J Gambl Stud (2016) 32:143–156
DOI 10.1007/s10899-015-9539-9

ORIGINAL PAPER

Betting on Illusory Patterns: Probability Matching in Habitual Gamblers

Wolfgang Gaissmaier[1] · Andreas Wilke[2] · Benjamin Scheibehenne[3] · Paige McCanney[2] · H. Clark Barrett[4]

Published online: 29 April 2015

Abstract Why do people gamble? A large body of research suggests that cognitive distortions play an important role in pathological gambling. Many of these distortions are specific cases of a more general misperception of randomness, specifically of an illusory perception of patterns in random sequences. In this article, we provide further evidence for the assumption that gamblers are particularly prone to perceiving illusory patterns. In particular, we compared habitual gamblers to a matched sample of community members with regard to how much they exhibit the choice anomaly 'probability matching'. Probability matching describes the tendency to match response proportions to outcome probabilities when predicting binary outcomes. It leads to a lower expected accuracy than the maximizing strategy of predicting the most likely event on each trial. Previous research has shown that an illusory perception of patterns in random sequences fuels probability matching. So does impulsivity, which is also reported to be higher in gamblers. We therefore hypothesized that gamblers will exhibit more probability matching than non-gamblers, which was confirmed in a controlled laboratory experiment. Additionally, gamblers scored much lower than community members on the cognitive reflection task, which indicates higher impulsivity. This difference could account for the difference in probability matching between the samples. These results suggest that gamblers are more willing to bet impulsively on perceived illusory patterns.

Keywords Gambling disorder · Pathological gambling · Probability matching · Cognitive reflection task · Misperception of randomness

✉ Wolfgang Gaissmaier
gaissmaier@uni-konstanz.de

1 Department of Psychology, Social Psychology and Decision Sciences, University of Konstanz, P.O. Box 43, 78457 Konstanz, Germany

2 Department of Psychology, Clarkson University, Potsdam, NY, USA

3 Department of Economic Psychology, University of Basel, Basel, Switzerland

4 Department of Anthropology, University of California at Los Angeles, Los Angeles, CA, USA

Introduction

From a money-maximization perspective, most gambling is irrational: the statistical expectation of losses is greater than that of gains. What, then, explains why gambling is appealing, and why do pathological cases of the compulsion to gamble exist? A large body of research suggests that cognitive distortions play an important role in the development, maintenance, and treatment of pathological gambling (e.g., Bechara 2001; Clark et al. 2014; Jefferson and Nicki 2003; MacLaren et al. 2011, 2012; Michalczuk et al. 2011; Toplak et al. 2007). Many of these distortions can be regarded as specific cases of a more general phenomenon: The misperception of randomness (e.g., Bar-Hillel and Wagenaar 1991; Falk and Konold 1997). People "see" patterns in actually random sequences of events. In light of this literature, it is plausible to assume that pathological gamblers are particularly prone to perceive illusory patterns and, more specifically, to also be willing to actually bet on them.

In this article, we follow up on this assumption and test whether gamblers are particularly prone to a specific anomaly of choice that is potentially related to illusory pattern perception: Probability matching. Probability matching describes the tendency to match response proportions to outcome probabilities when predicting repeated binary outcomes. From the perspective of a gambler attempting to maximize income, probability matching is an error; to maximize the probability of winning in a binary choice task, one should always bet on the most likely outcome. Probability matching has sparked much interest in psychology and economics over the past decades (see, e.g., a review by Vulkan 2000), but less so in the gambling literature. Following a call to move away from self-report data towards more observations of behavior, using laboratory tasks that resemble real-world gambling (Shaffer et al. 2010), we employed exactly such a setting to compare probability matching behavior of a sample of habitual gamblers to a sample of matched community members.

In what follows, we first summarize past work suggesting that betting on illusory patterns is an important contributor to pathological gambling, and describe the potential relationship between probability matching and betting on illusory patterns. Then, we explain the rationale for the prediction that gamblers should be particularly prone to probability matching, followed by our experimental design and results.

