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**CFS WORKING PAPER**

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No. 2012/09

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# Are Risk Preferences Dynamic? Within-subject Variation in Risk-taking as a Function of Background Music\*

Marja Liisa Halko<sup>1</sup> and Markku Kaustia<sup>2</sup>

March 28, 2012

## Abstract

This paper investigates whether preference interactions can explain why risk preferences change over time and across contexts. We conduct an experiment in which subjects accept or reject gambles involving real money gains and losses. We introduce within-subject variation by alternating subjectively liked music and disliked music in the background. We find that favourite music increases risk-taking, and disliked music suppresses risk-taking, compared to a baseline of no music. Several theories in psychology propose mechanisms by which mood affects risktaking, but none of them fully explain our results. The results are, however, consistent with preference complementarities that extend to risk preference.

**JEL Classifications:** D81, G11

**Keywords:** Risk Taking, Music, Preference Interaction

\* We thank Elvira Brattico, Petri Jylhä, Mikko Leppämäki, David Laibson, George Loewenstein, Charles Noussair, Terrance Odean, as well as the participants at the Nordic Conference on Behavioral and Experimental Economics 2010 for comments, and Mikko Niemenmaa for excellent research assistance. Part of this project was completed while Kaustia was visiting at the Ross School of Business, University of Michigan. The authors acknowledge the support from the aivoAALTO project, the Academy of Finland, and the Research Foundation of Cooperative Banks, Finland.

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## 1. Introduction

Several studies find that risk preferences are not stable across contexts (see Barseghyan, Prince, and Teitelbaum, 2011, and Einav, Finkelstein, Pascu, and Cullen, 2012 as examples of recent studies). This can be due to a behavioral bias, such as a framing effect. Alternatively, seemingly inconsistent behavior could be at least partly due to preference complementarities. Laibson (1999) presents a model of dynamic preferences in which environmental cues and consumption can act as complements. For example, hearing the sound of ice falling into a whiskey tumbler may increase the marginal utility from consuming Scotch for some individuals. Laibson argues that preferences are sensitive to such cues, which explains why preferences can vary from one moment to another. Loewenstein (1996; 2000) also argues for a decision-making framework that incorporates similar preference interactions, but focusing on different types of visceral factors (negative emotions such as fear, drive states such as hunger, and feeling states such as pain). In addition to preferences for consumption items, similar processes could operate with preference for risk. We suspect that risk preference interactions may be particularly relevant in domains that simultaneously involve risky decisions and entertainment value. Examples of such domains include casino gambling, certain sports, recreational driving by young adults, and perhaps to some extent individual investors' active trading in stocks.<sup>1</sup>

In this paper we investigate the possibility of risk preference interactions using music as the source of complementary utility. Given such preference complementarity, a person might derive more utility from a risky gamble while listening to their favorite music, and would thus be more

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<sup>1</sup> That entertainment value is one reason why individuals trade stocks is suggested by, e.g., Black (1986) and Barber and Odean (2000).

likely to accept the gamble. Music is a potentially powerful environmental factor, yet it operates in the background and does not consume conscious attention similar to, say, visual stimuli.<sup>2</sup> Both musical preferences and risk preferences show great variation amongst individuals (see North, Hargreaves, and Hargreaves, 2004, for music, and Dohmen et al, 2011, for risk). Differences in musical preferences have an impact on the kinds of emotions a single piece of music invokes in different people (Kreutz et al., 2008). These differences can lead to interesting preference interactions. For example, the Master of Puppets, a song by the famed thrash metal band Metallica, could invoke elation in one person and yet cause anxiety in another person, with correspondingly different effects on their marginal utilities for specific consumption items.

We employ an experimental setting that makes it easier to attribute any findings to a preference complementarity rather than a psychological bias. However, we want to stress at the outset that our point is not to argue against the idea that behavioral biases matter. Rather, our purpose is to test whether changes in risk-taking could partially be due to genuine preference dynamics arising from preference complementarities. We do not see these approaches as mutually exclusive.

We use binary-outcome, constant probability (50-50) gambles. We introduce two sources of variation. First, we varied the music being played in the background while the subjects were

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<sup>2</sup> Music is being used in this capacity, e.g., as film music, for marketing purposes, and in therapy (for example, reducing stress after undergoing surgery (Macdonald et al., 2003)). Music also has the capacity to enhance stress: experimental subjects playing a violent videogame (Quake III) with its built-in music turned on, showed a higher blood concentration of stress hormone cortisol compared to other subjects playing the same game in silence (Hébert et al., 2005). Music can induce emotions via several psychological mechanisms, including rapid and automatic responses (e.g., brain stem reflex) and higher order cognitive functions (e.g., invoking a memory of a particular event). Juslin and Västfjäll (2008) provide a review of these mechanisms.

choosing whether to participate in the gambles. Each subject was asked to bring along to the experiment some of their favorite music as well as some music that they despised. In addition to the liked and disliked music, choices were also made under silence. Second, we varied the gain and loss payoffs of the gambles. The probabilities were held fixed, so this resulted in variation in the expected values. Each subject went through 256 gambles with different payoffs, and we identify the effects from within-subject variation in the gamble acceptance rates. Rather than repeating the exact same gamble over different musical conditions, changing the payoffs forces the subjects to reconstruct their utility functions. We believe this results in less anchoring to past choices.

