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Abstract

Why do some individuals pirate digital music while others pay for it? Using data on a sample of undergraduate students, we study the determinants of music piracy by looking at whether a respondent's last song was obtained illegally or not. In doing so, we incorporate (i) the individual-specific transactions costs that constitute the effective price of illegal music; and (ii) individual willingness to pay (WTP) for digital music, which we elicit using a simple field experiment and which we use to control for the unobserved heterogeneity of preferences between respondents. Our empirical results indicate that a respondent's subjective probability of facing a lawsuit and her degree of morality both have a negative impact on the likelihood that her last song was obtained illegally. These results are robust whether WTP is estimated parametrically or nonparametrically. We conclude by discussing the practical implications of our findings.

Keywords: Music Piracy, Transactions Costs, Subjective Expectations
JEL Classification Codes: D12, D23, L86, K11, K42

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1. Introduction

Why do some individuals pirate digital music while others pay for it? With the development and proliferation of digital music over the past 15 years, the music industry has gone through a profound transformation in the way music is consumed. As a sign that an important milestone has been reached, Apple's iTunes online music store, which was launched in 2001, surpassed brick-and-mortar Walmart in early 2008 as the leading music retailer in the United States (NPD Group, 2008).

Concomitantly, digital music piracy has emerged as a crime of national scale and concern. A report cited on the website of the Recording Industry Association of America (RIAA) goes so far as to claim that music piracy causes global annual losses of about US$12.5 billion (RIAA, 2010). In the 2001 *A&M Records v. Napster* case, the US Court of Appeals ruled that peer-to-peer (P2P) networks could be held liable for contributory infringement of record companies' copyrights (Landes and Lichtman, 2003). Yet efforts to stem music piracy have been largely ineffective, as evidenced by the RIAA's announcement in December 2008 that it would put an end to its policy of filing lawsuits against individuals suspected of piracy (USA Today, 2008). Consequently, no major legal action is currently being pursued to address the widespread problem of music piracy.

Given that college-age individuals are among the most important consumers of music, college campuses deserve specific attention. The goal of this paper is thus to identify the determinants of music piracy among college students so as to distinguish the policy instruments that can effectively help reduce the prevalence of music piracy on college campuses, where it is most pervasive.

At its core, this paper studies the demand for illegally obtained digital music among college students. But while it is in principle relatively simple to estimate a demand function by regressing the quantity demanded of a specific good on its price; on the prices of substitutes and complements; and on consumer income, one rapidly encounters significant problems when trying to estimate such a demand function for illegal digital music. First are the twin facts that (i) the *market* price of illegal music is zero, so that its *effective* price is composed entirely of transactions costs;[1] and (ii) at the time of the survey, the price of legal music did not vary from one source to the other as both iTunes and Amazon – the two leading retailers of digital music – had set that price at $0.99. Second, and no less important, is unobserved heterogeneity in preferences between consumers, whose presence can lead to mistaken inferences if it is not dealt with satisfactorily.

We address the issue the lack of a market price for illegal music constitutes by measuring the transactions costs that are included in the effective price of illegal music. To do so, we first asked each respondent about (i) her subjective perception of the likelihood that she will face a lawsuit from the RIAA; and (ii) her subjective perception of the litigation costs in case of such a lawsuit. We then elicited each respondent's degree of morality using a proxy measure developed by Wood et al. (1988) and used elsewhere in the literature on music piracy (Gopal et al., 2004).[2] As for the price of legal music, which is everywhere the same, it effectively disappears into the constant term of a regression of the demand for illegal music.

We then address the issue of unobserved heterogeneity in preferences between respondents by estimating their willingness to pay (WTP) for digital music on the basis of a simple random pricing experiment. Each respondent was asked whether she would be willing to purchase a specific song at a price in cents equal to the last two digits of her social security number (SSN).[3] That specific song was the same for everyone (i.e., Flo Rida's "Right Round") and was chosen because it was the most popular song on iTunes when the survey was launched. Because the last two digits of a respondent's SSN are completely random, the variation in price was exogenous to whether a respondent was willing to purchase the song and to whether her last song was obtained legally or illegally, which is ultimately what we are interested in.

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[1] The difference between the market and effective prices of a good is that the former is only the nominal monetary price one must pay to acquire the good, whereas the latter is the nominal price plus the various (and often individual-specific) fixed and variable transactions costs that must be incurred in acquiring the good. In certain contexts, transactions costs have been shown to drive the choice to consume specific commodities. In other contexts, transactions costs determine whether a market for specific commodities exists at all (de Janvry et al., 1991).

[2] The questions used to elicit this measure can be found in the appendix.

[3] The random price was thus inferior or equal to the $0.99 price charged by either iTunes or Amazon at the time the survey was conducted, so that the random pricing experiment did not suffer from an over-representation of "No" answers which would have inevitably occurred had the random price exceeded $0.99.

Using a well-known method for contingent valuation (Mitchell and Carson, 1989; Arrow et al., 1993), we then estimate our respondents' WTP for digital music. The identifying assumption we make in this case is that a respondents' WTP for the particular song we chose is correlated with her "true" WTP for music (i.e., her expected WTP for a randomly selected piece of music in the entire universe of pieces of music), and that any discrepancy between a consumer's estimated and her "true" WTP is due purely to noise given the random pricing scheme adopted for the contingent valuation question. As such, because estimated WTP is a direct measure of the marginal utility a specific consumer derives from digital music, it can be used to control for the unobserved preference heterogeneity between consumers, which would otherwise be unobserved and would thus bias our coefficient estimates.

Using survey data collected at a Southern private research university, we combine our respondents' WTP for digital music with the various transactions costs they face to estimate the determinants of digital music piracy. Ultimately, we find that for a 1 percent increase in the average respondent's subjective probability that she will face a lawsuit as a result of pirating digital music, the likelihood that her last song was illegally obtained falls by about 0.4 percent. Similarly, for a 10 percent increase in the average respondent's degree of morality (see the appendix for the precise measure we use to elicit our respondents' morality), the likelihood that her last song was illegally obtained falls by about 4 percent. Robustness checks conducted with an alternative, nonparametric measure of WTP yield almost identical results.

Most of the previous studies analyzing online piracy have focused on software rather than music, although there is a growing literature on digital music piracy. Gopal et al. (2004) develop a conceptual model to explain digital music piracy among undergraduates and test it using survey data, but their analysis did not include economic variables such as prices or income. d'Astous et al. (2005) find that anti-piracy arguments have no effect on the intention to pirate digital music of their experimental subjects. Chiou et al. (2005) find that respondents' subjective perceptions of prosecution risk drive behavior in a sample of high school students in Taiwan. Altschuller and Benbunan-Fich (2009) find a discrepancy between what their respondents say others should do and what their respondents themselves would do when faced with the possibility of pirating music.

Likewise, Oberholzer-Gee and Strumpf (2007) contradicted the results in Zentner (2004) when they found that file sharing has essentially had no effect on music sales, a finding that has been contested by Liebowitz (2006). Bhattacharjee et al. (2006) find that even with well-publicized lawsuits against the worst offenders, the activity on illegal music sharing networks remains considerable, and Gopal et al. (2006) find that allowing consumers to sample at a lower cost significantly increases music sales.[4]

This paper uses survey data from a sample of college students, as in Rob and Waldfogel (2006), who study their respondents' WTP for music both before and after they have consumed it in order to study the impact of music piracy on the sales of legal music and on consumer welfare, and as in Shiller and Waldfogel (2009), who ask their respondents what their maximal WTP would be for a number of popular songs to compare different pricing schemes. The open-ended WTP questions in both Rob and Waldfogel and Shiller and Waldfogel, however, are not necessarily incentive compatible given that they are not attached to a second-price auction or a Becker-DeGroot-Marschak mechanism (Becker et al., 1964). The contingent valuation method used in this paper was first developed to deal with the incentive compatibility problem (Carson and Groves, 2007 and Poe and Vossler, 2009).

Although this paper focuses on students at only one institution of higher education, its contribution is to be the first paper to study the demand for illegal music while controlling for both (i) the various transactions costs associated with music piracy (i.e., the subjective likelihood of getting caught; the expected subjective legal costs; and the respondents' score on a morality proxy); and (ii) the respondents' WTP for music, elicited here by using a simple field experiment.

The remainder of this paper is organized as follows. Section 2 presents a simple theoretical model of consumer behavior. In section 3, we present the empirical framework and provide a detailed discussion of the identification strategy adopted in this paper. Section 4 presents the data

[4] Gopal et al. therefore empirically establish *avant la lettre* the anecdotal point made by Chris Anderson (2009) in his popular-press book. See also Edelman (2009) for a discussion of priced versus unpriced online goods.

as well as some descriptive statistics. In section 5, we present and discuss the empirical results. Section 6 concludes and offers some policy recommendations on the basis of our empirical results.

2. Conceptual Framework

This section develops a simple conceptual framework aimed at formalizing the reader's intuition regarding why some individuals pay for digital music while others pirate it. The conceptual framework developed in this section takes its roots in transactions cost economics (Williamson, 1989).