Perceiving Illusory Patterns, and Betting on Them

All humans, not only gamblers, are prone to perceiving illusory patterns to some degree. This can be illustrated by the gambler's fallacy: After one has observed a streak of five times black at the roulette table, it is very hard to avoid the feeling that "it is time for red" now, which may be a sufficient motivation to bet on it (Croson and Sundali 2005). However, there exist important individual differences with regard to how strongly people are prone to that misperception, and with regard to how much they give into that misperception and bet on it (Scheibehenne and Studer 2014; Scheibehenne et al. 2011). These individual differences may be related to proneness to gamble: gamblers may be particularly likely to misperceive randomness and to actually bet on this misperception. Supporting this assumption, it has been shown that habitual gamblers have a preference for a random slot machine over a negatively autocorrelated one, presumably because they mistakenly perceived the random slot machine to be less random than the negatively autocorrelated one, although in fact the opposite is true (Wilke et al. 2014). Similarly, a recent meta-analysis has summarized evidence that pathological gamblers are particularly prone to the gambler's fallacy and thus to the belief that they are actually more likely to win in the future if they have just lost (Goodie and Fortune 2013)—which is of course a potentially dangerous illusory belief. Such illusory beliefs in sequential dependencies (or patterns, more generally) in random sequences likely also fuel the well-documented illusion of control in gamblers (e.g., Goodie 2005; Goodie and Fortune 2013). Finally, there is evidence showing that pathological gamblers are more susceptible to superstition in the sense of erroneously perceiving a cause-effect association between two independent events (Joukhador et al. 2004).

For the compulsion to gamble, however, the mere perception of illusory patterns is not enough. One additionally needs to be willing to act upon these perceived patterns, that is, to bet on them. This precondition also seems to be fulfilled in habitual gamblers: There are many studies showing that they are more prone to act impulsively (e.g., MacLaren et al. 2012; Marmurek et al. 2015; Michalczuk et al. 2011; Miedl et al. 2014). The perception of, and willingness to impulsively bet on, illusory patterns appear to fuel the classic choice anomaly of probability matching, as the next section will describe.

Probability Matching and its Relation to Betting on Illusory Patterns

In typical experimental paradigms studying probability matching, people have to predict one of two events that occur with different probabilities. For example, event E1 may occur with a probability of $p(\text{E1}) = .75$, while event E2 occurs with $p(\text{E2}) = 1 - p(\text{E1}) = .25$. Given that successive events are independent and identically distributed (i.e., the probability of an outcome on any particular trial is independent of the outcome of previous trials), the *maximizing* strategy is to bet on the more frequent event E1 on every trial. This will achieve an expected accuracy of 75 %, and maximize the subject's expected income. In contrast, however, subjects often predict events in proportion to their probability of occurrence—hence *probability matching*—resulting in an expected accuracy of only 62.5 % on average ($.75 \times .75 + .25 \times .25$). Probability matching is highly persistent (Healy and Kubovy 1981; Shanks et al. 2002; for reviews, see Myers 1976; Vulkan 2000), even in tasks in which participants did not have to learn the outcome probabilities but were presented with a full description of outcomes and their probability (Gal and Baron 1996; Koehler and James 2009; Newell et al. 2013; Newell and Rakow 2007; West and Stanovich 2003).

One explanation for probability matching is that it results from illusory perception of patterns in random sequences. If people—erroneously—believe the sequence of binary events to be nonrandom, they will attempt to improve their predictions by searching for patterns in the sequence. Any plausible pattern a person might try has to match the marginal probabilities, thus yielding probability matching as an outcome (Wolford et al. 2000). If participants know, for instance, that the marginal probabilities are 75 % for E1 and 25 % for E2, respectively, then any pattern that could possibly be correct would need to include those events in exactly those proportions. Although any pattern search strategy is by definition misapplied for random data, such search strategies can be cognitively demanding. Ironically, then, if pattern search is impeded by distraction or by participants' low short-term memory capacity, more maximizing behavior can be observed, leading to higher success (Gaissmaier et al. 2006; Gaissmaier et al. 2008; Wolford et al. 2004).

The terminology of signal detection theory (SDT, e.g., Green and Swets 1966) helps to conceptualize the trade-off between perceiving illusory patterns on the one hand and successfully detecting actual patterns on the other. According to SDT, a person with a liberal criterion to classify something as a signal (i.e., due to a nonrandom process) instead of noise (i.e., due to a random process) is more likely to erroneously evaluate any random processes to be nonrandom than vice versa. These people err on the side of *not* missing meaningful patterns in their world by limiting the number of misses and accepting an inevitable increase in the number of false alarms (Lopes 1982; see also Haselton et al. 2009). In an empirical demonstration of this trade-off, Gaissmaier and Schooler (2008) showed that those people who fall prey to the choice anomaly probability matching were better at detecting true patterns in another part of the experiment. Similarly, Unturbe and Corominas (2007) showed that participants who falsely reported having found complex rules in a random sequence of binary events were closer to probability matching than those who did not report such rules (see also Yellott 1969). Finally, if participants have no reason to believe that there could be a patterned sequence, because they bet on 10 independent gambles rather than on one gamble with ten trials, more maximizing occurs (James and Koehler 2011).

