between the treatments. Means and standard deviations are also presented in Table 4.4. There appears to be a difference among treatments for the both the mean downloads and mean purchases, with the *Regulator* treatment having the greatest number of downloads, and a low number of purchases (*Record Producer* also appears to have a low number of purchases). The

¹³Due to subject recruiting constraints, pilot data for the regulator and record producer treatments did not include parents.

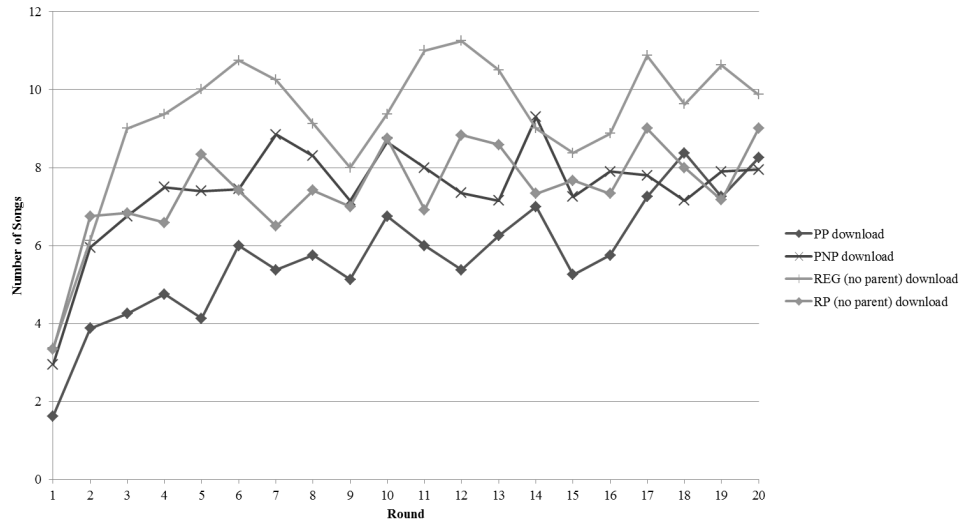


Figure 4.1. Mean Downloads per Round

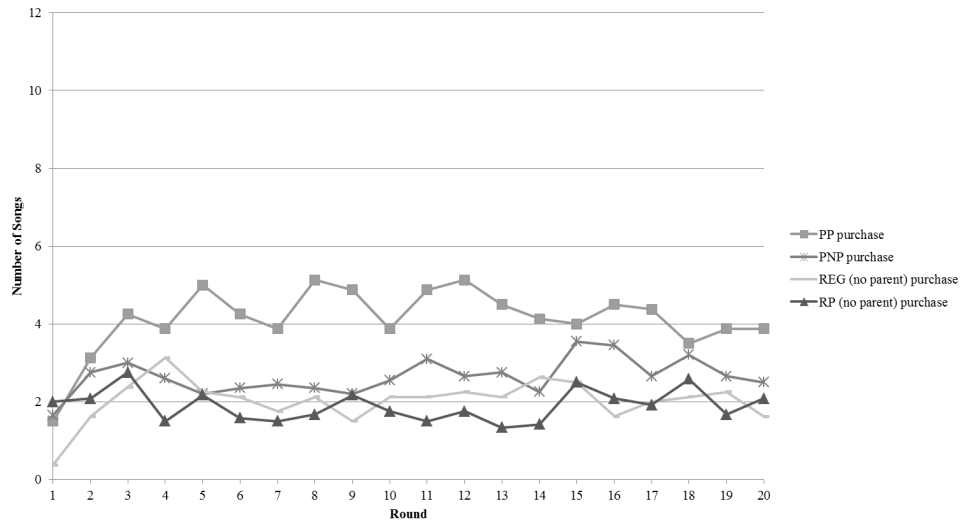


Figure 4.2. Mean Purchases per Round

Parent – Punishment treatment appears to be the best source of advice as it results in the lowest amount of downloads, and greatest amount of purchases.

We can immediately see in the downloads figure that subjects do respond to the advice by decreasing their pirating behavior – for a short while. There are three notable exceptions. First, subjects seem to disregard the advice given to them in the

Table 4.4
Mean Downloads and Purchases by Treatment: Rounds 3 – 20

Treatment	n	Mean Downloads	Std. Err.	Mean Purchases	Std. Err.
PP	144	6.05	0.44	4.33	0.28
PNP	360	7.77	0.20	2.69	0.15
REG	144	9.77	0.28	2.15	0.22
RP	216	7.70	0.16	1.88	0.15

Regulator treatment, as shown by the large increases in downloading just after the advice is received. Another interesting exception is the downloads increase slightly for the *Record Producer* treatment in round 15 compared to round 14. Every other instance of advice for every treatment always results in *decreased* pirating, with this single exception. The last quite interesting exception is the fact that in the *Parent – Punishment* treatment, subjects pirate at a lower rate compared to other treatments until the last several rounds. It appears that subjects are taking into consideration the penalty to their parents in the *Parent – Punishment* treatment, a result that would be expected, *until* the end of the experiment. It is unclear whether this is an end-of-game effect, but nonetheless, quite interesting.

When we consider purchasing behavior of the subjects, the *Parent – Punishment* treatment clearly has the highest rate. Given that subjects in the PP treatment pirate less than in other treatments, we expect purchases would be greater because subjects would certainly like to increase their utility. There is generally a slight increase in purchasing after receiving advice for all treatments, but the *Parent – No Punishment* treatment shows a large increase in purchasing after the last round of advice. Perhaps the repetitiveness of the advice has a cumulative effect in the PNP treatment.