Assume a consumer whose income is equal to w consumes three goods: a piece of music that is obtained legally $x_L \in \{0,1\}$; a piece of music that is obtained illegally $x_I \in \{0,1\}$; and a composite good of all other commodities in the economy $x_C \geq 0$, the respective prices of which are $p_L > 0$, $p_I > 0$, and $p_C > 0$. The consumer's preferences over these three goods can be represented by the well-behaved utility function $U(\cdot)$. The consumer's problem is thus to

$$\max_{\{x_L, x_I, x_C\}} U(x_L, x_I, x_C) \qquad (1)$$

subject to

$$p_L x_L + p_I x_I + p_C x_C = w, \qquad (2)$$

where the last equality follows from the fact that the consumer's utility function is strictly increasing.

In what follows, we assume that legal and illegal music are perfect substitutes, i.e., $U(1,0,x_C) = U(0,1,x_C)$, and so a consumer consumes one or the other but not both, i.e., $x_L \cdot x_I = 0$. The substitutability assumption stems from the fact that there is essentially no difference between a song that is purchased or pirated, as both are in mp3 format. While an mp3 file does offer a lower audio quality audio than a compact disc (CD), one practically needs to be a trained audio engineer to hear and appreciate most of the audio quality of a CD. The audio quality of an mp3 file does depend on its bit rate, for which 128 kbps is the accepted standard, i.e., songs purchased from iTunes are encoded at 128 kbps. For compressing a CD into mp3 format, however, most compression software also uses a baseline bit-rate of 128 kbps. Moreover, like all music consumers, music pirates prefer high- to low-quality files, and songs on P2P networks are maintained by such individual users. These networks essentially monitor themselves because poor quality songs are removed by individual users, thereby ending their proliferation across the entire network. Therefore, the quality of both legally- and illegally-obtained songs should be indistinguishable from one another in equilibrium.

If legal and illegal music are perfect substitutes, it follows that an optimizing consumer can either choose legal music, i.e., choose the consumption bundle $\left\{1,0,\frac{w-p_L}{p_C}\right\}$, or choose illegal music, i.e., choose the consumption bundle $\left\{0,1,\frac{w-p_I}{p_C}\right\}$. The consumer will thus make her choice solely on the basis of which consumption bundle allows her to consume more of the composite good x_C.

Empirically, however, the market price of illegal music p_I is everywhere zero, while the market price of legal music is $0.99 at leading retailers of digital music. Does this mean that a rational consumer should choose to only consume illegal music (and an infinite amount of it at that if one extrapolates beyond our model, which only considers one song)? In other words, does this mean that anyone who consumes legal music is irrational? No. Instead, the fact that online music retailers such as Amazon and iTunes are still in business indicates that our simple model should be refined to take into account an important source of heterogeneity between consumers, i.e., the individual-specific transactions costs associated with consuming illegal music.

Indeed, the argument we make in this paper is that the consumer incurs potentially important transactions costs when consuming illegal music, that these transactions costs are specific to individual i, and that the price of illegal music p_I is composed entirely of the individual-specific transactions costs tc_i, so that $p_{Ii} = tc_i$. Specifically, a consumer who consumes illegal music faces a subjective probability π_i of getting caught by the authorities and having to pay a fine that she subjectively expects to be equal to f_i. As with any illegal activity, music piracy means that individuals are exposed to the risk of legal repercussions. Up until recently, the RIAA had taken upon itself the burden of enforcement, pursuing legal action against the individuals it identified as music pirates. The lawsuits that the RIAA had filed over the past several years have been the primary tool the music industry has employed in addressing the issue of piracy. Rational individuals should therefore account for this threat when they decide whether to purchase or pirate music. This threat is especially important for college students. Between September 2003 and February 2007, the RIAA had sued roughly 18,000 individuals, including 1,062 at colleges and universities (USA Today, 2007). The likelihood of getting sued for any one individual is in principle low, but it is not uncommon for individuals to overweight small-probability events of an adverse nature (Kahneman and Tversky, 1979), and what affects behavior is the subjective perception of that risk.

Additionally, the consumer incurs a hedonic cost of m_i due to the guilt she may derive from consuming illegal music. Indeed, for any issue on which it has legislated, the state essentially sends a signal to individuals about what it believes is ethically acceptable. By making it illegal to pirate digital music, the state has made it known that music piracy is wrong. This judgment may affect how individuals act. But while the state has issued its own judgment on the issue of piracy, this by no means serves as the moral standard for each individual. Decisions are based not only on what the government tells individuals is ethical, but also on those individuals' internal moral opinion on the issue, which obviously need not coincide with that of the law. This ultimately affects how individuals behave and whether they will engage in an action, legal or illegal.

Thus, the price of illegal music is such that $p_I = tc_i = \pi_i f_i + m_i$, where the subscript i indicates that transactions costs are individual-specific because consumers make consumption decisions on the basis of subjective perceptions (Nyarko and Schotter, 2002; Manski, 2004). A consumer will thus consume legal music if $p_L \leq tc_i$, and she will choose to consume illegal music if $p_L > tc_i$. Figures 1 and 2 illustrate these two cases for two consumers i and j, where $i \neq j$, who differ in their subjective assessment of the transactions costs associated with consuming illegal music but who are otherwise identical.

Individual-specific transactions costs thus create a "price band" around the market price of illegal music. If the price of legal music falls within that price band, the consumer chooses to consume legal music. Conversely, if the price of legal music falls outside that price band, the consumer chooses to consume illegal music. A similar conceptual framework was developed by de Janvry et al. (1991) to explain the heterogeneous market participation of households in developing countries.

3. Empirical Framework

We begin this section with a broad discussion of the core equation to be estimated in this paper in section 3.1, which is an empirical version of the consumer's Marshallian demand function adapted to the context of this paper.

Because one of the contributions of this paper lies in the way it controls for the unobserved heterogeneity in preferences between consumers, we then discuss our identification strategy in section 3.2. More specifically, we discuss how we recover WTP for digital music from the simple pricing experiment we ran during the survey.

We return to the equation to be estimated in section 3.3, presenting specific versions thereof which incorporate WTP as a control for the unobserved heterogeneity between respondent as well as measures for the various transactions costs which combine to form the effective price of illegal music.

3.1. Estimation Strategy

Given the data at hand, the behavior we wish to study lends itself to a binary choice model. Letting $y = 1$ if the last song downloaded by the respondent was obtained illegally, and $y = 0$ if the last song downloaded by the respondent was purchased legally, we are primarily interested in estimating a Marshallian demand function, such that

$$y_i = \alpha + \beta_L p_{Li} + \beta_I p_{Ii} + \beta_w p_{wi} + \beta_z z_i + \varepsilon_i, \tag{3}$$

where, as in section 2, p_L is the price of legal music, p_I is a vector of transactions costs associated with digital music piracy, and w is the respondent's income, but where z is a vector of individual characteristics, and ε is an error term with mean zero.

The first problem one encounters when wanting to estimate equation 3 is that there is no variation in p_L, the price of legal music: at the time of the survey, both iTunes and Amazon – the two leading retailers of digital music – had set that price at $0.99. The solution to this problem is simple: because the price of legal music is common to all respondents, it can be ignored.

The second, more serious problem one encounters is that there is *also* no variation in the market price of illegal music: it is always zero. One could choose to ignore this problem and regress y only on income with some controls for the individual characteristics of the respondent thrown in. Assuming one is interested in β_w or β_z, however, ignoring the lack of variation in the (market) price of illegal music would lead to biased estimate of β_w and β_z because of two fundamental problems. First, the effective price of illegal music is composed entirely of transactions costs that add themselves to the market price of zero and which differ from one consumer to the other so as to have heterogeneous effects on consumers. If these transactions costs are correlated with any of the observable factors included on the right-hand side of equation 3, then our coefficient estimates will be biased. Second, consumers derive heterogeneous amounts of utility from the consumption of music. Once again, if the utility a consumer derives from her consumption of music is correlated with any of the observable factors on the right-hand side of equation 3, our coefficient estimates will be biased.

We control for the former problem by directly including (i) the individual-specific transactions costs one incurs when acquiring and consuming illegal music; and (ii) a measure of one's WTP for digital music, which is a direct measure of the marginal utility one derives from one's consumption of digital music.

The estimation of our respondents' WTP for digital music is the subject of the next two sections. As regards the transactions costs inherent to digital music piracy, we include each respondent's subjective perception regarding the likelihood she will get caught pirating music and get sued by the RIAA and her subjective perception regarding the total litigation costs if she were to get caught. We also elicited each respondent's degree of morality using a proxy adapted from Gopal et al. (2004) and which asks the subjects to rate the ethics of five questions on a scale ranging from zero to six. The scores from each question are added to one another to create a morality proxy on a 30-point scale. The appendix shows the questions used in constructing the morality proxy.

Although the data used in this paper are cross-sectional, one would not necessarily do better in terms of identification by using panel data. To deal with unobserved heterogeneity, one must typically collect longitudinal data in order to use individual fixed effects to control for all the confounding factors that remain constant over time for each individual. But then, there is little to no variation in most of the factors considered in this analysis over the few years an individual spends in college (e.g., one's WTP for music; whether one belongs to a fraternity or a sorority; one's major; one's subjective assessment of the likelihood of getting caught and the accompanying legal costs; one's morality; who pays for one's tuition; the annual income of one's parents; one's own annual income; etc.), and those for which there is some variation are of little to no interest in studying the decision to pirate digital music (e.g., one's age, one's grade point average).