Another explanation is that probability matching is an impulsive response that can be overridden by deliberation. Koehler and James (2010), for instance, showed that even people who adopted probability matching endorsed maximizing as the better strategy when asked to directly compare the two, and used it more when it was brought to their attention before the task. Also, studies have shown that the maximizing strategy is used more often by students with greater academic experience (Gal and Baron 1996), higher college admission test scores (West and Stanovich 2003), higher working memory capacity (Rakow et al. 2010), and higher cognitive reflection task scores (Koehler and James 2010), suggesting that education and cognitive capacity play a role in enhancing the use of a maximizing strategy.

Summary of Research Questions and Hypotheses

Importantly, these explanations—probability matching as a result of perceiving illusory patterns versus as a consequence of impulsivity—are not mutually exclusive. In fact, probability matching can be the outcome of various strategies (see Otto et al. 2011). But even more importantly, both of these explanations could work in concert: Probability matching should be particularly likely if people (1) have a strong perception of illusory patterns and (2) are prepared to—impulsively—bet on them. Both conditions are fulfilled in habitual gamblers, leading to the clear prediction that they should be more likely to exhibit probability matching. To test this prediction, we studied probability matching behavior in a typical probability learning task in a sample with high exposure to gambling (regular patrons of a local casino; *gamblers* subsequently) in comparison to a matched sample with low exposure to gambling (North Country residents; *community members* subsequently). Furthermore, we investigated whether gamblers and community members differed more generally with regard to impulsivity, and whether this difference explained potential differences in probability matching. Impulsivity was assessed with the cognitive reflection task (CRT, Frederick 2005), which was previously shown to predict probability matching (Koehler and James 2010).

Methods

Participants

The data collection was part of a larger project, in which 92 gamblers were compared to 72 community members who were closely matched on sex, age, and education (Wilke et al. 2014). The final sample was restricted to participants who provided valid data on the probability learning task, which were 91 gamblers [64 % female, mean age = 52.11, *SD* = 14.09 (median = 54.00, range 18–80), mean years of education = 13.79, *SD* = 3.22] and 70 community members [61 % female, mean age = 50.94, *SD* = 13.31 (median = 52.00, range 24–80), mean years of education = 14.74, *SD* = 3.40].[1]

Measures and Procedure

Gambling History

Gambling history was assessed with a standardized clinical measure—the South Oaks Gambling Screen (SOGS; Stinchfield 2002). SOGS scores vary between 0 and 20, with scores of five or higher indicating probable pathological gambling.

Prediction Behavior

Participants were shown a picture of a casino, with two slot machines highlighted. Their task was to predict on each trial whether a coin would be obtained from the slot machine on the right or the one on the left, similar to other probability learning tasks. While the probability of winning was $p = .67$ for one slot machine, it was only $1 - p = .33$ for the other. These probabilities of winning were not revealed to participants explicitly, but could be learned from experience via feedback. The sequence of events was serially independent. After ten training trials to acquaint participants with the task, there were 288 trials altogether, divided into three blocks of 96 trials. Participants received feedback about accuracy after each trial. Participants received a baseline show up fee of $100 (gamblers) and $60 (community members, who did not have to travel as far to participate in the study). Furthermore, each correct prediction earned them $0.10, with a total of four randomly selected participants also receiving their actual cash payout from the slot machine task after the study closed and all recruitment was completed. We scored how often each participant chose the more probable event in each block. This score is highly correlated with accuracy (the more often the more probable event is chosen, the higher the accuracy on average), but depends less on chance. We used those scores to classify participants into four choice categories depending on the proportion of trials in a block in which they predicted the more probable event: *guessing* (0–<62 %),[2] *probability matching* (62–<72 %, i.e., exact probability matching ±5 %), *overmatching* (72–<95 %), and *maximizing* (≥95 %).