We also present non-parametric comparisons of the decisions made by the subjects in Tables 4.5, 4.6, and 4.7. The results are split into three blocks: all rounds (3-20), the 6 rounds after the first instance of advice, and the 6 rounds after the second instance of advice. Breaking down the comparisons by block of rounds allows us the

Table 4.5
Comparison of Decisions: Rounds 3 – 20

	Downloads			Purchases		
Treatment	PNP	PP	REG	PNP	PP	REG
PP	3.87			-4.91		
REG	-5.38	-6.25		2.36	5.47	
RP	0.61	-4.17	7.13	3.10	6.66	0.16

Mann-Whitney U test. z -scores > 1.96 are statistically significant.

ability to tease out the effects of the advice when it occurs, as well as determine under which conditions a particular treatment is better or worse than another.

Each cell in Tables 4.5, 4.6, and 4.7, are populated with the z -score from a Mann-Whitney U test comparing the observations between two treatments. Although we present all z -scores, those with values > 1.96 are statistically significant with a p -value < 0.05 . To interpret the results, we compare the treatment in the column, to the treatment in the row. For example, in Table 4.5, the z -score of 3.87 can be interpreted as a significant difference in downloads between PNP and PP. Because 3.87 is a positive value, we can infer that PNP has a significantly greater number of downloads than PP. In contrast, the next row compares PNP with REG. Due to the negative value of -5.38, we can infer that REG has a significantly greater number of downloads than PNP.

The results in Table 4.5 reinforce the mean values discussed in Table 4.4. PP appears to have significantly lower downloads than the other treatments, as well as significantly greater purchases. Purchases are always higher in the parent treatments than the other two. Piracy is the greatest in the REG treatment. Purchasing is approximately the same between the REG and RP treatments.

Looking at the Tables 4.6 and 4.7, we observe very little differences in purchasing between all four treatments. As before, if parents have a losing stake (PP), their children tend to purchase more and download less. This difference however begins to disappear in the last block of rounds where the PNP and PP treatments have a z -

Table 4.6
Comparison of Decisions: Rounds 9 – 14

	Downloads			Purchases		
Treatment	PNP	PP	REG	PNP	PP	REG
PP	2.33			-3.16		
REG	-3.07	-3.22		1.53	3.33	
RP	0.50	-2.33	3.90	2.09	4.29	0.00

Mann-Whitney U test. z -scores > 1.96 are statistically significant.

Table 4.7
Comparison of Decisions: Rounds 15 – 20

	Downloads			Purchases		
Treatment	PNP	PP	REG	PNP	PP	REG
PP	0.72			-1.89		
REG	-2.47	-2.13		1.71	2.78	
RP	-0.38	-1.07	3.65	1.52	2.75	-0.61

Mann-Whitney U test. z -scores > 1.96 are statistically significant.

score of -1.89. A very interesting result that we see in these two tables is the fact that downloading still remains the greatest for the REG treatment, even when compared with the RP treatment. It seems if we were to rank these treatments, advice coming from the regulator would be least effective at curbing downloads, followed by the record producer, and then the parents. In regards to encouraging purchasing, the regulator and record producer are equally ineffective.

4.6 Conclusion

In conclusion, we develop a new game – *The Piracy Game* – in this research and implement it in an experimental setting, differentiating treatments by the source of advice about music piracy. The sources of advice vary in whether or not they have a stake in the game, and whether or not they have a social tie with the child receiving

the advice. Our results show that one of the strategies used by the music industry to curb piracy may be in fact be the best choice. When there is a tangible stake for the parent, purchasing behavior by the child is increased, and their pirating behavior is decreased. Even when there is not a stake for the parents, the advice is most effective when it comes from that source, and not a 3rd party such as the record producer or independent regulator. Interestingly, purchases are equally bad for these 3rd parties.

Our results suggest that regulators and record producers should perhaps be reaching out to parents and guardians to disseminate the information to their children and dependents. Delivering advice through 3rd party channels is the worst possible approach as supported by the results in our game, representing the grim reality used by the industry at this time (Jones, 2000; RIAA, 2011b). The results also suggest that the educational approach is quite useful in mitigating piracy and perhaps deserves additional exploration and testing by the industry. Further, although we do not explicitly test a strong non-parent figure such as a teacher or principal, it is quite possible that we may see similar results from that type of advice source.

Overall, music consumers are undeterred by the direct complaints from the music industry and – for better or for worse – it appears our results may in fact capture populist sentiment. Although the industry is attempting to shift to education strategies (RIAA, 2011a), in lieu of litigation (or technology controls for that matter), the current status quo of sending advice directly from 3rd parties could certainly be improved by coordinating advice through channels with greater social ties.

5. CONCLUSION

Digital piracy will continue to be a major source of friction and challenges in the foreseeable future for digital media producers, governmental entities, and consumers. The research presented in this dissertation makes many significant theoretical contributions to the information systems, economics, and social psychology literatures. The inter-disciplinary nature of this research builds our understanding of the role of information in developing behavioral strategies and also delivers practicable insights to be instituted by industry.

In Chapter 2, we find support for the notion that pirates perceive their crimes to be victimless. Although pirates may know their actions to be wrong, because they do not recognize a victim in their crime, they rationalize the behavior and allow their attitudes and norms to influence their moral obligations towards piracy. By finding support for this notion, we can implement information strategies in practice to mitigate the phenomenon by making moral obligations salient in the decision to purchase or pirate a product.

We explore the role of information targeting strategies in Chapter 3, by modeling the piracy context in an abstract framework. We find that targeting contribution rate information for a public good to those consumers that are either above or below the average, is a successful coordination mechanism. Implementing targeted information is most helpful for those that are contributing in an above average manner, but targeting information to those below the average is also quite useful. Both targeting approaches are significantly better in encouraging contributions than providing random information to subjects. Industry sources generally utilize either random information dissemination strategies, or do not send information to consumers at all. Our findings provide evidence that the random and no information strategies are the worst approaches if firms desire to increase contributions for their goods.