3.2. Identification Strategy

In this section, we discuss the method we use to elicit our respondents WTP for music in detail. To do so, we first present a well-known method to parametrically estimate WTP. Because this method makes the somewhat restrictive assumption that WTP is normally distributed, we then present a method to nonparametrically estimate a lower bound on each respondent's WTP, which will be used in section 5 to check the robustness of our empirical findings.

3.2.1. Willingness to Pay for Music: Parametric Estimation

In order to elicit our respondents' WTP for digital music, we ran the following simple field experiment. Each respondent was asked to give the last two digits of her SSN and was then asked whether she would be willing to buy a specific song for a price in cents equal to the last two digits of her SSN. Because we needed a song that would be the same for all respondents and well-known among them, we chose the most downloaded song on iTunes the week the survey was launched – Flo Rida's "Right Round."

Our argument for why our respondents' WTP for "Right Round" is a good proxy for their WTP for music is as follows. Because the price at which the song was offered is random, the variation used to identify WTP is fully exogenous to the dependent variable. In order to obtain a respondent's "true" WTP for music (i.e., her expected WTP for a randomly selected piece of legal music in the entire universe of pieces of music), we would need to elicit our respondents' WTP for a random sample of all the pieces of legal music in existence so as to compute, for each respondent, an average of her WTP for a piece of music that was obtained legally.

Coming up with such an estimate, however, would prove difficult, if not impossible, given that there is no centralized repository of all the digital music that is available legally. If one were to go on iTunes or Amazon with the intention of obtaining a random sample of the universe of possible songs, it would be very difficult to randomly select a sample of songs from either source, given that neither retailer offers a list – in statistical parlance, a sampling frame – from which one can readily sample. Instead, potential customers look for music on either retailer's website by entering keywords.

Our respondents' WTP for a given song, however, should be correlated with their "true" WTP (provided enough respondents are familiar with the chosen song, which is why we chose the most popular song on iTunes the week the survey was launched), which should itself be correlated with their WTP for the last song they obtained. Thus the identifying assumption we make is that the cases where a respondent has strong feelings about "Right Round" (and so her WTP for this particular song is not representative of her "true" WTP) are randomly distributed and are thus purely the result of noise in the data.

In this context, WTP is estimated as follows. Letting $z = 1$ if respondent i stated she would buy the song at a price in cents equal to the last two digits of her SSN and $z = 0$ otherwise, we estimate the following relationship

$$z_i = \beta x_i + \gamma s_i + \upsilon_i, \tag{4}$$

where x is a vector of controls that also includes a vector of ones, s denotes the last two digits of the respondent's SSN, and υ is an error term with mean zero. Following Cameron and James (1987) and Vossler and Kerkvliet (2003), we estimate equation 4 as a probit, which allows us to recover each respondent i's WTP, such that

$$WTP_i = -\left(\frac{\beta x_i + \gamma s_i}{\gamma}\right). \tag{5}$$

This WTP estimate is then used to control for the unobserved heterogeneity in preferences between respondents in equation 3 above.[5]

Rob and Waldfogel (2006) and Shiller and Waldfogel (2009) directly ask their respondents what their maximum WTP would be for specific songs. It is not clear, however, that such direct elicitation is incentive compatible. Generally, open-ended WTP questions are not incentive compatible unless they are attached to a second-price auction or a Becker-DeGroot-Marschak mechanism (Becker et al., 1964). The contingent valuation method used in this paper was first developed to deal with the incentive compatibility problem (see Carson and Groves, 2007 and Poe and Vossler, 2009 for discussions).

3.2.2. Willingness to Pay for Music: Nonparametric Estimation

The WTP estimation method presented in the previous section has the disadvantage that it imposes that WTP be normally distributed, which some readers may not be comfortable with. In order to relax the normality assumption, this section discusses an estimation method that allows recovering a lower bound on each respondent's WTP but which does not make any distributional assumption. The method developed in this section also gives us a convenient way to check the robustness of our empirical results with respect to changes in the way WTP is estimated.

[5] The WTP estimate in equation 3 is not a lower bound on WTP but rather a direct estimate of respondent i's WTP given the formula in equation 3. See Cameron and James (1987) for details. The next section derives a nonparametric lower bound estimate of each respondent's WTP.

The nonparametric lower-bound WTP estimation proceeds as follows (Bellemare, 2010). For a given random price (i.e., SSN) of s_i, if a respondent says she would buy the song at that price, we know that she would be willing to pay at least s_i for the song. Alternatively, if the respondent says she would not buy the song at that price, we know that she would not be willing to pay anything for the song. Thus, one can ascribe a value of s_i as WTP for any respondent who answered "Yes" to the contingent valuation question and a value of zero for any respondent who answered "No" to the contingent valuation question, which yields a nonparametric lower-bound estimate for each respondent's WTP.

The nonparametric WTP estimate has the advantage of relaxing the normality assumption, but it has the disadvantage of assuming that WTP is nonnegative. Generally, this assumption would not be innocuous given that WTP for certain goods can be negative (i.e., consumption needs to be subsidized for some individual). This is most obvious in those cases where consuming the good would have a clear cost. In the case of legal music, however, it is unlikely that any respondent would incur a cost if she were merely given a song for free (i.e., if s_i were equal to zero). In other words, it is unlikely that a respondent would require a subsidy in order to be given a song for free simply because once the respondent owns the song, nothing forces her to listen to it, and the cost of storing one more piece of music is essentially zero.

3.2.3. Reverse Causality and Cognitive Dissonance

Before returning to our estimation strategy, we must address the issue of whether the individual-specific subjective transactions costs we treat as our variables of interest could be causally affected by whether the respondent's last song was obtained legally or illegally. Indeed, it is entirely plausible that a respondent who has chosen to pirate rather than purchase her last song has revised her subjective probability of facing a lawsuit and her subjective expectation of the cost she would incur if she were to get caught pirating music, or that her degree of morality has changed as a consequence of her behavior.

When choices affect rather than reflect preferences, social psychologists talk of cognitive dissonance, a phenomenon that has been known to economists since the work of Akerlof (1982) on the topic. If there were cognitive dissonance in this context, i.e., if the causality ran from whether a respondent's last song was obtained legally or not to the individual-specific measures of transactions costs rather than the other way around, our estimations would suffer from an endogeneity problem, and our coefficient estimates would be biased as a result.

We rule out the possibility that cognitive dissonance and reverse causality pose a problem in our analysis for the following reasons. First, recent research at the intersection of psychology and economics has invalidated almost every study that had previously found evidence in favor of the hypothesis that choices affect rather than reflect preferences, i.e., in favor of cognitive dissonance (Chen, 2008).

Second, and perhaps more importantly, even if choices did affect rather than reflect preferences and the individual-specific subjective transactions costs we include in our analysis were affected by our respondents' habitual behavior, the fact that we include our respondents' WTP for music would take care of this problem.

Indeed, our WTP estimate (which itself does not suffer from cognitive dissonance because it was generated from a field experiment) is a direct measure of the marginal utility one derives from consuming digital music. If a respondent's subjective perceptions of the transactions costs involved in consuming illegal music increase, the marginal utility the consumer derives from consuming music will vary, given that in equilibrium, a consumer's marginal utility from consuming a given good is proportional to the price paid for that good.

In the notation of section 2, one's marginal utility from consuming digital music is equal to

$$\frac{\partial U}{\partial x_I} I(x_I = 1) + \frac{\partial U}{\partial x_L} I(x_L = 1) = \lambda[\pi_i f_i + m_i] \cdot I(x_I = 1) + \lambda p_L \cdot I(x_L = 1), \qquad (6)$$

where λ is the Lagrange multiplier attached to the consumer's budget constraint, which is equal to the consumer's marginal utility of income, and where $I(\cdot)$ is an indicator function equal to one if the condition in parentheses is true and equal to zero otherwise. That is, an optimizing consumer equates the marginal utility she derives from consuming music (whether legal or illegal, since both goods are perfect substitutes) with the product of the marginal utility of her income and the (effective) price she pays for music. Thus, there is a clear positive relationship between one's marginal utility from digital music and $tc_i = \pi_i f_i + m_i$.

Thus, by controlling for our respondents' marginal utility of music by including their exogenous WTP for music, we also control for the causal relationship that may potentially run from a respondent's consumption bundle to her subjective transactions costs perceptions by exogenizing the variables that make up tc_i. In other words, there is no correlation between tc_i and the error term ε, and our estimates are not contaminated by the endogeneity problem caused by the potential for reverse causality.

3.3. Estimation Strategy (Reprise)

We start from the simplest, most parsimonious specification of equation 3, progressively augmenting it so as to include more and more control variables. The first specification of equation 3 that we estimate is such that

$$y_i = \alpha_1 + \beta_{p1} p_i + \beta_{w1} w_i + \beta_{z1} z_i + \varepsilon_{1i}, \tag{7}$$

where, in a slight abuse of notation, p is the respondent i's WTP for digital music; w is her income (i.e., the income derived from working during the summer and during the school year); z is a vector of individual characteristics of the respondent; and ε is an error term with mean zero.