We chose teenagers (aged 12–17;  $N = 25$ ) as experimental subjects for two reasons. First, music is an important consumption item in this age group. Second, it is easier to create effective monetary incentives due to the subjects' low level of income. The loss amounts from a single gamble ranged from 0.5 to 2 euros, and the win amounts ranged from 2 to 4 euros. These amounts are roughly comparable to a couple of days worth of disposable income for the average subject.

We find that favorite music increases risk-taking, and disliked music depresses risk-taking relative to the baseline of no music. The frequency for accepting a gamble is 54.1% for good music versus 47.4% for bad music. When no music was playing the acceptance rate is 51.4%. The effects of music are evident in all kinds of gambles but the difference in acceptance rates in favor of liked versus disliked music is greatest (about 10 percentage points) when the ratio of gains to losses is 2:1 (see Figure 3 for a preview of the results). The positive effect of good music and the negative effect of bad music are both statistically significant at the 5% level under various alternative estimation methods. In particular, they are present in a logit regression with

subject fixed effects, in a random effects regression including surveyed subjective risk attitude as a control variable, and in the distribution of coefficients from subject specific regressions, when controlling for the gain and loss amounts of the gambles.

These results are consistent with preference interactions of the type described by Laibson (1999) and Loewenstein (1996; 2000), and imply that such effects can extend to risk preference, in addition to preferences for consumption goods. Such preference structures can create what seems like unstable preferences in the context of the standard economic model of a constant risk preference in which the marginal propensity to take risk is independent of utility derived from other sources. In subsequent work involving neuroimaging methods, Halko et al. (2012) find that the behavioral effect of music on risk-taking, first documented in this paper, co-varied with brain activation in left amygdala. This evidence is consistent with our preference-based interpretation as the amygdala is known to be a key component of the value computation and coding of preference information (Seymour and Dolan, 2008). The preference-based interpretation is also consistent with the neuroimaging results of Berns et al. (2010) showing that the activation in the reward areas of the brain are proportional to subjective ratings of music.

Alternatively, rather than having preference-based underpinnings, the results could arise through decision psychologic influences. Prior literature has proposed at least four mechanisms that mediate the effect of mood on risk-taking: mood maintenance hypothesis, subjective probability weighting, affect infusion, and impact on cognitive processing strategies. We defer a more detailed discussion of the psychological mechanisms to Section 6 of the paper, where we argue that none of these theories can adequately account for our findings.

## 2. Prior literature

Several experimental studies link mood and risk-taking by way of a between-subjects study-design, in which good/bad/neutral mood is being induced on the subjects in different experimental conditions. Yuen and Lee (2003) and Chou, Lee, and Ho (2007) use movie clips to induce different moods using happy, neutral, and sad content, respectively. They find that subjects in the negative mood condition are significantly less likely to take risks compared to those in the neutral group. Guiso, Sapienza, and Zingales (2011) find that subjects viewing a scene from a horror movie choose a significantly lower certainty equivalent in a hypothetical lottery question.

However, people on good moods do not necessarily make riskier choices (Isen and Patrick, 1983; Isen and Geva, 1987). Arkes, Herren, and Isen (1988) find that subjects on good mood shy away from risk-taking when the potential loss is emphasized. Nygren et al. (1996) find that subjects on good mood overestimate the probabilities of winning, yet are less likely to gamble. Overall the evidence is mixed. Kahneman and Lovallo (1993) argue that risky decisions can be affected by several cognitive biases.

These papers do not attempt to make a connection to dynamic preferences. We believe that a within-subjects design, as used in this paper, is much better suited for that purpose. There are two related studies that also use a within-subjects design to study changes in the tendency to take risk, although focusing on different issues. In a neuroimaging study, Knutson et al. (2008) find that nucleus accumbens, a part of the brain associated with positive arousal, shows increased activation before financial risk-taking. In their experiment male subjects increased financial risk-taking when they were anticipating to view rewarding stimuli (erotic pictures). Self-selected music, as used in this paper, is presumably more neutral a cue. In their experiment, as in ours, the



subjects know the probability distributions of the outcomes and thus their beliefs are fixed. However, in their experiments, unlike in ours, the subjects were shown the outcomes of their chosen gamble after each trial, as well as their cumulative earnings. Prior earnings have been shown to influence risk-taking (Thaler and Johnson, 1990; Gneezy, Kapteyn, and Potters, 2003; Coval and Shumway, 2005; Weber and Zuchel, 2005). In addition, subjects may get conditioned to associate a particular type of stimulus with a particular outcome. Kuhnen and Knutson (2011) also conduct a within-subjects analysis of risk-taking using images as stimuli. Their experiment, unlike ours, features a complex estimation task in which the subjects must infer an unknown payoff probability distribution from the outcomes they observe.