Chapter 4 integrates several of the implications from the other two chapters in a laboratory experiment with a non-standard subject pool. We develop a new *Piracy Game* by extending an existing public goods game, and show how piracy advice impacts the purchase and pirate decisions made by teens. We vary the source of the advice in this game with some advisors having a stake in the outcome of the game, while others do not have a stake in the outcome. Advisors also vary in the strength of their social tie with the advisee. Depending on the stage of the piracy game, the information sent in our design makes morals salient to the subjects. We find that advice is most effective when it is sent by a parent of the child, because the parent has both a stake in the game, as well a social tie to their child. Advice sent from industry regulators or record producers represent the worst outcome in terms increasing piracy behavior. The implications from this chapter show that the current approach used to send anti-piracy advice should be refocused to allow for anti-piracy education to come from other sources that have a stronger social tie with the population of pirates.

In conclusion, the role of information in developing behavioral strategies to mitigate digital piracy is in its infancy. The digital piracy domain has presented, and will continue to present, many great opportunities to contribute to knowledge. This dissertation represents a substantial first effort of using an interdisciplinary approach to understand and define behavioral strategies for mitigating the piracy problem, providing the foundation for further study of piracy in the literature. Because we are the first to utilize experimental economics to research the piracy problem, there remain a wealth of significant and meaningful opportunities to contribute novel theoretical contributions using the groundwork laid by this dissertation.

APPENDICES

APPENDICES

Appendix A: Survey Instrument**Notes:**

1. An asterisk next to a question represents a reverse-coded response.
2. This particular survey represents the treatment that receives the message from the company. The non-message treatment is identical except for the block of text starting with “XYZ-Soft is promoting ...” and ending with “...from an authorized retailer.”
3. Questions 20-24 are pilot questions and thus at the end of the survey.

INSTRUCTIONS:

Please read the following hypothetical software purchase scenarios carefully and answer each question in the order presented. The following facts apply for each scenario: 1) XYZ-Soft is an imaginary software development firm, 2) It would be a stretch financially to afford the program in each scenario, but you could pay for it if you chose to, and 3) “software program” refers to an application, game, or other type of program that you might be interested in.

Q1 (IP): You plan to acquire a software program for your personal computer that will prove useful throughout your studies. The program was developed by XYZ-Soft. You previously used this program on a friend’s computer but now you need your own copy.

XYZ-Soft is promoting their product and you receive the following message from them:

“Thank you for your interest in XYZ-Soft’s software. Your purchase helps the overall software industry, benefits our employees, increases tax revenue, and reduces job loss. Click here to purchase our software from an authorized retailer.”

The program is available for purchase online, or you can pirate it for free.

How likely do you see yourself purchasing the program? (Very Likely - Very Unlikely)

Q2 (CP): You have a pirated software program on your personal computer that will prove useful throughout your studies. The program was developed by XYZ-Soft. You previously used this program on a friend’s computer but now you need your own copy.

XYZ-Soft is promoting their product and you receive the following message from them:

“Thank you for your interest in XYZ-Soft’s software. Your purchase helps the overall software industry, benefits our employees, increases tax revenue, and reduces job loss. Click here to purchase our software from an authorized retailer.”

The program is available for purchase online, or you can continue using the pirated version.

How likely do you see yourself purchasing the program? (Very Likely - Very Unlikely)

Q3 (A1): To me, committing software piracy is: (Very Good - Very Bad)*

Q4 (A2): To me, committing software piracy is: (Very Pleasant - Very Unpleasant)*

Q5 (A3): To me, committing software piracy is: (Very Wise - Very Foolish)*

Q6 (A4): To me, committing software piracy is: (Very Attractive - Very Unattractive)*

Q7 (N1): If I committed software piracy, most of the people who are important to me would: (Strongly Approve - Strongly Disapprove)*

Q8 (N2): Most people who are important to me would be disappointed with me if I committed software piracy. (Very Likely - Very Unlikely)

Q9 (N3): No one who is important to me thinks it is okay to commit software piracy. (Strongly Agree - Strongly Disagree)

Q10 (C1): I feel that prices charged for software today are: (Very High - Very Low)*

- Q11** (C2): In my opinion, software today is: (Very Inexpensive - Very Expensive)
- Q12** (C3): If I wanted to buy software today, it would cost me a lot of money. (Strongly Agree - Strongly Disagree)*
- Q13** (B1): Technically, for me to commit software piracy is: (Very Easy - Very Difficult)*
- Q14** (B2): If I want to, I can commit software piracy. (Strongly Agree - Strongly Disagree)*
- Q15** (B3): I can imagine times when I might commit software piracy even if I hadn't planned to. (Strongly Agree - Strongly Disagree)*
- Q16** (B4): Even if I had a good reason, I could not bring myself to commit software piracy. (Strongly Agree - Strongly Disagree)
- Q17** (M1): I would feel guilty if I pirated software. (Strongly Agree - Strongly Disagree)
- Q18** (M2): Engaging in software piracy goes against my principles. (Strongly Agree - Strongly Disagree)
- Q19** (M3): It would be morally wrong for me to pirate software. (Strongly Agree - Strongly Disagree)
- Q20** (P1): When considering all types of digital goods, the likelihood of me pirating is: (Very Likely - Very Unlikely)*
- Q21** (P2): What is your perception of XYZ-Soft? (Favorable Perception - Unfavorable Perception)
- Q22** (G1): I feel obligated to purchase digital goods. (Strong Obligation - Weak Obligation)
- Q23** (G2): I feel tempted to pirate digital goods. (Strong Temptation - Weak Temptation)*
- Q24** (G3): If I paid for software last time, it is acceptable to me to pirate this time. (Strongly Agree - Strongly Disagree)*
- Q25**: What is your gender?
- Q26**: What is your age?

Appendix B: Supplementary Output and Analysis

Tables B.1, B.2, and B.3 provide additional validation to the tables included in the body of this manuscript. Our reasoning behind this approach is to provide additional reassurance of validity in our data. Initially, we utilize a principal axis factoring technique with a promax oblique rotation in order to test for convergent reliability of the items (Fabrigar et al., 1999). Our choice of rotation method aids in interpretation of the resulting factor loadings as behavioral factors should be expected to be correlated (correlations among the composite measures are listed in Table B.3). The items load as we expect and we do not observe any substantial cross loading as shown in Table B.1. Next, we measure discriminant reliability by generating correlations amongst each of the items and all of the constructs in our study in Table B.2. Each of the items correlate higher with its own construct, than with other constructs.