The specification in equation 3 is a simple Marshallian demand function that fails to control for the transactions costs of digital music piracy. Because omitting these transactions costs may lead to biased estimates, the second specification of equation 3 we estimate is such that

$$y_i = \alpha_2 + \beta_{p2} p_i + \beta_{w2} w_i + \beta_{t2} tc_i + \beta_{z2} z_i + \varepsilon_{2i}, \tag{8}$$

where tc is a vector of the transactions costs involved in digital music piracy (i.e., respondent i's subjective assessment of the likelihood she will get caught and sued by the RIAA for pirating music; her subjective assessment of the total litigation costs when getting caught; and her degree of morality).

Because the average college student typically has a low income, however, and because she typically has other sources of income to which she has access (e.g., parental income, grants, scholarships, etc.), the last two specifications of equation 3 allow for a wider definition of income. Therefore, the third specification of equation 3 we estimate is such that

$$y_i = \alpha_3 + \beta_{p3} p_i + \beta_{w3} w_i' + \beta_{t3} tc_i + \beta_{z3} z_i + \varepsilon_{3i}, \tag{9}$$

where w_i' is a vector that includes both the personal income of the student as well as the student's sources of tuition money. Likewise, the fourth specification of equation 3 that we estimate is such that

$$y_i = \alpha_4 + \beta_{p4} p_i + \beta_{w4} w_i'' + \beta_{t4} tc_i + \beta_{z4} z_i + \varepsilon_{4i}, \tag{10}$$

where w_i'' is a vector that includes the student's personal income, her sources of tuition money, as well as controls for parental income.

Equations 7 to 10 are estimated by ordinary least squares (OLS) to simplify the interpretation of the estimated coefficients and so as to not to have to make any distributional assumption on the error term.[6] In addition, because the respondents' WTP to purchase music is a generated regressor in the LPM defined by equations 7 to 10, their standard errors are all bootstrapped in the empirical results below. Lastly, equations 7 to 10 are each estimated twice for robustness: once with the parametric WTP, and once with the nonparametric lower-bound WTP estimate.

4. Data and Descriptive Statistics

The data used in this paper were collected using a web-based survey that we developed. On March 3, 2009, the survey was sent to the entire undergraduate student body (i.e., over 6,000 students) of a Southern private research university through the undergraduate email distribution

[6] The reader may have noted a discrepancy between our reliance the probit in the previous section and our estimating a linear probability model (LPM) in this section. The former is because the WTP estimate we use is articulated around the probit in the contingent valuation literature. The latter is so as to obtain coefficients that can be directly interpreted as marginal effects.

list. Because access to this email list is restricted, and to make sure the respondents understood that the data were collected as part of a serious research effort, the survey was sent by the student government in one of its weekly emails to the entire undergraduate student body. The specific part of the email that linked to our survey read as follows:

> "Music piracy and lawsuits against students have been ongoing issues at college campuses across the nation. We would like your assistance in addressing this issue by helping us gather more information about the nature of music piracy here at [Southern private research university]. Click on the link below to take a short (5-minute) online survey about your music downloading behavior so we can get more information about why students choose to purchase or pirate music. The survey is completely anonymous, and you will have the opportunity to enter into a raffle for four Visa gift cards, worth $200, $100, $50, and $50."

By having the survey sent to every individual within the population, selection bias was reduced, and sample size was maximized. University-provided unique identifiers were collected so as to be able to give the winners their prize, but respondents were explicitly told that their responses were to be kept strictly confidential.

The raw data set comprised 309 observations. Two observations were dropped because the same respondent had taken the survey twice; four observations were dropped because they were incomplete; and one was dropped because the respondent had clearly not taken the survey seriously, e.g., by claiming they were 9 years old, by claiming their expected graduation year was 2008, etc. In this paper, an incomplete observation is one for which the respondent stopped responding to the survey before she could submit it. Incomplete observations are thus distinct from observations for which some data is missing.

4.1 Willingness to Pay for Music

Table 1 presents descriptive statistics for the sample on which WTP for music is estimated. In this case, the dependent variable is a dummy variable equal to one if the respondent would be willing to buy "Right Round" for a price in cents equal to the last two digits of their SSN. Almost 40 percent of our respondents would be willing to do so for a price equal to $0.46 on average and ranging from $0.00 to $0.98.

The average respondent is 20 years old, has a grade point average (GPA) of 3.48 and the modal respondent was a junior at the time of the survey given that she expected to graduate in 2010. Over a quarter of the respondents took part in Greek life on campus (i.e., they were members of a fraternity or a sorority), 17 percent were engineering majors, and 5 percent were undecided.[7] Combining her income from the previous summer with her income from whatever employment she may have during the school year, the average respondent had an annual income of $4,300.[8,9]

Although estimating a selection equation to account for the difference between respondents and nonrespondents is well beyond the scope of the data, we can still assess our survey's comparability with the population from which we sampled.[10] In the population, the average GPA is equal to 3.44, well within our survey's 99 percent confidence interval, which is equal to [3.437, 3.534]. Likewise, in the population, the proportion of engineering majors is 18.9 percent, and in our survey, the 99 percent confidence interval is equal to [0.11, 0.23]. Similarly, in the population, the proportion of students who are in a fraternity or a sorority is 34 percent, and in our survey, the 99 percent confidence interval is equal to [0.21, 0.34]. Therefore, the degree of comparability between our survey and the population from which we sampled is within the conventional levels.

Because a respondent's own annual income is a strict definition of income – many students do not work during the school year and only take on unpaid internships during the summer – we include two more variables to account for a respondent's full income constraint: the income of her parents, and how her tuition is paid for. The parents of the respondent made less than $50,000 per year in 14.8 percent of cases; between $50,000 and $100,000 in 24.4 percent of

[7] While the breakdown of students between engineering and other majors may strike the reader as odd, undergraduates are seen as belonging to one of two colleges (i.e., engineering or arts and sciences) at the university level.

[8] A better measure of a student's ability to pay might be her total consumption expenditures for the week or month before the survey, but the survey did not collect information on consumption expenditures.

[9] Although we collected data on the gender of each respondent, that variable was dropped by the application we used to run the survey, and was deemed irrecoverable by the administrators of the university network through which the survey was run.

[10] The population proportions for whether one is in a fraternity or in a sorority and whether one is an engineering major were found on the university's website. The average GPA in the population was found in an article published in the university's student-run independent daily newspaper.

cases; between $100,000 and $150,000 in 21.3 percent of cases; between $150,000 and $200,000 in 10 percent of cases; between $200,000 and $250,000 in 8.6 percent of cases; and $250,000 or more in 21 percent of cases. Unsurprisingly, the bimodal nature of the distribution of parental income – a peak in the $50,000 and $100,000 category and another in the more than $250,000 category – is seemingly reflected in how students pay for tuition: in almost 85 percent of cases, the respondent's parents partially pay the respondent's tuition, but over 40 percent of respondents have a scholarship, and over 30 percent of them have a grant.

We also include the perceived popularity of the last song downloaded either legally or illegally by the respondent so as to crudely control for the respondent's tastes when studying her willingness to purchase "Right Round," under the assumption that the respondent's last song is representative of her tastes, and that departures from this representativeness are purely due to noise. The last song downloaded was also distributed bimodally, as it was deemed "unique" (and therefore very unpopular) by 15.1 percent of respondents; unpopular by 22 percent of respondents; somewhat popular by 16.5 percent of respondents; popular by 17.9 percent of respondents; and very popular by 28.5 percent of respondents. Finally, given the timing of the survey, we include a dummy variable equal to one if the respondent has received an iTunes gift card – a source of "income" that can only be used for the specific purpose of purchasing legal music – for Christmas and equal to zero otherwise. Omitting this variable could bias our estimate of WTP for music, given that almost 35 percent of respondents have received such a gift card.

4.2 Music Piracy

Table 2 presents descriptive statistics for the sub-sample used to study the determinants of digital music piracy.[11] In this case, the dependent variable is a dummy variable equal to one if the last song downloaded by the respondent was obtained illegally and equal to zero if was obtained legally. Once again, the assumption we make is that this last song is representative of the average behavior of each respondent, and that cases where the respondent's last song is not representative of her habitual behavior are purely due to noise.

[11] The sample size in this case (n=262) was smaller than in the previous case (n=291), both because there were a number of observations for which the value of some variable was missing and because we threw way four observations for which the expected cost of a lawsuit were entered frivolously (i.e., values in the billions of dollars; a value of $1,111,111).

A little over 30 percent of our respondents reported that their last song had been obtained illegally, a finding that is consistent with the average WTP for music – which was equal to $0.69 in our sample with a nonparametric lower bound of $0.13 – being well below the $0.99 market price of music. Figure 3, which shows the distribution of WTP for music in our sample, indicates that the vast majority of respondents have a WTP that is below $0.99.

The variables carried over from the estimation of our respondents' WTP for music (i.e., individual characteristics; sources of tuition money; annual income of parents; whether the respondent received an iTunes gift card for Christmas) do not differ substantially between the sample used to study WTP and the sub-sample retained to study the determinants of digital music piracy. Three new variables, however, are included as transactions costs in the equation used to study digital music piracy, viz. the respondent's subjective assessment of the likelihood that she will face a lawsuit in case of music piracy; her expected settlement cost in case there is such a lawsuit; and the value of the respondent's morality proxy.