### **3. Methods**

We recruited 25 adolescents (aged 12–17 years) in Helsinki, Finland, in spring 2009, by announcing an invitation to participate in an experiment that concerns music and attitude towards monetary gains and losses. Participants were told that the experiment consists of two separate sessions. For the first session they were asked to select, and bring with them four pieces of their favorite music and four pieces of music they disliked (on music CDs or mp3-files). We recognize the possibility that locating and bringing in the disliked music requires more effort than what is required for the favorite music. If this is indeed the case the impact of disliked music could be understated in our empirical tests.

The announcement also explained the payment structure: the subjects would be paid 10 euros for participating in the first session, while earnings in the second session would depend on the decisions they make during the experiment as well as chance outcomes. The subjects could either win or lose money in the second session. We adopted this two-session structure to make the

subjects feel that they would face actual potential losses in the gambles, and less likely to feel as if they were “gambling with the house money”.<sup>3</sup> The maximum amount that the subjects could win was 20 euros, and the maximum amount they could lose was 10 euros. An informed consent was solicited from the subjects’ parents prior to the experiment.

#### *A. Session 1*

The eight pieces of music that each subject brought with them were first copied onto a computer for later use in the second session. The subjects then filled out a questionnaire surveying their risk attitude and some background information. The date of the second session was agreed on, leaving at least one week between the sessions. The fixed payment of 10 euros was paid and the subjects were reminded that in the second session they would participate in a computerized experiment in which one can either win or lose money.

#### *B. Session 2*

In the main experiment, which took place after at least a week had passed since session 1, the task of subjects was to accept or reject gambles that offered a 50–50 chance to win or lose money. Accepting a gamble, for example [1.50, –1.20], meant that the subject was willing to participate in a gamble that offered a 50% chance of winning 1.50 euros and a 50% chance of losing 1.20 euros. The experiment was conducted individually in a private room using a computer program. Figure 1A shows the computer screen plot for the aforementioned example. The gain and loss amounts were shown for 2.5 seconds, after which the subjects had 2.5 seconds to choose “accept” or “reject” by pressing designated buttons on the computer keyboard. After

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<sup>3</sup> Subsequent to having carried out the experiments we came across a recent paper by Rosenboim and Shavit (2012) who argue and present supporting evidence in favor of this kind of prepaid mechanism that we used.

deciding on the gamble, there was a break of 0.5 to 3.5 seconds until the next gamble was shown. We varied the length of this break to avoid unreflected automatic responses and to keep the subjects focused.

The results of the gambles were not shown during the course of the experiment. Knowledge on prior gains or losses can influence behavior (Thaler and Johnson, 1990; Gneezy, Kapteyn, and Potters, 2003). While these effects are interesting in their own right, for the purposes of this paper they represent a confounding effect that we wanted to avoid. At the start of the experiment the subjects were informed that five randomly determined gambles would be played for real at the end of the session. There were 16 different win outcomes ranging from 1 to 4 euros, and 16 loss outcomes ranging from 0.5 to 2 euros. Each subject went through the full payoff matrix and none of the gambles were repeated. This corresponds to  $16 \times 16 = 256$  gambles (Figure 1B).

Gambles were presented under three conditions: while the subjects' favorite music was playing (64 gambles), while disliked music was playing (64 gambles), and gambles with no music playing (128 gambles). Sixteen gambles under one condition were assembled into a block of 80 second duration. Each block of music was followed by a block without music. The order of blocks was either L-L-D-D-L-L-D-D- or D-D-L-L-D-D-L-L- (where L stands for liked music, D for disliked music, and - for no music), counterbalanced across subjects (Figure 1C). During all conditions gambles were randomly drawn from the payoff matrix. We applied random sampling that ensured an even mix of different types of gambles under all three conditions (Figure 1B).

The complete session lasted about 40 minutes. At the end, five gambles were randomly drawn, and the ones that the subject had accepted were played for real. Payoffs were determined by the roll of a dice (values of one to three indicated a loss, and four to six indicated a win). The

average total payment was 13.80 euros ( $SD = 3.93$ ) which is, according to our survey, somewhat more than the average weekly disposable income for our subjects.

The data of two subjects were discarded: one due to misunderstanding the task, and one due to a technical error with the music that was played. The analysis is thus based on data for 23 subjects, 12 females and 11 males, mean age 14.6 years,  $SD = 1.62$ , range 12–17 years.

#### **4. Main results**

In the first session of the experiment, the subjects filled a questionnaire where we surveyed their risk attitude. They first rated their general willingness to take risk on a visual analog scale, that is, by indicating a position along a horizontal line, 10 cm in length, with the end-points labeled ‘Not willing to take risk’ and ‘Completely willing to take risk’. The distribution of the responses to the general risk question is depicted in Figure 2A. The average willingness to take risk was 5.07 ( $SD = 1.92$ ).