Table B.3 lists the overall correlations amongst the variables as well as the Cronbach's alpha for internal consistency of the factors. Rather than generate factor scores for the latent variables, we chose to create composite variables by calculating the mean across the items for each construct for this test. When using multiple regression, the composite variables become the overall measures, allowing us to retain some similarity to the PLS analysis (Section 2.4 provides the equivalent tests).

Table B.1
Principle Axis Factoring with Promax Oblique Rotation: Factor Loadings and Cross-Loadings

Construct	Items	Attitude	Subj.		
			Norms	PBC	PMO
Attitude	A1	0.587	-0.107	0.001	0.278
	A2	0.598	0.088	0.032	0.057
	A3	0.686	-0.050	-0.025	0.143
	A4	0.676	0.165	0.025	-0.108
Subj. Norms	N1	0.133	0.585	0.072	0.002
	N2	-0.027	0.610	-0.056	0.116
PBC	B1	0.027	-0.064	0.870	0.015
	B2	-0.023	0.054	0.855	-0.073
	B3	0.020	0.001	0.568	0.157
PMO	M1	0.241	0.021	0.045	0.602
	M2	-0.012	0.109	0.055	0.785
	M3	0.026	0.012	-0.030	0.835

Table B.2
Item-to-Construct Correlations vs. Correlations with Other Constructs

Construct	Items	Attitude	Subj.		
			Norms	PBC	PMO
Attitude	A1	0.709	0.343	0.331	0.603
	A2	0.696	0.448	0.360	0.495
	A3	0.740	0.377	0.322	0.549
	A4	0.706	0.484	0.356	0.414
Subj. Norms	N1	0.480	0.686	0.363	0.398
	N2	0.348	0.629	0.214	0.373
PBC	B1	0.398	0.298	0.862	0.329
	B2	0.348	0.341	0.838	0.261
	B3	0.380	0.311	0.637	0.386
PMO	M1	0.658	0.460	0.390	0.783
	M2	0.574	0.505	0.389	0.851
	M3	0.553	0.419	0.302	0.846

Table B.3
Reliabilities and Correlations amongst Variables

Construct	Items	Attitude	Subj. Norms	PBC	PMO
Attitude	A1, A2, A3, A4	0.815			
Subj. Norms	N1, N2	0.446	0.675		
PBC	B1, B2, B3	0.406	0.300	0.831	
PMO	M1, M2, M3	0.652	0.456	0.394	0.881

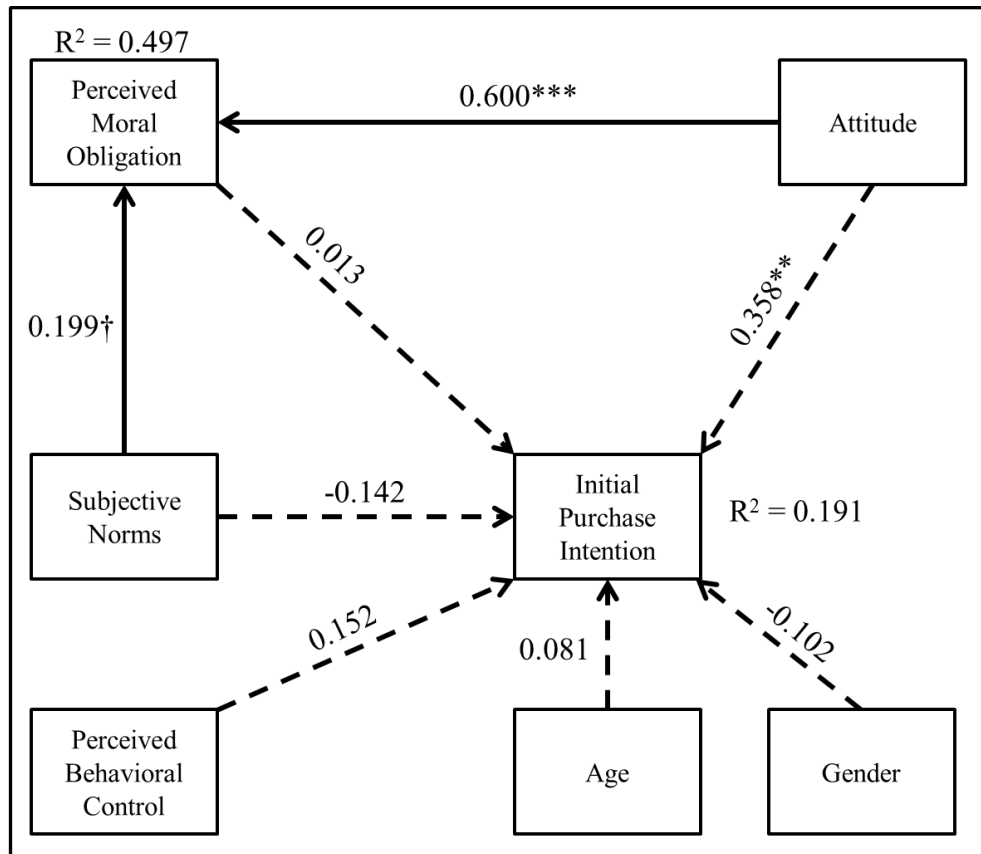
Cronbach's alpha is in bold along the main diagonal. Correlations are below the main diagonal.