Distance to Probability Matching

These categories are arbitrary to some degree, so we also compared the continuous absolute distance to probability matching between the samples: the absolute value of the difference between the proportion of choosing the more probable event, ranging from 0

[1] Note that the education was slightly higher among community members, $t(1{,}159) = 1.82$, $p = .071$. Including education as a control variable in any of the subsequent analyses did not alter the results in any important way.

[2] Note that actual guessing would be at about 50 %, and most participants in that category were around that value. Yet the extremely few participants who consistently predicted the less event more often (i.e., below 50 %) were included in this category as (1) there were so few of them that an extra category was not warranted and (2) their behavior is similar to guessing in the sense that they have not learnt to perform well in the task.

(always choosing the less likely event) to 1 (always choosing the more probable event), and probability matching (0.67).

Cognitive Reflection Task (CRT)

The three problems of the CRT (Frederick 2005) were administered after the probability learning task. A sample item is: "A bat and a ball cost $1.10. The bat costs $1.00 more than the ball. How much does the ball cost?" The answer 10¢ comes quickly to many people's minds, while the correct answer (5¢) requires more thought. The CRT score is the number of correctly answered problems and varies between 0 and 3.

Control Variables

As control variables, we also collected additional measures of cognitive capacity to assess participants' ability to deliberately control attention and manipulate information in working memory (digit span, symbol task, trail making test; see Mata et al. 2007; Tombaugh 2004).

Results

Gambling History

The distribution of SOGS scores revealed that recruiting gamblers by advertising to regular local casino attendees was successful and yielded a sample that was distinct from the community members with regard to gambling behavior. Among gamblers, the SOGS identified 28.6 % as pathological gamblers, in contrast to only 2.9 % among community members, Chi squared ($N = 161$) = 18.61, $p < .001$. Note that the proportion of probable pathological gamblers among community members is comparable to what has been found in the literature (see Kessler et al. 2008; Shaffer et al. 1997). Gamblers had much higher mean SOGS scores than community members, $M = 3.14$ versus $M = .50$, $t(135.7) = 7.00$, $p < .001$, $d = 1.06$.[3]

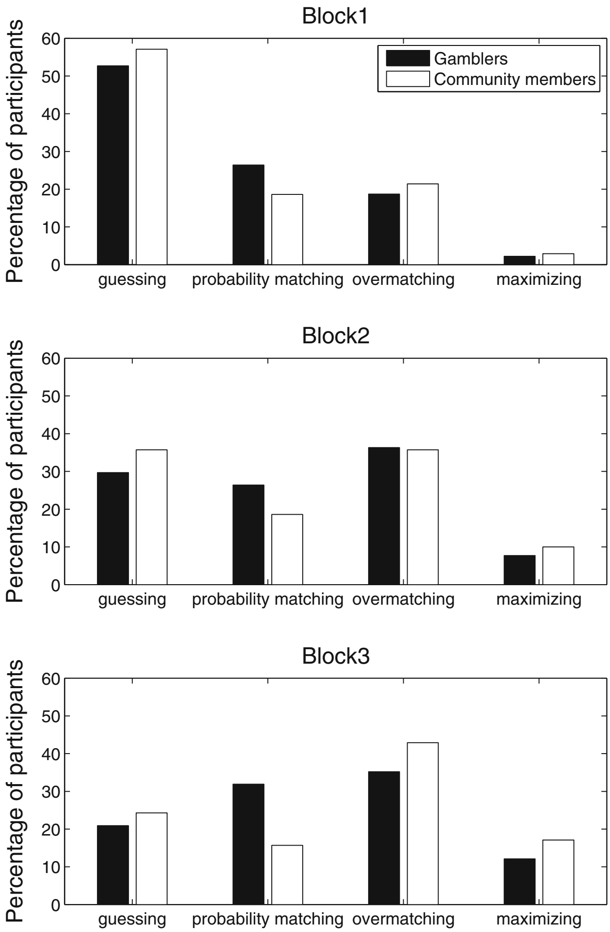
Do Gamblers Exhibit More Probability Matching?

Figure 1 shows prediction behavior as proportion of participants in each choice category for both samples for the three blocks. Both gamblers and community members reduced the amount of guessing over time, as would be expected. Also, there was an increase in overmatching and maximizing over time. Most importantly and consistent with our hypothesis, there was a specific difference with regard to probability matching, with a higher percentage of gamblers than community members in that choice category, particularly in the final block (31.9 vs. 15.7 %, 2-sample z-test $z = 2.35$, $p = .019$), whereas there was no difference in any other choice category.