The average subjective probability of a lawsuit, at almost 9 percent, is *a prima facie* high. In this case, however, the mean is particularly sensitive to outliers. Indeed, almost 75 percent of responses report subjective perceptions of 5 percent or below. The seven respondents whose subjective perceptions were of 75 percent or above drive the mean upward, and the median subjective perception is 1 percent. Regarding the expected cost of a lawsuit, the distribution follows a pattern similar to that of the respondent's subjective probability of a lawsuit since the mean expected cost is $8,600. In truth, the average cost in case of an RIAA lawsuit is $3,000 (USA Today, 2007). This distortion could be due to a genuine lack of information on the part of our respondents, or it could be due to the way the question was asked, which did not differentiate between lawsuit settlement costs and total legal costs, of which lawsuit settlement costs are only a fraction. About 75 percent of respondents responded with values of $3,000 or less (in fact, 36 respondents out of 262, or 14 percent responded exactly $3,000, reflecting scant knowledge of the RIAA's practices among our respondents), and the median value was $1,000. The presence of outliers thus drives the mean upwards.

Finally, as regards our morality proxy, figure 4 shows the distribution of morality within our sample and shows that it is roughly normal. Cronbach's α, a measure commonly used by psychometricians to assess the internal consistency and reliability of a survey question such as this one (Cronbach, 1951), was equal to 0.74, which indicates that our morality proxy is consistent and reliable, as it is above the 0.7 threshold for a reliable instrument. Given that the average respondent has a morality of 24.3 and that the modal morality is equal to 25, both the mean and modal respondents lie relatively high on the morality scale. There is considerable variation in the morality of our respondents, however, given that the standard deviation for the morality proxy was equal to 4.6. After estimating the WTP for music in our sample, the next section investigates whether these transactions costs affects the decision to pirate digital music, *ceteris paribus*.

5. Estimation Results

We now turn to the empirical analysis, which first consists in estimating the WTP for digital music using a method for contingent valuation (Mitchell and Carson, 1989; Arrow et al., 1993) that is well known in environmental economics (Cameron and James, 1987; Vossler and Kerkvliet, 2003), and then consists in estimating the determinants of the decision to pirate digital music.

5.1. Willingness to Pay

Table 3 reports the marginal effect of each explanatory variable on whether respondents' are willing to purchase Flo Rida's "Right Round." These marginal effects are derived from the estimated coefficients in equation 4. Evidently, the most important finding in this case is that the random price (i.e., the last two digits of a respondent's SSN in cents) has the expected effect, and that this is statistically significant: for a \$0.01 increase in the price the average respondent faces, the probability that the respondent will be willing to buy the song is decreased by 0.6 percent. Income also matters in that for every additional \$10,000 of own income, the probability that the respondent will be willing to buy the song falls by 16 percent, indicating that "Right Round" is an inferior good when considering only one's own income. When controlling for the annual income of the parents, respondents whose parents are in all income categories are less likely to wish to purchase the song than respondents whose parents are in the more than \$250,000 category (i.e., the omitted category), but this is only significant in the less than $50,000 and the $150,000 to $200,000 categories. Unsurprisingly, a student who has received an iTunes gift card was 26 percent more likely to be willing to download the song.

Respondents who are members of the Greek system, i.e., fraternities and sororities, are 16 percent more likely to be willing to buy “Right Round.” A student who rated the last song she had downloaded as very unpopular was 22 percent less likely to be willing to purchase “Right Round,” which indicates that taste matters in this setting. Finally, respondents on scholarships were 13 percent less likely to be willing to download the song.

5.2. Music Piracy

The estimation results in table 3 are then used to estimate respondents’ WTP for music, which was shown in figure 3 and which we use as a measure related to the price of substitutes in the demand for pirated digital music. Table 4 presents estimation results for equations 7 to 10. As regards the variables of interest (i.e., price and income), digital music piracy decreases as WTP for music increases to the tune of a 1 percent decrease for every $0.04 increase in WTP in columns 1 to 3. This effect is present only insofar as one fails to control for the annual income of the respondent’s parents: in column 4, the respondent’s WTP no longer has a significant impact on the decision to pirate music. One’s own income has no impact on the decision to pirate music, but respondents whose parents are poorer are more likely to pirate digital music, a relationship that is roughly monotonic along income categories, save for a peak in the $100,000 to $150,000 category. Likewise, a student who has received an iTunes gift card for Christmas is 15 percent less likely to pirate music in column 4.

If price only matters as long as one fails to control for full income, what are the factors that actually drive digital music piracy? As it turns out, individual-specific subjective perceptions of transactions costs have a significant negative impact at the margin: for a 1 percent increase in the subjective probability of getting sued for obtaining music illegally, the likelihood that a respondent will pirate music falls by about 0.4 percent in columns 2 to 4. This is similar to Chiou et al.’s (2005) findings for Taiwanese high school students. Likewise, for a 10 percent (i.e., 2.4-

point) increase in the average respondent's morality score, the likelihood that she will choose to pirate digital music falls by over 4 percent.

Because the results in table 4 rely on the assumption that our respondents' WTP for digital music is normally distributed (i.e., the WTP estimate discussed in section 3.2.1), we re-estimate equations 7 to 10 in table 5 using a nonparametric lower bound on our respondents' WTP (i.e., the estimate discussed in section 3.2.2) in table 5. These last results show that our estimation results are robust to changes in the method used to estimate WTP.

The empirical results in tables 4 and 5 thus offer strong support for the hypothesis that transactions costs exert an important influence on the decision to pirate digital music. When considering the decision to pirate digital music in our sample, WTP for music only matters insofar as one assumes that parental income is constant across respondents, but the subjective probability of getting caught and of subsequently facing a lawsuit by the RIAA and the respondents' sense of morality always matter. Finally, while it may seem a priori surprising that a respondent's subjective assessment of the litigation cost she would bear in case of a RIAA lawsuit has no impact on the decision to pirate music, this is due to the fact that very few of our respondents knew the actual cost of a lawsuit, as witnessed by the large standard errors around the mean of this variable in table 2.

6. Conclusion and Policy Implications

We have studied the determinants of digital music piracy using survey data collected from undergraduates at a Southern private research university. To do so, we first asked respondents whether they would be willing to buy a specific song for a price in cents equal to the last two digits of their SSN.

Doing so allowed us to treat that price as completely exogenous to whether respondents are willing to buy the song as well as to estimate each respondent's WTP for music. We then asked each respondent whether the last song they had downloaded was obtained legally or illegally. We then estimated the determinants of digital music piracy by regressing their answer to that question on their WTP for music and on the transactions costs incurred when pirating digital music, i.e., each respondent's subjective assessment of the probability she will get caught pirating music; her expected legal settlement costs if she gets caught; and a proxy for the respondent's morality.

Our empirical results show that WTP for music only has a significant negative effect on music piracy insofar as controls for parental income are omitted. In other words, one's WTP for music is driven largely by one's full income, which includes parental income for the college students considered in this paper. More importantly, we find that transactions costs significantly affect the decision to pirate music. For a 1 percent increase in a respondent's subjective assessment of the likelihood that she will get caught pirating music, the likelihood that her last song was pirated decreases by almost 0.5 percent. For a 10 percent increase in a respondent's morality proxy, the likelihood that her last song was pirated decreases by 0.2 percent. Finally, respondents who had recently received an iTunes gift card were 15 percent less likely to have pirated their last song, and the lower the annual income of a respondent's parents, the more likely she was to have pirated her last song.

These findings point to an important policy recommendation. If the goal of the RIAA was solely to deter piracy, it should not have abandoned its policy of suing the people it caught pirating digital music. Indeed, after suing 30,000 people over five years, the RIAA announced on December 19, 2008 that it would stop suing people over digital music piracy. Our findings nevertheless indicate that the threat of legal action had a significant impact at the margin on our respondent's decision to pirate music.

Moreover, given that our sample is composed of college students, a university that wants to reduce music piracy could use our estimate of WTP for music to sign a licensing agreement with an online music retailer wherein students can download music at a subsidized price below mean estimated WTP. For example, suppose that the university we sampled from wanted to completely eliminate music piracy based on our results. It could do so by signing a licensing agreement with an online music retailer that allows students to buy songs for $0.10 a piece, given that the lower bound of our parametric WTP estimate was $0.11. Such a policy would evidently be costly, so it may be more reasonable to argue for a reduction in music piracy, which our WTP estimate also allows one to compute. For example, ignoring the transactions costs of music piracy and assuming that people only pirate music when their WTP falls below $0.99, a quick back-of-the-envelope calculation indicate that pricing each song at $0.81 would allow decreasing music piracy by 25 percent, and that pricing each song at $0.63 would allow decreasing music piracy by 50 percent. Recall that iTunes has announced a new, three-tiered pricing structure wherein some songs retail for $0.69, some for $0.99, and some for $1.29 in early April 2009. While the lower tier of that new pricing structure will almost surely contribute to eliminating music piracy, the upper tier, which is usually reserved for popular new releases, is slightly below the upper bound of our WTP estimate and, as such, may be set a bit too high.