Appendix C: Supplementary PLS Output

Figure C.1 provides a parallel result to that shown by Figure 2.4 in the body of this manuscript. We introduced perceived moral obligation as a mediator in this model, but did not invoke consistency of behavior. As expected, attitude is significant in predicting initial purchase intentions. Significant paths are shown to the construct for perceived moral obligation from both attitude and subjective norms. However, we did not observe a significant mediating effect for the path to the dependent variable. This is due to consistency of behavior not being invoked, thus the individual was not compelled to rationalize prior unethical behavior.

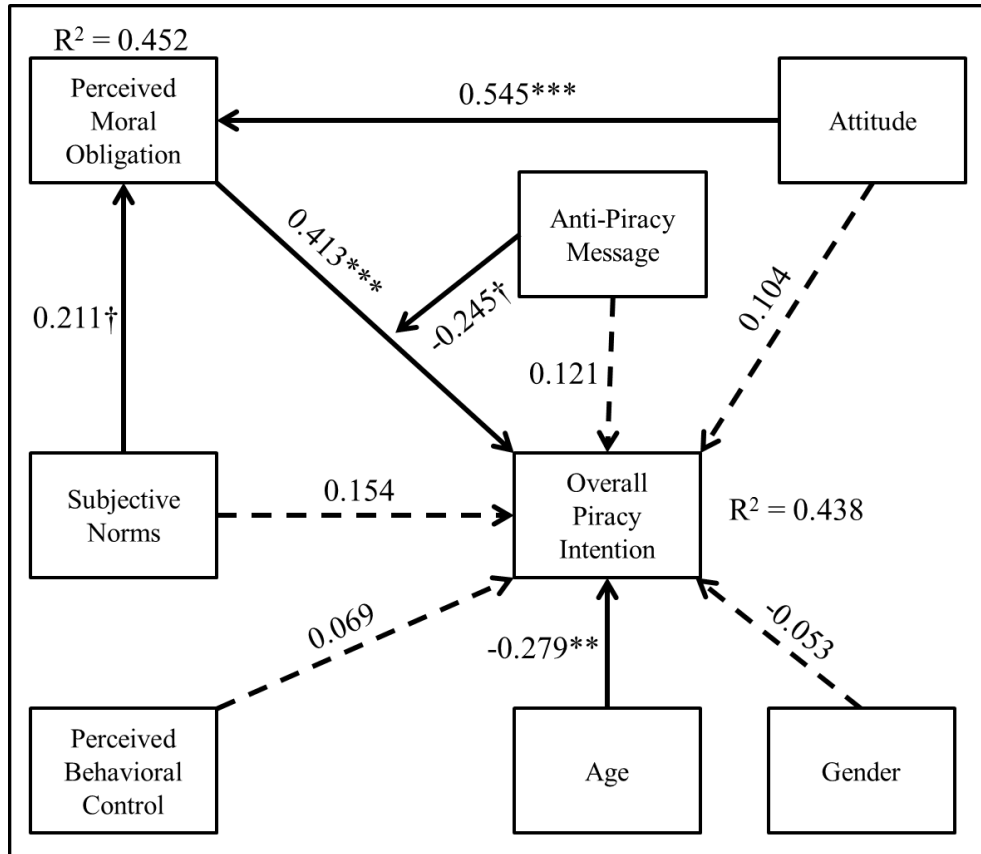
Figure C.2 includes both scenarios as the dependent variable. Figure C.2 complements the results in the body of the manuscript and presents a general result that takes into account both initial purchase and piracy conversion scenarios. As before, perceived moral obligation mediates both attitude and subjective norms. The moderating effect in Figure C.2 may be classified as medium to small as the Cohen's f^2 for this effect is 0.0921 (Chin et al., 2003; Cohen, 1988).¹ Further, the ΔR^2 when the moderating effect is included in the overall piracy intention model is 0.057.

¹ $f^2 = (0.438 - 0.381) / (1 - 0.381)$, calculated for the model having perceived moral obligation as a mediator



Note: Paths represented by dashes are not significant ($p > 0.10$). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Figure C.1. Perceived Moral Obligation as a Mediator in our Refined TPB: Consistency of Behavior Not Invoked



Note: Paths represented by dashes are not significant ($p > 0.10$). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Figure C.2. Overall Piracy Intention as the Dependent Variable in our Refined TPB: Consistency of Behavior Invoked

Appendix D: Information Targeting Experiment Instructions

This is an economic experiment about decision making under uncertainty. Listening carefully to these instructions will help you to earn a significant amount of money, which you will receive in cash privately at the end of the experiment. Your earnings in this experiment will depend on your performance in the individual rounds. Your final payout will be determined by three random draws done by the computer at the conclusion of the experiment. The three draws will correspond to three rounds during the experimental session. The total earnings over these three randomly selected rounds will be taken to calculate your final payout. All earnings in this experiment will be presented to you in tokens and converted to US dollars at the conclusion of the experiment. The conversion rate is: **20 tokens per 1 US dollar**. The conversion rate is identical for everyone.

You are welcome to ask questions at any time by raising your hand. Please wait for an experimenter to come to your seat before asking your question. While the experiment is in progress, please do not speak or in any other way communicate with other participants. This is important to the validity of the study.

Specific Guidelines:

You will participate in 46 rounds in a group with four other participants. **Participants are re-matched randomly at the beginning of each round to a new group of five participants.** You will not know who is in your group. In each round you will receive an endowment of 50 tokens. The endowment is identical for everyone. You and every member in your group have to individually decide how much of this endowment to allocate to a group account. This allocation must be a whole number, between 0 and 50 tokens. All decisions are made simultaneously and without communication. No other group member will ever know how much you choose to allocate to the group account.

Your earnings in each round are determined by combining what is left of your endowment after the allocation, plus the consumption of a product. The earnings equation is presented below.

$$\text{Your earnings} = \text{endowment} - \text{your allocation} + \text{product quality value}$$

The value from the product depends on the total group allocation. If the group allocation is between 0 and 49, the quality of the product is Poor and the product quality value for you is 0 tokens. If the group allocation is between 50 and 99, the quality of the product is Medium and your product quality value is 18.5. If the group allocation is between 100 and 149, the quality of the product is Good and your product quality value is 45.5. If the group allocation is between 150 and 199, the quality of the product is Very Good and your product quality value is 81. Lastly, if the group allocation is greater than 200, the quality of the product is Excellent and your product quality value is 125. These are summarized in the table below.