A risk neutral subject would be indifferent between participating in and rejecting a gamble with a win-loss ratio of 1:1. Even a normal risk-averse decision maker, provided that he or she is optimizing lifetime consumption and is not pathologically risk-averse, would accept a small-scale gamble as long as the win-loss ratio is slightly over 1 (Rabin, 2000). However, experimental studies show that people generally tend to be more sensitive to losses than to gains. Indifference between accepting and declining equiprobable binomial gambles typically obtains when the ratio of the win amount to the loss amount is 2:1 (Kahneman and Tversky, 1979; Tom et al., 2007). Figure 2B illustrates the distribution of the acceptance rates for the gambles for different combinations of gains and losses in our experiment. The acceptance rates are around 50% along the diagonal where the ratio of the win amount to the amount of loss is 2:1, and

decrease when moving towards less favorable gambles. These results show that our adolescent subjects conform to the general population in their degree of loss aversion.

Table 1 shows the impact of music on the tendency to participate in gambles. Univariate results reported in Panel A show that the frequency for accepting a gamble is 47.4% for bad music versus 54.1% for good music. When no music was playing the acceptance rate is 51.4%. Good music thus alleviates, and bad music exacerbates loss aversion. Figure 3 graphs the acceptance rates as a function of the win-loss ratios of the gambles. The effect of music is evident in all kinds of gambles. The difference in acceptance rates in favor of liked versus disliked music is about 10 percentage points along the diagonal of the payoff matrix, that is, when the ratio of gains to losses is 2:1 (Figure 4). The mean effects of good music and bad music, compared to no music, are statistically significant at the 5% level under various estimation methods which we describe in detail in Section 4.

One way of judging the magnitude of these effects is to consider an offsetting change in a gamble's loss amount that is needed for keeping the acceptance rate statistically equal, while music is being varied. Calculated in this way, good music offsets a 3.1% increase in the loss amount, and bad music offsets a 4.6% reduction in the loss amount. These magnitudes are economically relevant.

The effect varies for different types of gambles. Good music only slightly further increases acceptance rates among the most favorable gambles (above the payoff matrix diagonal) where acceptance rates are already high, but bad music still further lowers the acceptance rates in the least favorable gambles (below the payoff matrix diagonal). In these least favorable gambles the acceptance rate is only 16%. However, the impact of music, again judged against an offsetting

loss amount, is very large: a change of 25-30% in the loss amount is required to statistically offset the impact of either good or bad music on the acceptance rate.

## 5. Multivariate analysis

To assess the statistical significance and robustness of the result we estimate three types of regression models and implement two alternative assumptions about unobserved heterogeneity. We estimate all regressions with maximum likelihood and use standard errors that are robust to heteroskedasticity. Using all methods we find that subjectively liked music increases risk-taking, while disliked music decreases risk-taking, and the results are statistically significant at the 5% level.

We start by estimating the propensity to accept a gamble using a linear probability model (OLS regression). The dependent variable ( $y_{ij}$ ) is a binary choice variable representing an acceptance (“1”) or a rejection (“0”) of gamble  $j \in \{1, \dots, 256\}$  by subject  $i \in \{1, \dots, 23\}$  and the model is

$$y_{ij} = \alpha + \beta_E E_j + \beta_G G_{ij} + \beta_B B_{ij} + \varepsilon_{ij} \quad (1)$$

where  $E_j$  is the expected value of gamble  $j$ ,  $G_{ij}$  and  $B_{ij}$  are zero-one indicator variables for subjectively liked (“Good”) and disliked (“Bad”) music, respectively, being played while subject  $i$  was considering gamble  $j$ . The betas ( $\beta$ ) represent the coefficients to be estimated with subscripts corresponding to the variables, and  $\alpha$  is the constant term. As an alternative specification to using the expected value ( $E$ ) to model the attractiveness of the gamble we include the amount to win and the amount to lose as two separate variables in all the models. The

results are similar. Panel B of Table 1 reports the results from estimating (1), yielding coefficients of 0.031 for  $G$  ( $t$ -value 2.07) and  $-0.030$  for  $B$  ( $t$ -value  $-2.00$ ).

We then add subject specific regression constants, i.e., estimate a fixed effects linear probability model

$$y_{ij} = \alpha + \beta_E E_j + \beta_G G_{ij} + \beta_B B_{ij} + c_i + \varepsilon_{ij} \quad (2)$$

where  $c_i$  is the subject specific regression constant which captures between-subject variation in the tendency to participate in the gambles. Estimating (2), as reported in Panel B of Table 1, yields coefficients of 0.033 for  $G$  ( $t$ -value 2.37) and  $-0.031$  for  $B$  ( $t$ -value  $-2.25$ ).