In a repeated measures analysis of variance, we next analyzed distance to probability matching. The analysis included the within-subjects factor block (consisting of the absolute distance from probability matching in three blocks of 96 trials each) and the between-subjects factor sample (gamblers vs. community members). Both samples moved further

[3] d expresses the difference between two means in terms of its (pooled) standard deviation. See Cohen (1992) for details.

Fig. 1 Proportion of participants in each sample (gamblers, community members) and each block (three blocks with 96 trials each) who showed (1) guessing, (2) probability matching, (3) overmatching, and (4) maximizing, respectively. There was a higher percentage of probability matchers among gamblers than among community members, particularly in the final block, but no difference in any other choice category



away from probability matching across blocks, as reflected in the linear within-subjects contrast of block $F(1,159) = 4.84$, $p = .029$, $\eta_p^2 = .030$.[4] This trend did not differ between gamblers and community members, as there was no linear contrast between block and sample $F(1,159) = 0$, $p = .997$, $\eta_p^2 = 0$. However, gamblers consistently showed a smaller absolute distance to probability matching than community members, as shown by the between-subjects effect of sample, $F(1,159) = 4.12$, $p = .044$, $\eta_p^2 = .025$ (Fig. 2).

Can the Cognitive Reflection Task (CRT) Account for Differences Between the Samples?

Comparison of CRT scores between the samples revealed a substantial difference: while the proportion of participants answering at least one question correctly was 47.1 % among

[4] "The η_p^2 statistic is simply the ratio of the sum of squares for the particular variable under consideration divided by the total of that sum of squares and the sum of squares of the relevant error term. It describes the proportion of variability associated with an effect when the variability associated with all other effects identified in the analysis has been removed from consideration." (Fritz et al. 2012, p. 8).

community members, it was only 18.7 % among gamblers. The mean number of correct items (out of 3) was 0.81 among community members, and only 0.32 among gamblers, $t(1,124.3) = 3.37$, $p = .001$, $d = .54$.

Importantly, this difference between the samples in the CRT could not be explained by other demographic variables or other measures of cognitive capacities. To examine this, we compared the CRT between samples with an ANOVA and included a large set of control variables in the analysis to see whether they would make the difference between the samples disappear. The control variables included basic demographics (age, sex, and education) and all four measures of cognitive capacity (i.e., the symbol test, digit span test, and trail making tests A and B). The ANOVA revealed that men had higher CRT scores than women [$F(1,152) = 5.69$, $p = .018$, $\eta_p^2 = .036$], and both higher digit span and education had small effects on CRT, $F(1,152) = 3.20$, $p = .075$, $\eta_p^2 = .021$ and $F(1, 152) = 3.04$, $p = .083$, $\eta_p^2 = .020$; age, symbol test, and trail making A and B did not. Most importantly, the difference between the samples remained and was the strongest predictor of CRT, $F(1, 152) = 8.08$, $p = .005$, $\eta_p^2 = .050$.

To test whether the CRT can, in turn, account for the difference between gamblers and community members with regard to probability matching, we reran the aforementioned repeated measures analysis of variance with the within-subjects factor block (consisting of the absolute distance from probability matching in three blocks of 96 trials each) and the between-subjects factor sample (gamblers vs. community members), but this time included the CRT (from 0 to 3) as a covariate to see whether it would make the difference between the samples disappear. Indeed, with the CRT as a covariate, the difference between the samples was not present anymore, $F(1,158) = .24$, $p = .626$, $\eta_p^2 = .002$, whereas CRT strongly predicted the absolute distance from probability matching, $F(1,158) = 40.24$, $p < .001$, $\eta_p^2 = .203$. In short, gamblers' lower CRT scores could account for the smaller distance of the gamblers' choice behavior to probability matching compared to that of community members (Fig. 3).