Examples:

1. If your combined group account for a round is 70 tokens, the quality of the product delivered to your group in that round is Medium. This will result in 18.5 tokens added as your Product Quality Value.
2. If your total payout for the three randomly chosen rounds is 232 tokens, you will earn \$11.60. In this case **the experimenter will pay you a total of \$11.75 in cash** at the conclusion of the experiment.

Are there any questions?

Table D.1
Group Allocation, Quality, and Value

If your Total Group Allocation is:	Then your Product Quality is:	And your Product Quality Value is:
0 - 49	Poor	0
50 - 99	Medium	18.5
100 - 149	Good	45.5
150 - 199	Very Good	81
200 +	Excellent	125

Appendix E: Information Targeting Supplemental Instructions

Subjects receive the following supplemental instructions if their session begins with an information condition. These instructions will also be used after a restart if the subject's session began with a no feedback information treatment.

IMPORTANT:

Some participants in each group might receive information at the beginning of each round. If you receive information, you will see the average number of tokens the participants in your current group allocated to their prior group accounts in the previous round. The average number of tokens is presented as if you were in the same group last round.

Examples:

1. If every participant in your current group chose to allocate 10 tokens to the group account last round, the average allocation presented to you in the current round is 10 tokens.
2. If two participants in your current group chose to allocate 10 tokens to the group account last round, and three participants chose to allocate 20 tokens to the group account last round, the average token allocation presented to you in the current round is 16 [$= (10 + 10 + 20 + 20 + 20) / 5$] tokens.

Appendix F: Information Targeting Experiment Screenshots

Period 1 of 46 Remaining time [sec]: 29

What is your estimate of the average tokens allocated to the group account this round?:

The maximum value you can enter is 50 and the minimum is 0.

Continue

Figure F.1. Elicit Beliefs Screenshot

Period 2 of 46 Remaining time [sec]: 28

Your endowment is: 50

Your allocation to the group account last period was: 44

Select the amount you would like to allocate to the group account:

The maximum value you can enter is 50 and the minimum is 0.

Continue

Figure F.2. No Information Feedback Allocation Decision Screenshot

Period 2 of 46 Remaining time [sec]: 27

Your endowment is: 50

The participants in your group THIS period allocated on average **33 of their tokens LAST period.**

Your allocation to the group account last period was: 23

Select the amount you would like to allocate to the group account:

The maximum value you can enter is 50 and the minimum is 0.

Continue

Figure F.3. Targeted Below Information Feedback Allocation Decision Screenshot

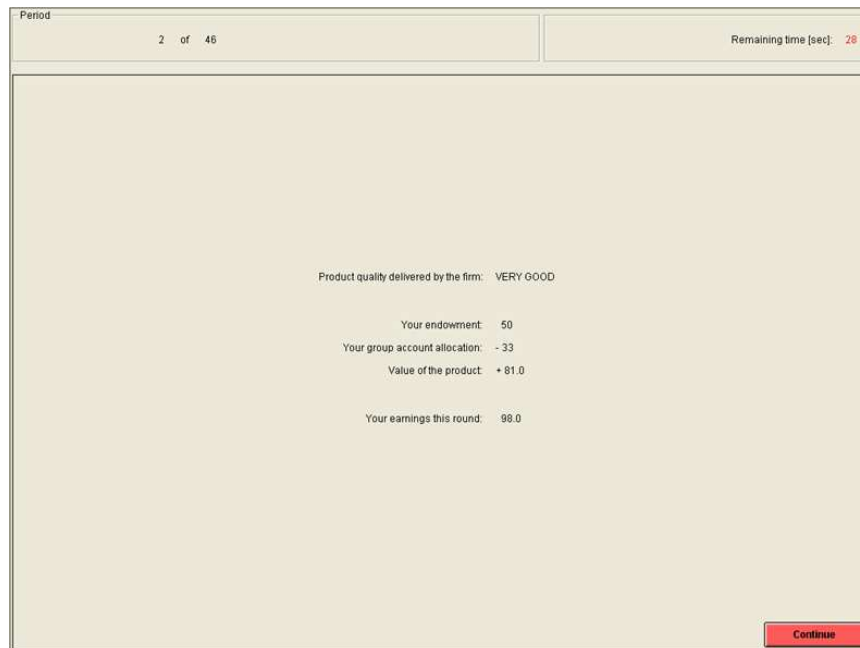


Figure F.4. Results Screenshot

Appendix G: Source of Advice Experiment Instructions

General Guidelines:

Thank you for participating in this economic experiment. You will be paid in cash for your participation, and the amount of money you earn depends on the decisions that you and other participants make in individual rounds. Your final payment will be determined by three random draws done by the computer at the conclusion of the experiment. Each draw will correspond to one round of the experimental session. **The average earnings over these three randomly selected rounds will be used to calculate your final payment.** All earnings in this experiment will be presented to you in tokens and converted to US dollars at the conclusion of the experiment. The conversion rate, which is identical for everyone, is: **1 token per 0.8 US dollar.**

You will never be asked to reveal your identity to anyone during the experiment. Your name will never be associated with any of your decisions. In order to keep your decisions private, please do not reveal your choices to any other participant.

You are welcome to ask questions at any time by raising your hand. Please wait for an experimenter to come to your seat before asking your question. While the experiment is in progress, please do not speak or in any other way communicate with other participants. This is important to the validity of the study.

Specific Guidelines:

In this experiment, you are taking part in a study about the decisions to purchase and download music. In the game, there are **three types of participants**: Record producers, music consumers, and non-consumers. The roles are fixed for the entire experiment and assigned in the following manner: University senior students will play the role of record producers; new students will be assigned the role of consumers; and parents will be given the role of non-consumers.