An analysis of a dichotomous dependent variable is frequently conducted with a logit model, an approach that we also follow. However, the interpretation of coefficients is less straightforward, and fixed effects estimation may cause problems, compared to the linear probability model. Our logit model relates the probability of subject  $i$  accepting gamble  $j$  to the explanatory variables as follows

$$\ln\left(\frac{p_{ij}}{1-p_{ij}}\right) = \alpha + \beta_E E_j + \beta_G G_{ij} + \beta_B B_{ij} + \varepsilon_{ij} \quad (3)$$

where  $p_{ij}$  is the probability that  $y_{ij} = 1$  conditional on the explanatory variables. We estimate two types of unobserved effects models.

First, a conditional fixed effects logit which additionally conditions the probabilities on a subject specific count of accepted gambles  $Y_i = \sum_{j=1}^{256} y_{ij}$ . We obtain robust standard errors by bootstrapping (50 repetitions). Panel B of Table 1 shows coefficients of 0.167 for  $G$  ( $z$ -value 2.46) and  $-0.155$  for  $B$  ( $z$ -value  $-2.64$ ).

Second, we estimate a subject random effects model. Maximum likelihood gives consistent and efficient estimates of a random effects model assuming that the unobserved effects do not correlate with the explanatory variables. As a control variable we include the subjects' general risk attitude that was surveyed in the first part of the experiment, about a week prior to the main experiment. In this model we effectively assume that the probability of subject  $i$  accepting gamble  $j$  is as follows

$$p_{ij}(y_j = 1) = f(E_j, G_{ij}, B_{ij}, R_i, \alpha_i) \quad (4)$$

i.e., related to gamble characteristics ( $E_j$ ), the musical condition prevailing during the decision ( $G_{ij}$  and  $B_{ij}$ ), the subject' general risk attitude ( $R_i$ ), as well as the subject specific random effect ( $\alpha_i$ ), and that the random effect remaining after controlling for  $R_i$  is independent of the explanatory variables. One can think of these random effects as deviations from the subjects' baseline risk attitude, arising from day-to-day variation, or from differences in context specific reactions. We again use bootstrapped standard errors. Panel B of Table 1 shows coefficients of 0.167 for  $G$  ( $z$ -value 3.03) and  $-0.154$  for  $B$  ( $z$ -value  $-2.70$ ).

We also run a standard logit model for each subject separately estimating coefficients for the musical condition dummies and controlling for the expected value of the gamble. Each regression thus has 256 observations corresponding to the number of all different gambles. The coefficients for liked music are positive for 83% of the subjects and the coefficients for disliked music are negative for 74% of the subjects. The means of the coefficients across all subjects are similar to the coefficient estimates obtained by the other methods (0.17 for  $G$  and  $-0.17$  for  $B$ ), and the median values of the coefficients are somewhat larger in absolute magnitude. We test for statistical significance of the averages of the individual  $G$  and  $B$  regression coefficients with a



standard  $t$ -test and obtain  $t$ -values of 2.51 (for  $G$ ) and  $-2.61$  (for  $B$ ). These results are reported in Panel C of Table 1.

## 6. Discussion

This section first briefly discusses the role of subject demographics in this study. It then evaluates potential underlying psychological mechanisms, as well as discusses the theoretical implications of the results.

The experimental subjects were teenagers, and musical preference is likely an important parameter in this demographic group. We acknowledge that the effect of music can be weaker for subjects for whom music plays a less important role. However, the importance of music does not necessarily decline with age. For example, Laukka (2007) reports that listening to music is a common leisure activity and a source of positive emotions for older adults, and Fox, Knight, and Zelinski (1998) show that music provides for an effective mood induction tool with older adults. Furthermore, more important than to specifically quantify the effect of music per se, the purpose of this paper is to study dynamic preference complementarities in general.

Several theories in psychology propose mechanisms by which mood affects risk-taking. Mood maintenance theory—also referred to as mood regulation—says that people in good mood have more to lose compared to people in bad mood, and thus avoid taking risks with potential negative consequences that could erode their good mood. Correspondingly, people in negative mood may downplay the consequences of a bad outcome because they are already in a bad mood and thus have less to lose (Mischel, 1973; Mischel, Ebbesen, and Zeiss, 1976; Isen and Simmonds, 1978; Leith and Baumeister, 1996). This theory is not valid in our setting since the

subjects did not observe the outcomes of the gambles until at the very end of the experiment. Furthermore, our results are opposite from the predictions of this theory.

Subjective probability weighting can also be responsible for mood effects in risk-taking. People on positive moods generally assess bad outcomes as being less likely compared to people on negative moods (Johnson and Tversky, 1983; Wright and Bower, 1992). However, in our case the probabilities stay constant and are easy to understand. Furthermore, subjective probability weighting should be less of an issue with the 50% probabilities that we use (Tversky and Kahneman, 1992). It is thus unlikely that mood changes would impact the perception of probabilities in our experiment.