Cornell University adopted such a policy between 2004 and 2006, when an anonymous donor paid for two years worth of Napster service for the university community. According to the web site of Cornell's Center for Information Technology, however, "[t]he continuation of the program into the 2006-07 academic year and beyond depended on the inclusion of a part or all of future expenses in the Student Activity Fee. During the fall 2005 Student Activity Fee deliberations, the Student Assembly chose not to pick up the issue. Therefore, Cornell's contract with Napster was allowed to expire."[12] It seems the student government chose not to renew the agreement with Napster because the agreement was seen as "anti-Apple," both because Napster did not support the Mac operating system and because the music purchased on Napster could not be played on the Apple iPod.

Finally, an important caveat applies to our findings in that our sample includes only college students, and that these students were all surveyed from a single university. Researchers interested in music piracy should aim to both compare between various institutions of higher learning as well as to expand the scope of analysis to the population at large.

[12] See http://www2.cit.cornell.edu/services/music/napster/faq.shtml.

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Appendix

The morality proxy we use as one of our transactions costs for digital music piracy was originally developed by Wood et al. (1988) and is adapted from Gopal et al. (2004). To eliminate potential framing effects, each respondent was asked to answer the following five questions at the very beginning of the survey (Tversky and Kahneman, 1981) by giving an answer ranging from 0 (for "Never acceptable") to 6 (for "Always acceptable") for each question:

1. An executive earning $50,000 a year padded his expense account by about $1,500 a year.
2. In order to increase profits, a general manager used a production process which exceeded legal limits for environmental pollution.
3. Because of pressure from his brokerage firm, a stockbroker recommended a type of bond which he did not consider a good investment.
4. A small business received one-fourth of its gross revenue in the form of cash. The owner reported only half of the cash receipts for income tax purposes.
5. An engineer discovered what he perceived to be a product design flaw, which constituted a safety hazard. His company declined to correct the flaw. The engineer decided to keep quiet, rather than taking his complaint outside the company.

Each respondent's morality proxy can then be computed by summing over the answers given to these five questions and by subtracting the amount from 30. Indeed, because the six-point scale of the answer is increasing in the respondent's amount of *im*morality; we simply invert the proxy so as to use a morality proxy in our empirical work.

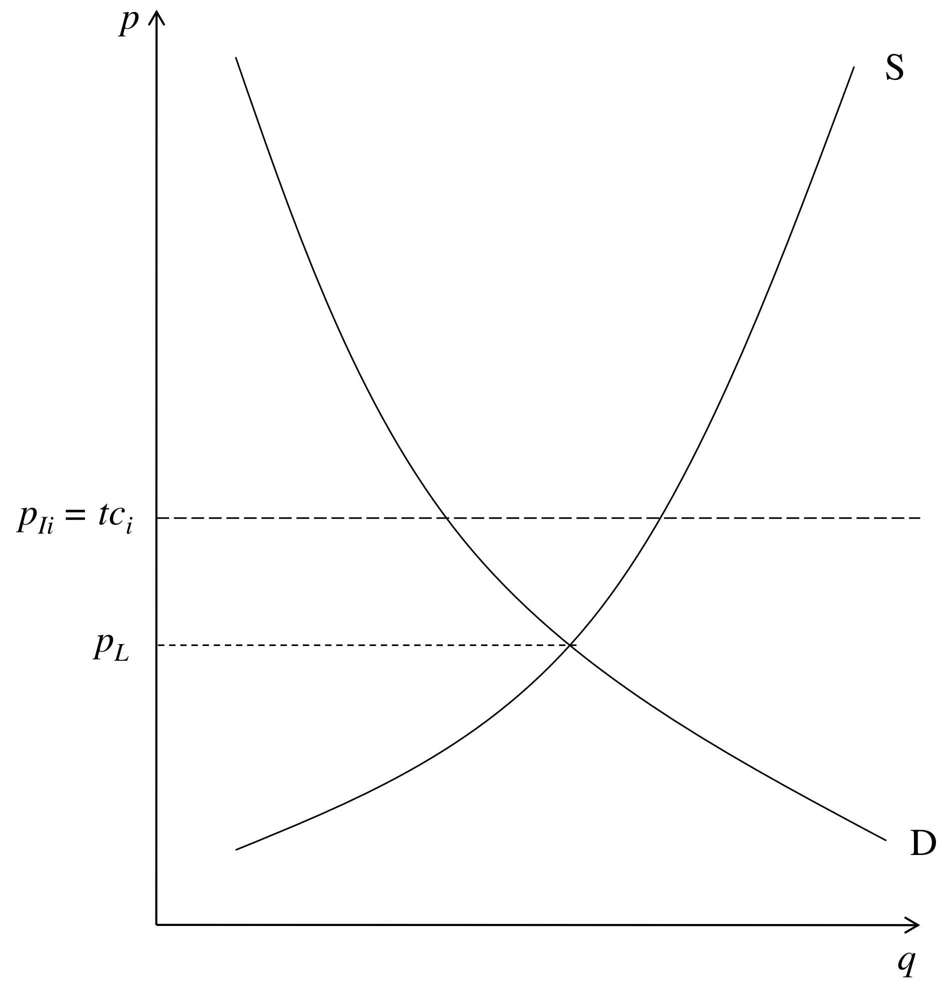

Figure 1. The market for digital music for a consumer whose individual-specific transactions costs of consuming illegal music drive the effective price of illegal music above the market price of legal music.

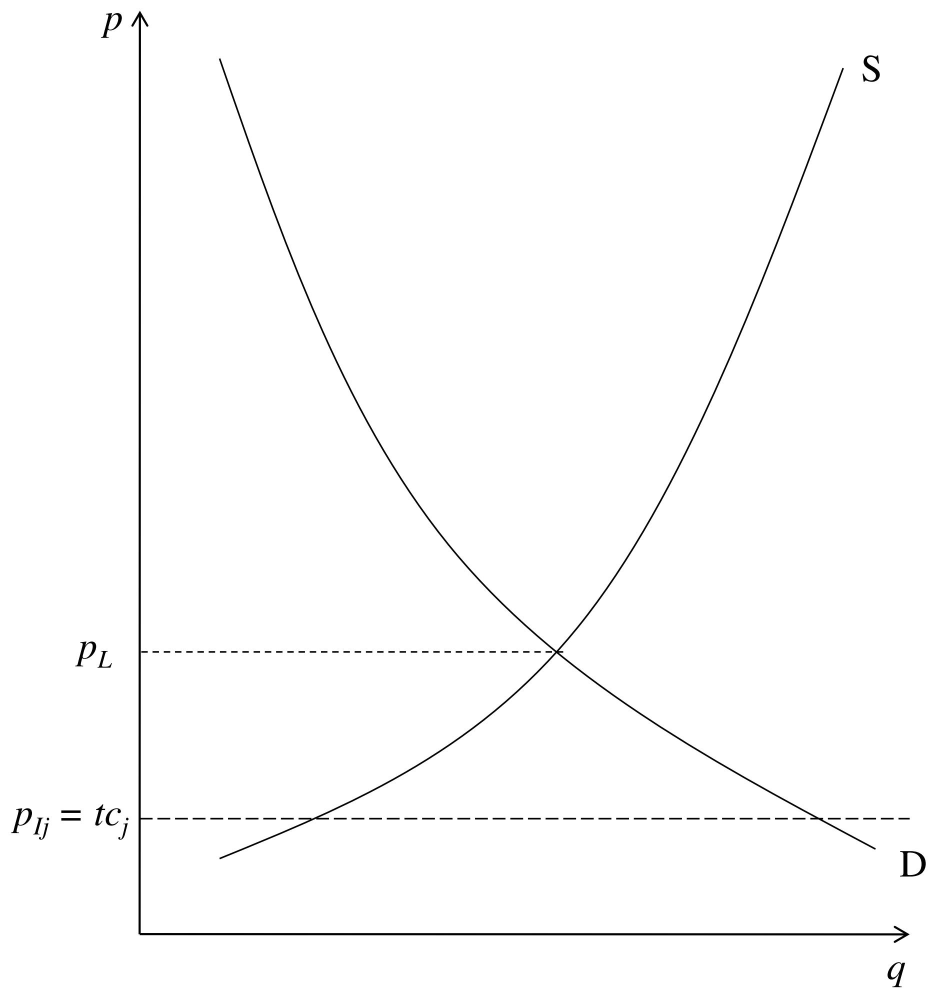

Figure 2. The market for digital music for a consumer whose individual-specific transactions costs of consuming illegal music drive the effective price of illegal music below the market price of legal music.