In this experiment you are a music buyer

In the experiment, you are going to play a game in a **group of 9 participants**. Each group will consist of 1 senior University student (a record producer), 4 new students (the music consumers), and their respective parents (non-consumers). Groups are randomly formed in the beginning of the experiment and remain fixed for the entire experiment. Apart from your family member, you will never know the identities of the other participants in your group.

You will play a total of **20 rounds**. Each round lasts 25 seconds. In each round, the player's decisions and earnings are as follows:

Record Producer:

The record producer does not make any decisions for the entire experiment. In the beginning of **each round**, the record producer has **32 songs** to sell. The record producer gets 1 token for each song that is sold and 0.1 tokens for each unsold song.

Record Producer's earnings in each round = 1 * number of songs sold in the round + 0.1 * number of songs not sold in the round

Music Buyers:

In this experiment you are a music buyer. In the beginning of **each round**, every music-buyer will receive an identical allowance of 8 tokens and 2 songs. Each round spans 25 seconds, within which you and every music buyer in your group will make a series of decisions. **During each round please make as many decisions as possible**. Specifically, your decision involves choosing one of the following options:

1. buy 1 song from the record producer (if you have any tokens available)
2. download 1 song for free from the Internet (if there are new songs available)
3. do nothing

If you decide to buy a song from the record producer, it costs you 1 token. Purchasing a song earns you 1.1 tokens.

The Internet source will have **all the songs** that you and other music buyers own, including those purchased. You can download a song from the Internet source so long as you do not own it. Because of the initial allowance of 2 songs, there are 6 other songs from the Internet source available for download at the beginning. As other music-buyers purchase songs, the number of songs available for download increases. Downloading a song from the Internet costs you nothing and earns you 0.5 tokens.

If you decide to do nothing you have no costs or earnings.

Remember that you will never be informed about the decisions of any other music-buyer in your group. Your earnings in each round will depend on the number of songs you initially owned, bought from the record producer, and downloaded from the Internet source, plus the tokens you retained without purchasing.

Your earnings in each round = $8 - 1 * \text{number of songs you bought in the round} + 1.1 * \text{number of songs you bought in the rounds} + 0.5 * \text{number of songs you downloaded in the round}$

At the end of each round, you will be informed about your own earnings for that round.

Non-consumers (parents):

Parents will get an allowance of 12 tokens per round. **Your parent will never be informed about the choices you made in the experiment.** However, at times parents are informed about the average number of songs downloaded from the Internet by your group and your parent will send you a message regarding the experiment.