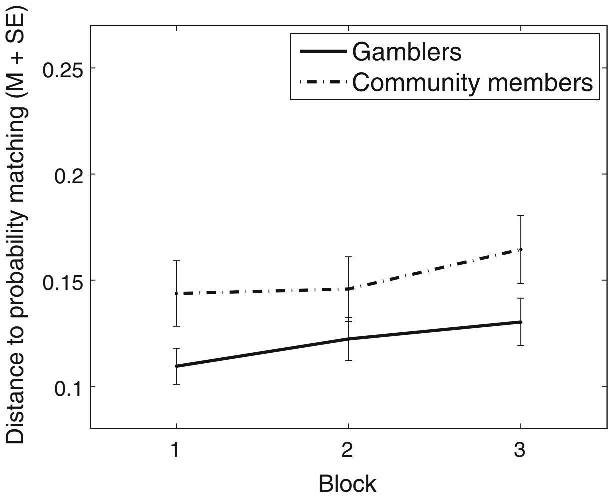


Fig. 2 The graph depicts the absolute distance between choice behavior and probability matching in three blocks of 96 trials each, compared between gamblers and community members. A value of 0 would indicate exact probability matching, while larger values indicate larger distances to probability matching. Across the three blocks, participants were (on average) moving away from probability matching, yet gamblers' choice behavior was consistently closer to probability matching than that of community members

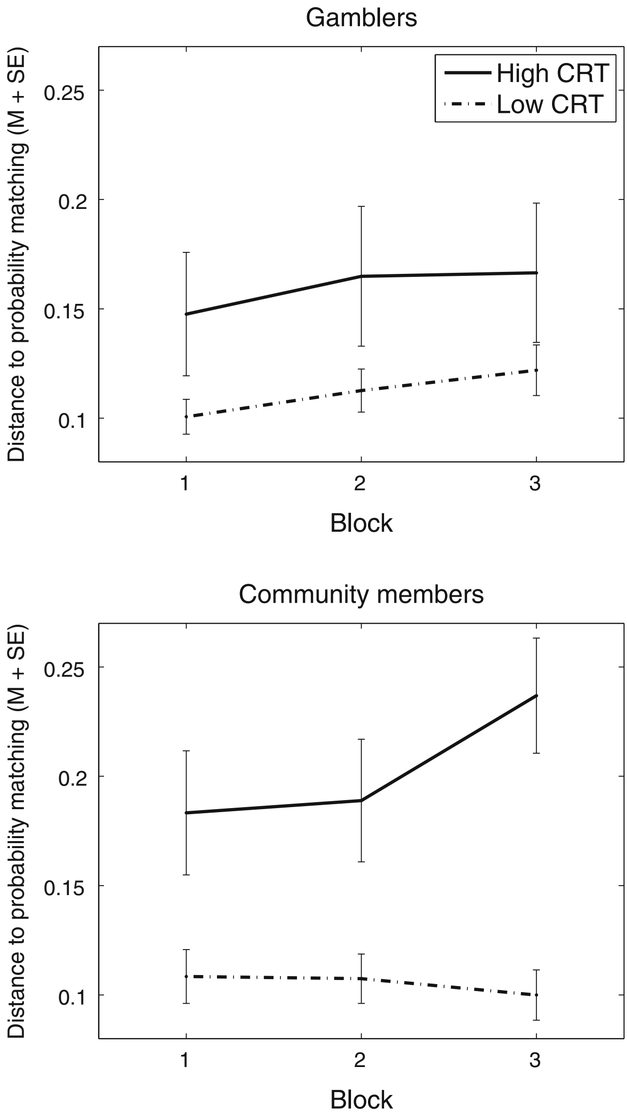


Fig. 3 The graph depicts the absolute distance between choice behavior and probability matching in three blocks of 96 trials each for participants with either high or low cognitive reflection task (CRT) scores, separately for gamblers (*upper panel*) and community members (*lower panel*). People with low CRT scores were closer to probability matching in both samples, and further analyses (see *text*) revealed that gamblers' lower CRT scores could account for why gamblers were, on average, closer to probability matching than community members. For graphing purposes, CRT scores are dichotomized into low (CRT $= 0$) and high (CRT > 0)

Interestingly, in addition to predicting probability matching behavior, the CRT also separated the more problematic from the less problematic gamblers according to the SOGS within the sample of gamblers. While gamblers with high CRT had a mean SOGS score of 1.18, gamblers with low CRT had a mean SOGS score of 3.59, $t(58.7) = -4.71$, $p < .001$, $d = .95$.

Discussion

As predicted, gamblers showed more probability matching than a matched sample of community members. Furthermore, gamblers scored much lower on the CRT than community members. That is, they much more often provided impulsive rather than reflective answers. Interestingly, this difference on the CRT between gamblers and community members could account for the difference in probability matching behavior. That is, those with lower CRT scores showed more probability matching than those with higher CRT scores, and as the proportion of people with lower CRT scores was larger among gamblers, they showed more probability matching on average. This relation between probability matching and CRT mirrors previous findings in the literature (Koehler and James 2010).