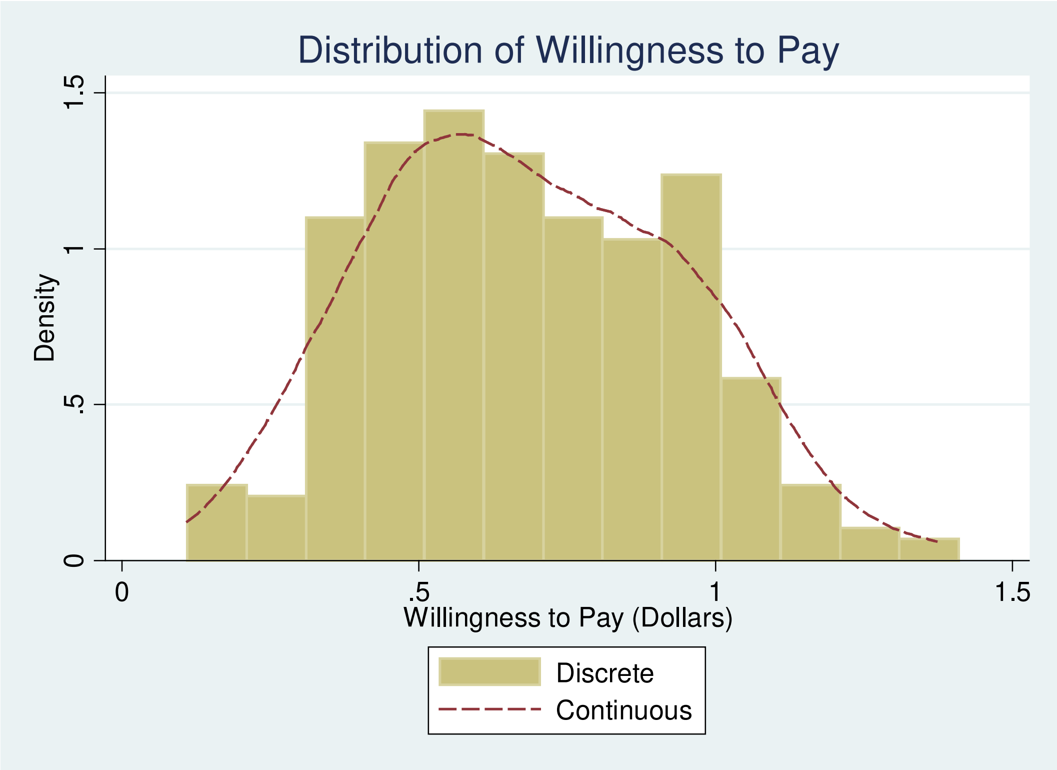

Figure 3. Histogram and Kernel Density Estimate of the WTP for Digital Music with Epanechnikov Kernel and $0.10 Bandwidth.

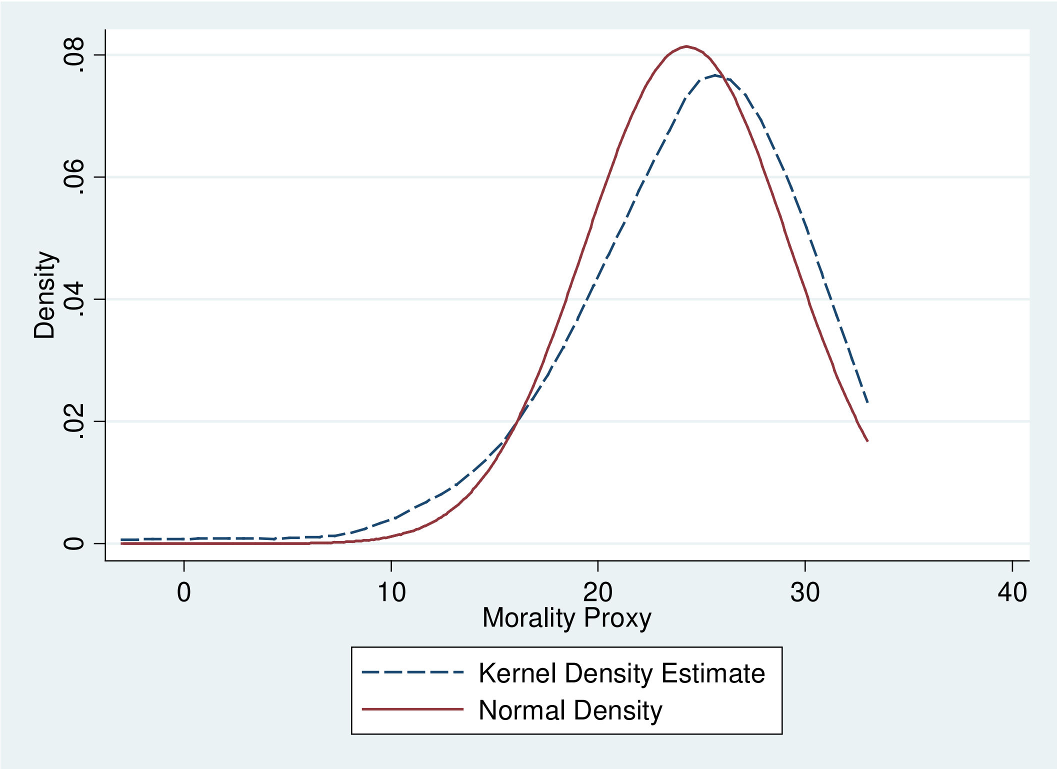

Figure 4. Kernel Density Estimate of the Morality Proxy with Epanechnikov Kernel and Three-Point Bandwidth.

Table 1. Descriptive Statistics for Willingness to Pay for Digital Music (n=291)

Variable	**Mean**	**(Std. Dev.)**
Would Buy "Right Round" at Random Price Dummy	0.361	(0.481)
Random Price (Dollars)	0.461	(0.303)
Individual Characteristics		
Age (Years)	19.849	(1.376)
Grade Point Average (Four-Point Scale)	3.480	(0.316)
Greek Dummy	0.271	(0.445)
Expected Graduation Year	2010.553	(1.092)
Engineering Major Dummy	0.168	(0.375)
Undecided Major Dummy	0.048	(0.214)
Annual Income ($10,000)	0.432	(0.620)
Popularity of Last Song		
Very Unpopular Dummy	0.151	(0.359)
Unpopular Dummy	0.220	(0.415)
Somewhat Popular Dummy	0.165	(0.372)
Popular Dummy	0.179	(0.384)
Very Popular Dummy	0.285	(0.452)
Sources of Tuition Money		
Parents Dummy	0.835	(0.372)
Family Dummy	0.041	(0.199)
Savings Dummy	0.203	(0.403)
Loans Dummy	0.371	(0.484)
Grants Dummy	0.302	(0.460)
Scholarships Dummy	0.409	(0.492)
Other Sources Dummy	0.103	(0.305)
Annual Income of Parents		
Less than $50,000 Dummy	0.148	(0.355)
Between $50,000 and $100,000 Dummy	0.244	(0.430)
Between $100,000 and $150,000 Dummy	0.213	(0.410)
Between $150,000 and $200,000 Dummy	0.100	(0.300)
Between $200,000 and $250,000 Dummy	0.086	(0.281)
More than $250,000 Dummy	0.210	(0.408)
Received an iTunes Gift Card for Christmas Dummy	0.347	(0.477)

Table 2. Descriptive Statistics for the Decision to Pirate Music (n=262)

Variable	**Mean**	**(Std. Dev.)**
Last Song Illegally Obtained Dummy	0.302	(0.460)
Parametric Willingness to Pay (Dollars)	0.691	(0.254)
Nonparametric Lower Bound on Willingness to Pay (Dollars)	0.131	(0.240)
Annual Income ($10,000)	0.450	(0.646)
Individual Characteristics		
Age (Completed Years)	19.809	(1.232)
Grade-Point Average (Four-Point Scale)	3.476	(0.317)
Greek Dummy	0.286	(0.453)
Expected Graduation Year	2010.546	(1.088)
Engineering Major Dummy	0.164	(0.371)
Undecided Major Dummy	0.046	(0.209)
Transactions costs		
Subjective Probability of Lawsuit	0.077	(0.169)
Subjective Cost of Lawsuit ($1,000)	8.602	(69.081)
Morality Proxy (Thirty-Point Scale)	24.412	(4.690)
Sources of Tuition Money		
Parents Dummy	0.844	(0.364)
Family Dummy	0.046	(0.209)
Savings Dummy	0.206	(0.405)
Loans Dummy	0.385	(0.488)
Grants Dummy	0.294	(0.456)
Scholarships Dummy	0.405	(0.492)
Other Sources Dummy	0.103	(0.305)
Annual Income of Parents		
Less than $50,000 Dummy	0.134	(0.341)
Between $50,000 and $100,000 Dummy	0.256	(0.437)
Between $100,000 and $150,000 Dummy	0.214	(0.411)
Between $150,000 and $200,000 Dummy	0.095	(0.294)
Between $200,000 and $250,000 Dummy	0.088	(0.284)
More than $250,000 Dummy	0.214	(0.411)
Received an iTunes Gift Card for Christmas Dummy	0.370	(0.484)

Table 3. Probit Estimation Results for Willingness to Pay for Digital Music

Variable	Marginal Effect		(Std. Err.)
(Dependent Variable: = 1 if Willing to Purchase "Right Round"; = 0 Otherwise.)			
Random Price	-0.578	***	(0.107)
Age	-0.002		(0.047)
GPA	-0.007		(0.098)
Greek	0.163	**	(0.076)
Expected Graduation Year	0.010		(0.055)
Engineering Major	0.059		(0.086)
Undecided Major	0.146		(0.172)
Income	-0.157	**	(0.063)
Last Song Very Unpopular	-0.228	**	(0.073)
Last Song Unpopular	-0.084		(0.080)
Last Song Somewhat Popular	-0.123		(0.082)
Last Song Popular	-0.035		(0.088)
Tuition: Family	-0.086		(0.134)
Tuition: Savings	-0.063		(0.082)
Tuition: Loans	0.081		(0.082)
Tuition: Grants	-0.033		(0.093)
Tuition: Scholarships	-0.128	*	(0.073)
Tuition: Other	-0.133		(0.093)
Parents: Less than $50,000	-0.197	*	(0.092)
Parents: Between $50,000 and $100,000	-0.157		(0.093)
Parents: Between $100,000 and $150,000	-0.113		(0.088)
Parents: Between $150,000 and $200,000	-0.202	*	(0.081)
Parents: Between $200,000 and $250,000	-0.053		(0.113)
Received an iTunes Gift Card	0.257	***	(0.071)
Number of Observations	291		
p-value (All Coefficients)	0.00		
Pseudo R^2	0.25		

Note: The symbols ***, **, and * respectively denote statistical significance at the 1, 5, and 10 percent levels. Variables of interest are highlighted.