Appendix H: Source of Advice Experiment Screenshots

Round 3 of 20 Remaining time [sec]: 1

My tokens: 8
My songs: 2
Songs on the Internet I can download: 6

Buy a song from a record producer
 Download a song from the Internet
 Do Nothing

OK

Figure H.1. Music Consumer Decision Screenshot

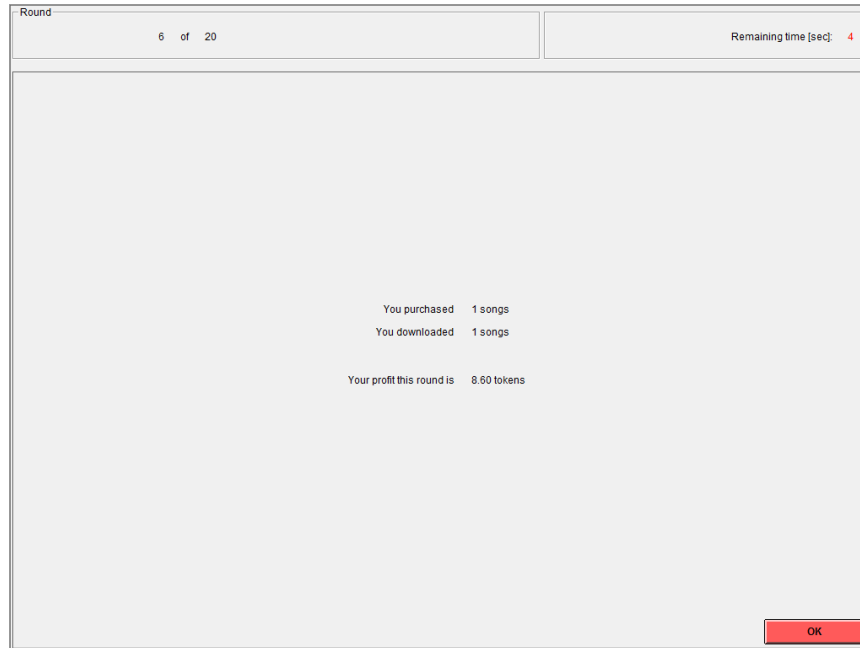


Figure H.2. Music Consumer Profit Screenshot

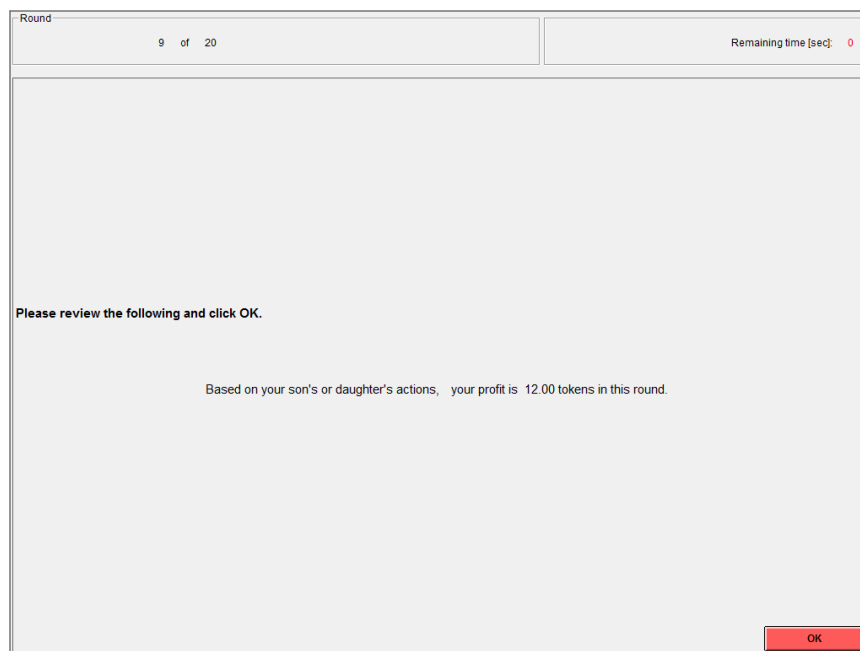


Figure H.3. Non-Consumer (Parent) Profit Screenshot

Round 14 of 20 Remaining time [sec]: 0

Please make a selection and click OK.

Which advice would you like to send to your group?

- It is probably morally acceptable for you to pirate music.
- It is probably morally wrong for you to pirate music.
- I strongly believe it is probably morally wrong for you to pirate music.

OK

Figure H.4. Moral Component of Advice to Music Consumers Screenshot

Round 14 of 20 Remaining time [sec]: 24

Please read the following sentences and click OK to send this advice to the members of your group when you are done.

As a record producer, I could be making 32 tokens each round and am making 3.20 tokens on average.

Also, your group is pirating 0.00 songs on average from the Internet each round.

It is probably morally acceptable for you to pirate music.

OK

Figure H.5. Record Producer Advice to be Sent to Music Consumers Screenshot

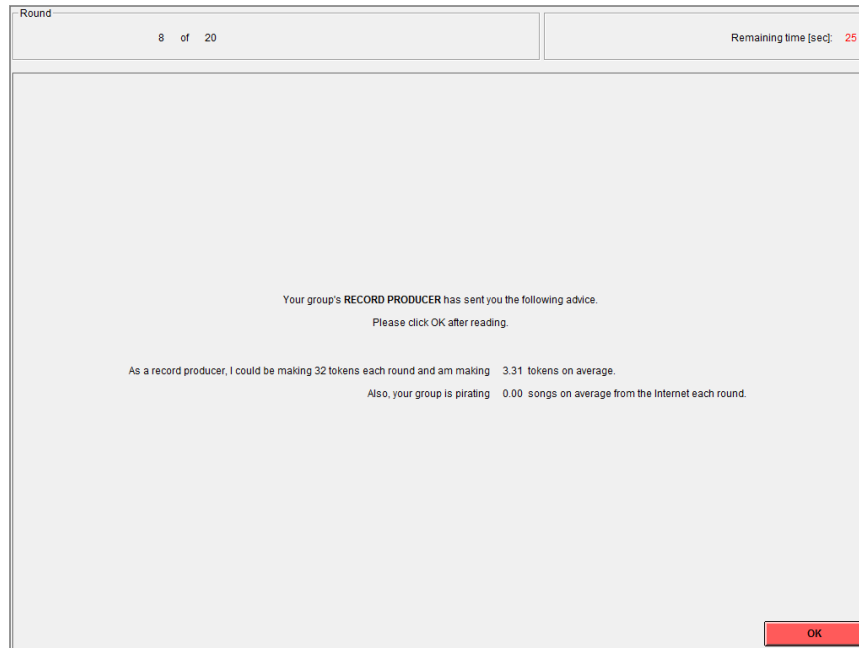


Figure H.6. Advice Received from Record Producer Screenshot

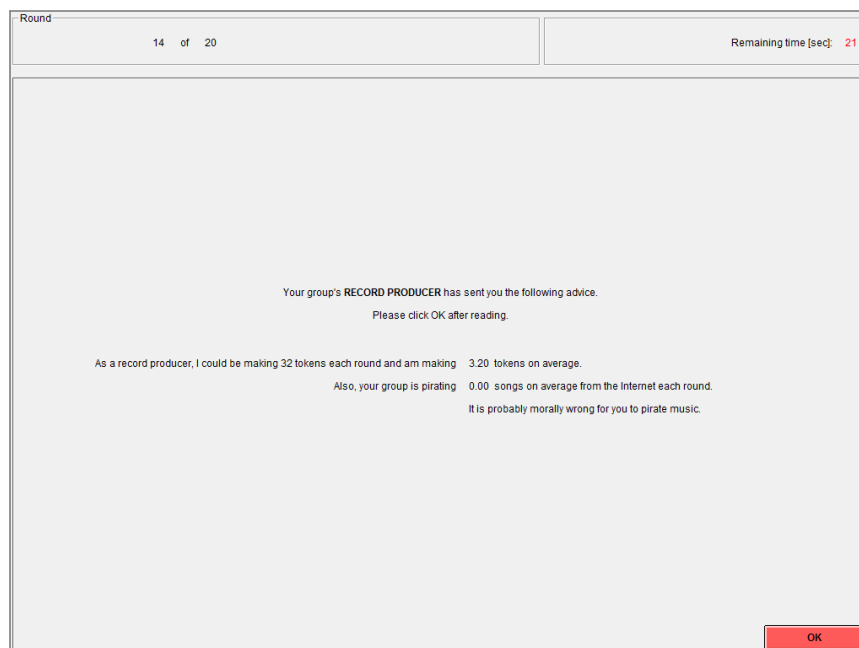


Figure H.7. Advice Received from Record Producer with Moral Component Screenshot

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Working Papers

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Hashim, M., and Tang, Z. “Delivery of Movies via the Internet: Uncovering Strategies for the Release of Digital Formats,” additional data collection and analysis underway. Target outlet: *MIS Quarterly*.

Work in Progress

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“Nudging the Digital Pirate,” with Karthik Kannan and Duane Wegener, The 2010 Annual CERIAS Information Security Symposium, poster session, West Lafayette, Indiana, March 31, 2010.

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