The affect infusion model (Forgas, 1995) predicts that good mood should increase risk-taking and negative mood should depress risk-taking if the current mood primes access to memories of mood congruent outcomes from risky choices. However, this theory is predicted to apply in situations requiring considerable processing: selecting, learning, and interpreting new information about the risky situation, and incorporating it to existing knowledge and experiences. It is therefore unlikely that affect infusion strategies would be responsible for the rapid alteration of risk-taking tendency in our simple binomial gambles with constant probability.

Mood states can also interplay with the type of cognitive processing strategies utilized, which might mediate the impact of mood on risk-taking. Schwarz and Bless (1991) argue that people are more likely to employ analytical problem-solving under negative moods, while more likely resorting to heuristics under positive moods. Forgas (1998) finds evidence in support of this hypothesis: subjects in sad mood made less attribution errors and made more effective use of memory relative to controls, while subjects in happy moods performed worse. However, our simple binary gambles do not require elaborate processing. In any case we find that subjects

listening to their favorite music, which arguably elevates their mood, if anything, perform closer to the normative benchmark of participating in all the gambles. That is, good music makes the subjects less loss-averse, and less biased in that sense. Our results are thus inconsistent with Schwarz and Bless (1991). They are, however, consistent with Isen and Labroo (2003) who argue that positive affect leads to better judgment. That idea may nevertheless have difficulty in accounting for the reduced risk-taking effect of bad music.

Finally, we note that classical Pavlovian conditioning, nor a ‘hedonic forecasting mechanism’ leading to a biochemical response to cues and rewards discussed e.g. in Berheim and Rangel (2004, p. 1562), should be at work in our experiment. This is because in our experiment the gambles are only played at the end, so the outcomes can not affect choices. Although there is no such mechanism being created in the context of our experiment, it is nevertheless possible that such mechanisms have been at play earlier in life when musical preferences have formed. For example, consider a youngster who ventures to ask a girl of his dreams for a dance while a particular song is playing. An affirmative response could lead not only to liking the song, but also to associating the song with reward from taking risk.

While psychological theories of mood driven changes in risk-taking have a hard time explaining our findings, the results on the whole are consistent with preference interactions of the type described by Laibson (1999) and Loewenstein (1996; 2000). Some earlier evidence on the effect of music could also be interpreted as being supportive of this idea. Herrington and Capella (1996) find that people spend more time and money in a supermarket when the background music conforms to their musical taste. Other studies find some evidence that classical music leads to higher sales in restaurants (North and Hargreaves, 1998; North, Shilcock, and Hargreaves, 2003). If the average restaurant customer prefers classical music, then these

results would be consistent with the idea that an enjoyable musical experience enhances the utility of restaurant consumption.

## **7. Conclusion**

Using an experimental setting which involves real money stakes, constant probabilities of winning, and rapid within-subject alteration of the type of background music, we find that hearing one's favorite music playing increases risk-taking, and disliked music suppresses risk-taking, compared to a baseline of no music. The difference in acceptance rates in favor of good music is about 10 percentage points along the diagonal of the payoff matrix.

We interpret these results as suggesting that preference complementarities extending beyond the realm of goods and services are possible. Listening to one's preferred music increases experienced utility per se, and simultaneously increases the marginal utility of participating in a gamble. Bad music, on the other hand, would lead to a marginal utility of taking the gamble that is lower than what prevails under silence. The preference-based interpretation of the results is supported by recent research in neuroscience. Berns et al. (2010) show that the activation in the reward areas of the brain are proportional to subjective ratings of music, and Halko et al. (2012) show that the behavioral effect of music on risk-taking co-varies with brain activation in left amygdala – a brain region known to be a key component of value computations.

Preference complementarities can explain time-varying risk preferences. Earlier studies have attributed such effects on behavioral bias. We wish to point out that these explanations are not mutually exclusive, however. How such preference complementarities would arise provides a potential topic for future research. Understanding the formation of preferences is a central issue in economics.