Table 4. LPM Estimation Results for the Decision to Pirate Music Conditional on Parametric WTP

	(1)			(2)		
Variable	**Coefficient**		**(Std. Err.)**	**Coefficient**		**(Std. Err.)**
(Dependent Variable: = 1 if Last Song was Obtained Illegally; = 0 Otherwise.)						
Willingness to Pay	-0.204	*	(0.116)	-0.253	**	(0.113)
Income	0.014		(0.053)	-0.007		(0.051)
Age	0.046		(0.048)	0.054		(0.047)
GPA	-0.070		(0.085)	-0.083		(0.087)
Greek	-0.030		(0.068)	-0.024		(0.068)
Expected Graduation Year	0.017		(0.055)	0.027		(0.053)
Engineering Major	0.109		(0.082)	0.105		(0.081)
Undecided Major	0.008		(0.126)	0.036		(0.127)
Subjective Probability of Lawsuit				-0.434	***	(0.118)
Subjective Cost of Lawsuit				0.001		(0.002)
Morality				-0.018	***	(0.006)
Tuition: Other Relative						
Tuition: Savings						
Tuition: Loans						
Tuition: Grants						
Tuition: Scholarships						
Tuition: Other						
Parents: Less than $50,000						
Parents: $50,000 to $100,000						
Parents: $100,000 to $150,000						
Parents: $150,000 to $200,000						
Parents: $200,000 to $250,000						
Received an iTunes Gift Card						
Intercept	-34.447		(112.021)	-54.548		(106.776)
Number of Observations	262			262		
Bootstrap Replications	500			500		
p-value (All Coefficients)	0.26			0.00		
R^2	0.04			0.10		

Note: The symbols ***, **, and * respectively denote statistical significance at the 1, 5, and 10 percent levels. Standard errors are bootstrapped throughout. Variables of interest are highlighted.

Table 4. LPM Estimation Results for the Decision to Pirate Music Conditional on Parametric WTP (Continued.)

	(3)			(4)		
Variable	**Coefficient**		**(Std. Err.)**	**Coefficient**		**(Std. Err.)**
(Dependent Variable: = 1 if Last Song was Obtained Illegally; = 0 Otherwise)						
Willingness to Pay	-0.265	**	(0.130)	-0.089		(0.135)
Income	-0.005		(0.052)	0.014		(0.050)
Age	0.055		(0.047)	0.055		(0.043)
GPA	-0.091		(0.089)	-0.118		(0.090)
Greek	-0.028		(0.069)	-0.033		(0.067)
Expected Graduation Year	0.029		(0.054)	0.043		(0.051)
Engineering Major	0.107		(0.083)	0.094		(0.083)
Undecided Major	0.021		(0.138)	-0.008		(0.145)
Subjective Probability of Lawsuit	-0.433	***	(0.128)	-0.481	***	(0.127)
Subjective Cost of Lawsuit	0.001		(0.002)	0.001		(0.003)
Morality	-0.018	***	(0.006)	-0.017	***	(0.006)
Tuition: Other Relative	0.050		(0.147)	0.047		(0.139)
Tuition: Savings	0.016		(0.082)	0.005		(0.085)
Tuition: Loans	-0.002		(0.069)	-0.040		(0.070)
Tuition: Grants	-0.081		(0.088)	-0.142		(0.092)
Tuition: Scholarships	0.036		(0.070)	-0.001		(0.070)
Tuition: Other	0.031		(0.110)	0.054		(0.111)
Parents: Less than $50,000				0.339	***	(0.106)
Parents: $50,000 to $100,000				0.216	**	(0.090)
Parents: $100,000 to $150,000				0.244	***	(0.085)
Parents: $150,000 to $200,000				0.204	*	(0.116)
Parents: $200,000 to $250,000				0.079		(0.101)
Received an iTunes Gift Card				-0.148	**	(0.060)
Intercept	-58.086		(108.916)	-85.742		(102.730)
Number of Observations	262			262		
Bootstrap Replications	500			500		
p-value (All Coefficients)	0.01			0.00		
R^2	0.11			0.18		

Note: The symbols ***, **, and * respectively denote statistical significance at the 1, 5, and 10 percent levels. Standard errors are bootstrapped throughout. Variables of interest are highlighted.

Table 5. LPM Estimation Results for the Decision to Pirate Music Conditional on Nonparametric Lower Bound WTP

	(1)			(2)		
Variable	**Coefficient**		**(Std. Err.)**	**Coefficient**		**(Std. Err.)**
(Dependent Variable: = 1 if Last Song was Obtained Illegally; = 0 Otherwise)						
Nonparametric WTP	-0.246	**	(0.116)	-0.211	*	(0.116)
Income	0.012		(0.051)	-0.005		(0.050)
Age	0.046		(0.046)	0.054		(0.045)
GPA	-0.071		(0.084)	-0.079		(0.084)
Greek	-0.035		(0.070)	-0.040		(0.069)
Expected Graduation Year	0.018		(0.053)	0.026		(0.051)
Engineering Major	0.117		(0.082)	0.115		(0.082)
Undecided Major	0.016		(0.125)	0.040		(0.128)
Subjective Probability of Lawsuit				-0.386	***	(0.120)
Subjective Cost of Lawsuit				0.001		(0.002)
Morality				-0.016	***	(0.006)
Tuition: Other Relative						
Tuition: Savings						
Tuition: Loans						
Tuition: Grants						
Tuition: Scholarships						
Tuition: Other						
Parents: Less than $50,000						
Parents: $50,000 to $100,000						
Parents: $100,000 to $150,000						
Parents: $150,000 to $200,000						
Parents: $200,000 to $250,000						
Received an iTunes Gift Card						
Intercept	-35.822		(108.085)	-52.315		(103.178)
Number of Observations	262			262		
Bootstrap Replications	500			500		
p-value (Joint Significance)	0.07			0.00		
R-square	0.04			0.10		

Note: The symbols ***, **, and * respectively denote statistical significance at the 1, 5, and 10 percent levels. Standard errors are bootstrapped throughout. Variables of interest are highlighted.

Table 5. LPM Estimation Results for the Decision to Pirate Music Conditional on Nonparametric Lower Bound WTP (Continued.)

	(3)			(4)		
Variable	**Coefficient**		**(Std. Err.)**	**Coefficient**		**(Std. Err.)**
(Dependent Variable: = 1 if Last Song was Obtained Illegally; = 0 Otherwise)						
Nonparametric WTP	-0.202	*	(0.119)	-0.082		(0.122)
Income	-0.003		(0.051)	0.014		(0.050)
Age	0.054		(0.046)	0.054		(0.043)
GPA	-0.080		(0.087)	-0.115		(0.087)
Greek	-0.042		(0.070)	-0.037		(0.068)
Expected Graduation Year	0.027		(0.052)	0.042		(0.050)
Engineering Major	0.116		(0.084)	0.097		(0.083)
Undecided Major	0.027		(0.139)	-0.007		(0.146)
Subjective Probability of Lawsuit	-0.387	***	(0.131)	-0.468	***	(0.129)
Subjective Cost of Lawsuit	0.001		(0.002)	0.001		(0.003)
Morality	-0.016	***	(0.006)	-0.016	***	(0.006)
Tuition: Other Relative	0.062		(0.145)	0.052		(0.138)
Tuition: Savings	0.018		(0.083)	0.006		(0.085)
Tuition: Loans	0.003		(0.069)	-0.038		(0.070)
Tuition: Grants	-0.061		(0.084)	-0.136		(0.089)
Tuition: Scholarships	0.045		(0.072)	0.000		(0.071)
Tuition: Other	0.061		(0.109)	0.064		(0.107)
Parents: Less than $50,000				0.349	***	(0.107)
Parents: $50,000 to $100,000				0.216	**	(0.093)
Parents: $100,000 to $150,000				0.247	***	(0.086)
Parents: $150,000 to $200,000				0.213	*	(0.120)
Parents: $200,000 to $250,000				0.087		(0.102)
Received an iTunes Gift Card				-0.149	**	(0.061)
Intercept	-54.013		(105.635)	-84.102		(101.839)
Number of Observations		262			262	
Bootstrap Replications		500			500	
p-value (Joint Significance)		0.01			0.00	
R-square		0.10			0.18	

Note: The symbols ***, **, and * respectively denote statistical significance at the 1, 5, and 10 percent levels. Standard errors are bootstrapped throughout.