Importantly, the difference between gamblers and community members with regard to the CRT could not be explained by other demographic variables (sex, age, education) or other measures of cognitive capacity (digit span, symbol task, trail making test). This suggests that the CRT actually does tap into cognitive processes that are specifically related to gambling (or perhaps more accurately, to resist gambling), and that cannot be reduced to general cognitive capacity. Congruently, the CRT was related to a widely used clinical measure of gambling disorders, the SOGS (Stinchfield 2002), and could separate more problematic from less problematic gamblers.

The effect sizes of the differences between gamblers and non-gamblers with regard to probability matching and the CRT were small to moderate. Could those effects stem from differences in motivation rather than being related to gambling behavior? Recall that, because they needed to travel further to participate, gamblers received a higher show-up fee than non-gamblers, which could, theoretically, undermine their motivation to perform well in those tasks whose payment is based on accuracy. However, gamblers did not generally score worse on those tasks so that there did not seem to be a difference in their general motivation. In line with our predictions, gamblers specifically showed more probability matching behavior, but not more guessing behavior, which should also be enhanced if gamblers generally lacked motivation; they also specifically showed worse CRT scores, but did not score lower on other measures of cognitive capacities, again speaking against a general lack of motivation. It is therefore unlikely that the differences between gamblers and non-gamblers with regard to probability matching and the CRT stem from differences in motivation. However, it is important to note that the correlations between gambling, probability matching behavior, and CRT scores do not demonstrate causation, even after controlling for a range of other variables. Rather, in line with a cognitive approach to the study of gambling, we assume that gamblers' cognitive processes differ systematically from those of non-gamblers (in degree, though not in kind), and that those differences could contribute both to probability matching as well as to low CRT scores. More specifically, in light of related results in the literature and the results presented here, we propose that gamblers are more likely to perceive illusory patterns and reason more impulsively than non-gamblers, which is reflected in more probability matching behavior and lower CRT scores.

Our finding that gamblers' lower CRT scores accounted for their increased probability matching suggests that gamblers are more willing to readily accept illusory patterns as real, and to impulsively bet on them—just as they are more willing to readily "bet on" the intuitive but wrong answer in the CRT. The CRT was originally developed to detect precisely such differences, such as impulsivity on inter-temporal choice tasks, and has been shown to do so (Frederick 2005). Consequently, our results are in line with other studies suggesting that gamblers are more impulsive (e.g., MacLaren et al. 2012; Marmurek et al. 2015; Michalczuk et al. 2011; Miedl et al. 2014), have higher levels of narcissism (e.g., Lakey et al. 2008), have lower levels of self-control (e.g., Slutske et al. 2012), more frequently show gambling-related irrational thinking patterns (e.g., Ellery and Stewart 2014; Fortune and Goodie 2012; Studer et al. 2014; Rogers 1998), and are more susceptible to superstition (Joukhador et al. 2004). Beyond gambling and related tasks, lower CRT scores also predict religious and other paranormal beliefs (Gervais and Norenzayan 2012; Pennycook et al. 2012; Shenhav et al. 2012). Pennycook et al. suggest that "supernatural belief is a default state that requires some level of analytic processing to override" (p. 344). Similarly, perceiving illusory patterns in a random gambling task could be a default state that needs to be overridden or at least resisted with regard to betting, which habitual gamblers fail to do.

From a signal detection viewpoint, one can interpret illusory beliefs as having a liberal criterion to accept a series of events as systematic or patterned. While this leads to greater sensitivity to real patterns in the world, it comes at the cost of false alarms: detecting a pattern or correlation where none exists (Lopes 1982; Kareev and Trope 2011; Zhao et al. 2014). From an evolutionary point of view, this liberal criterion could be a cognitive adaptation to environments of our ancestral past in which resources that would have been useful to detect, such as food, water, material, and conspecifics, were often clumped (see Wilke and Barrett 2009; cf. Blanchard et al. 2014). Following this functional logic, a tendency to assume or look for patterns or regularities in a given sequence of events may be a reasonable default foraging strategy as the fitness costs of misperceiving illusory streaks were smaller during the course of evolution than the costs of making wrong predictions in environments were streaks naturally occur (Fawcett et al. 2014; Navarette et al. 2015; Wilke and Todd 2012). However, for habitual gamblers, it seems to be the case that this criterion is problematically liberal. From this perspective, at least part of the explanation for why people gamble is because they are overly prone to accept random series of events as, in fact, nonrandom—and nonrandom enough to be worth betting on.