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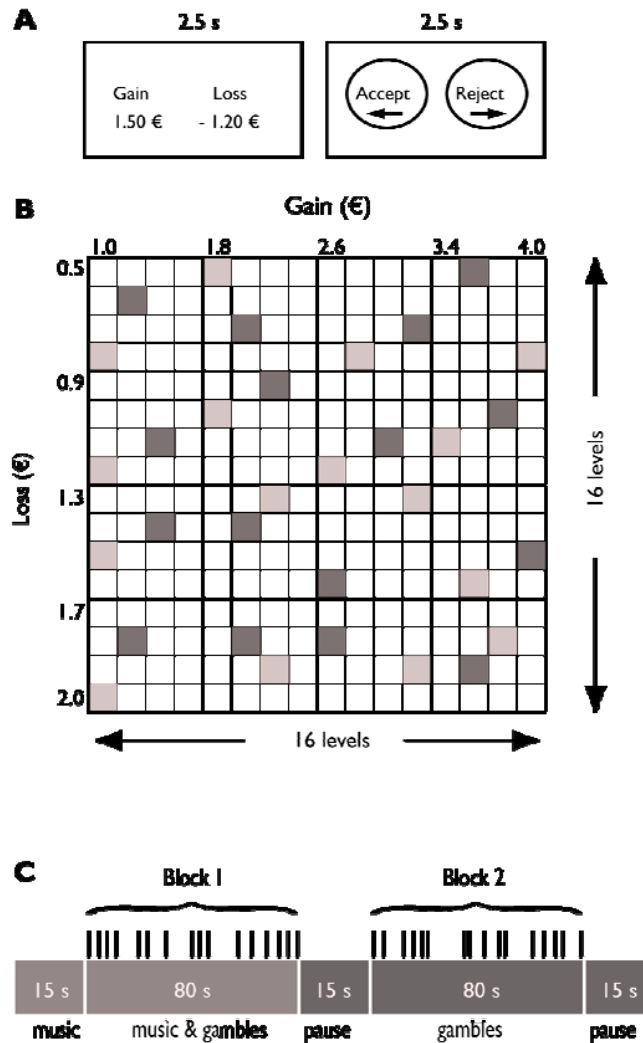
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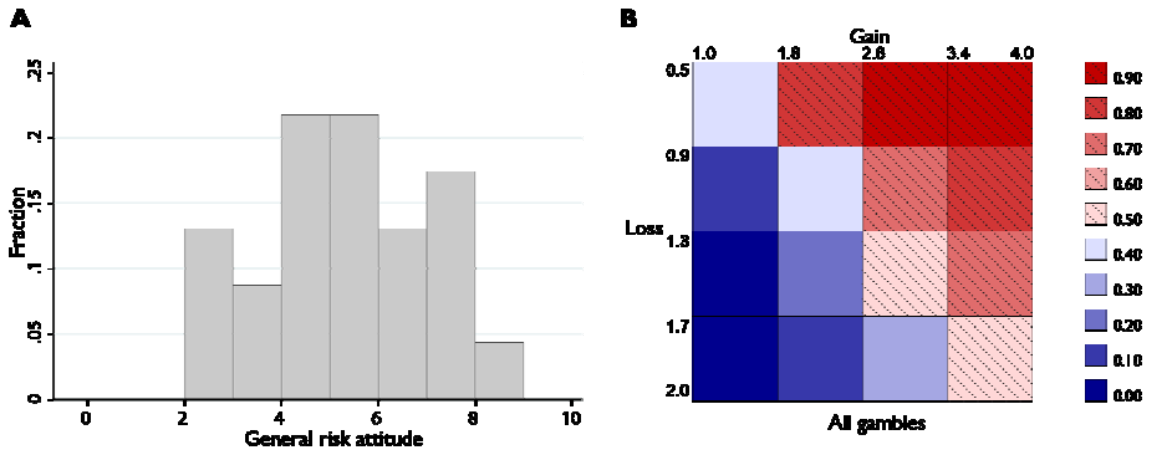
**Table 1****The effect of music on risk-taking, statistical tests**

Panel A shows the mean acceptance rates of binary gambles in which subjects ( $N = 23$ ) could either win or lose money with equal probability. The number of observations for each subject is 256, of which 128 are for 'No music', 64 are for 'Favorite music', and 64 are for 'Disliked music'. Panel B. shows results from four different regression models testing the effect of the musical condition on the decision to accept the gamble.  $T$ -statistics ( $z$ -statistics for logit regressions) are presented below the coefficients. In calculating the  $t$ -statistics we use standard errors robust to heteroskedasticity in all analyses. For fixed effects and random effects models such standard errors are obtained with bootstrapping. Panel C. shows results from running separate Logit regressions for each subject (256 observations in each regression), and taking averages of the subject-specific coefficients. The  $t$ -statistics in Panel C are from a standard  $t$ -test of means. All regressions include the expected value of the gamble as a control variable (not reported). Statistical significance at the 5% level is indicated by \*\*.

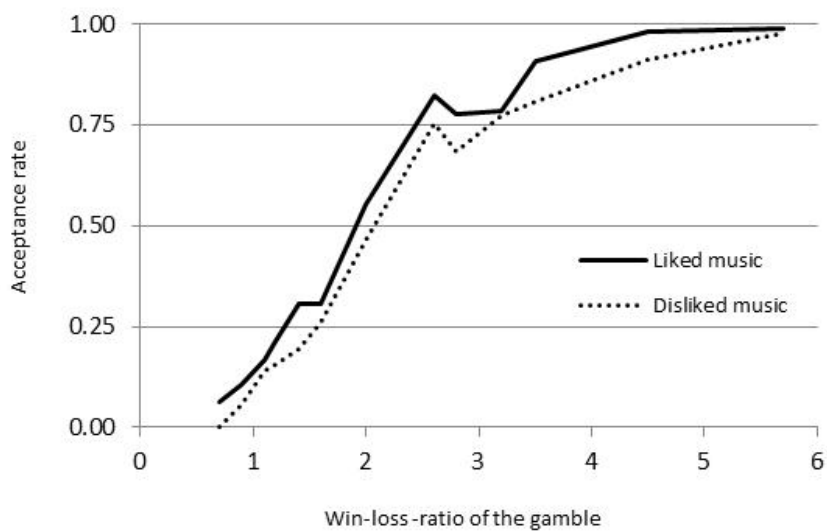
Panel A. Mean acceptance rate			
	Favorite music	No music	Disliked music
	0.541	0.514	0.474
Difference compared to 'No music'	0.027		-0.040
Difference between 'Favorite music' and 'Disliked music'		0.067	
Panel B. Tests of differences in acceptance compared to 'No music'			
Linear probability model (OLS)	0.031** 2.07		-0.03** -2.00
OLS with subject fixed effects	0.033** 2.37		-0.031** -2.25
Logit, conditional subject fixed effects	0.167** 2.46		-0.155** -2.64
Logit, subject random effects	0.167** 3.03		-0.154** -2.70
Panel C. Subject-specific Logit regressions			
Mean coefficient	0.169** 2.51		-0.168** -2.62



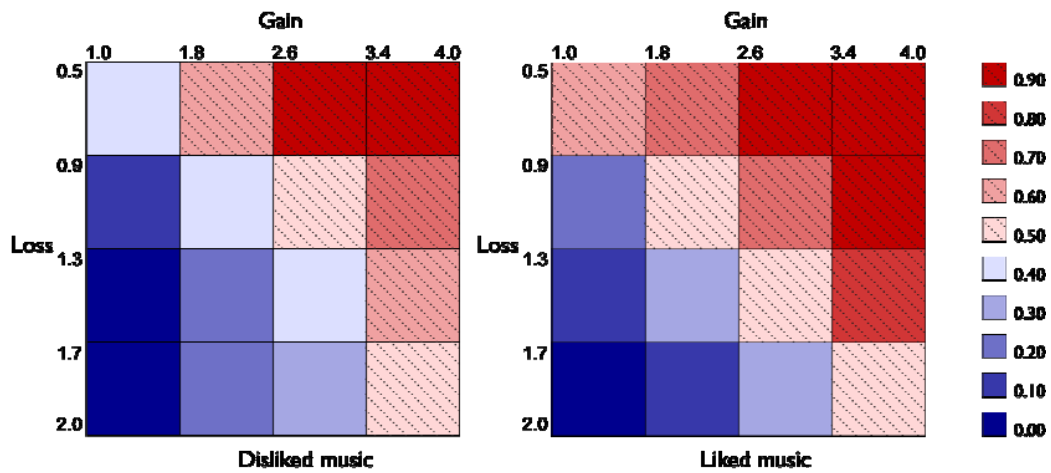
**Figure 1 (black and white).** (A) Exemplary computer screen plot from the experiment. The task of the subjects was to accept or reject gambles that offered a 50–50 chance of gaining or losing money. Gains ranged from 1 to 4 euros and losses from 0.5 to 2 euros. (B) The payoff matrix comprised 256 different gambles. The 256 gambles were divided into 16 sets of 16 gambles each. Within a set, the 16 gambles were scattered around the payoff matrix such that only one gamble came from each of the separate 4 by 4 areas in the matrix. The two different shades of grey rectangles in the figure represent two examples of a set of gambles. (C) Subjects played 16 different blocks, 16 gambles in each block, and a block with music was always followed by a block without music. To keep subjects' attention high and to avoid unreflected automatic response we varied the length of the interval between the gambles (from 0.5 to 3.5 seconds).



**Figure 2 (color).** (A) The distribution of risk attitude; 0 = not willing to take risk, 10 = completely willing to take risk. The average willingness to take risk was 5.07 (SD = 1.92). (B) Payoff matrix and mean acceptance rates, all gambles.



**Figure 3 (black and white).** Acceptance rates under liked music (solid line) and disliked music (dotted line) as a function of the win-loss –ratio of the gambles. The win-loss –ratio is formed by dividing the potential win amount by the potential loss amount.



**Figure 4 (color).** Payoff matrix and mean acceptance rates in two conditions: subjectively disliked music and liked music. In a 2 by 4 by 4 ANOVA (music, gain, loss), the main effect of music (disliked vs. liked) on the mean acceptance rate was statistically significant ( $F(1,22) = 12.04$ ,  $p = 0.002$ ), likewise main effects of gain ( $F(3,66) = 102.04$ ,  $p < 0.001$ ) and loss ( $F(3,66) = 94.47$ ,  $p < 0.001$ ). As expected, the interaction was between gain and loss was significant ( $F(9,198) = 5.09$ ,  $p < 0.001$ ); none of the interactions with music was significant.

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