Acknowledgments We thank the members of the Evolution and Cognition Lab at Clarkson University for their help in data collection, Dominique Schmidt for programming the experiment, and the executive director of the St. Regis Mohawk Tribal Gaming Commission Todd Papineau for his support. The research was supported by grants from the National Center for Responsible Gaming and the T. Urling and Mabel Walker Research Fellowship Program of Northern New York that were awarded to the second author.

References

Bar-Hillel, M., & Wagenaar, W. A. (1991). The perception of randomness. *Advances in Applied Mathematics, 12*, 428–454.

Bechara, A. (2001). Risky business: Emotion, decision-making, and addiction. *Journal of Gambling Studies, 19*, 23–51.

Blanchard, T. C., Wilke, A., & Hayden, B. Y. (2014). Hot hand bias in rhesus monkeys. *Journal of Experimental Psychology: Animal Learning and Cognition, 40*, 280–286.

Clark, L., Studer, B., Bruss, J., Tranel, D., & Bechara, A. (2014). Damage to insula abolishes cognitive distortions during simulated gambling. *Proceedings of the National Academy of Sciences of the USA, 111*, 6098–6103.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*, 155–159.

Croson, R., & Sundali, J. (2005). The gambler's fallacy and the hot hand: Empirical data from Casinos. *Journal of Risk and Uncertainty, 30*, 195–209.

Ellery, M., & Stewart, S. H. (2014). Alcohol affects video lottery terminal (VLT) gambling behaviors and cognitions differently. *Psychology of Addictive Behaviors, 28*, 206–216.

Falk, R., & Konold, C. (1997). Making sense of randomness: Implicit encoding as a basis for judgment. *Psychological Review, 104*, 301–318.

Fawcett, T. W., Fallenstein, B., Higginson, A. D., Houstan, A. I., Mallpress, D. E. W., Trimmer, P. C., & McNamara, J. M. (2014). The evolution of decision rules in complex environments. *Trends in Cognitive Sciences, 18*, 153–161.

Fortune, E. E., & Goodie, A. S. (2012). Cognitive distortions as a component and treatment focus of pathological gambling: A review. *Psychology of Addictive Behaviors, 26*, 298–310.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives, 19*, 25–42.

Fritz, C. O., Morris, P. E., & Richler, J. J. (2012). Effect size estimates: Current use, calculations, and interpretation. *Journal of Experimental Psychology: General, 141*, 2–18.

Gaissmaier, W., & Schooler, L. J. (2008). The smart potential behind probability matching. *Cognition, 109*, 416–422.

Gaissmaier, W., Schooler, L. J., & Mata, R. (2008). An ecological perspective to cognitive limits: Modeling environment-mind interactions with ACT-R. *Judgment and Decision Making, 3*, 278–291.

Gaissmaier, W., Schooler, L. J., & Rieskamp, J. (2006). Simple predictions fueled by capacity limitations: When are they successful? *Journal of Experimental Psychology. Learning, Memory, and Cognition, 32*, 966–982.

Gal, I., & Baron, J. (1996). Understanding repeated choices. *Thinking and Reasoning, 2*, 81–98.

Gervais, W. M., & Norenzayan, A. (2012). Analytic thinking promotes religious disbelief. *Science, 336*, 493–496.

Goodie, A. S. (2005). The role of perceived control and overconfidence in pathological gambling. *Journal of Gambling Studies, 21*, 481–502.

Goodie, A. S., & Fortune, E. E. (2013). Measuring cognitive distortions in pathological gambling: Review and meta-analyses. *Psychology of Addictive Behaviors, 27*, 730–743.

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics* (Vol. 1). New York, NY: Wiley.

Haselton, M. G., Bryant, G. A., Wilke, A., Frederick, D. A., Galperin, A., Frankenhuis, W. E., & Moore, T. (2009). Adaptive rationality: An evolutionary perspective on cognitive bias. *Social Cognition, 27*, 733–763.

Healy, A. F., & Kubovy, M. (1981). Probability matching and the formation of conservative decision rules in a numerical analog of signal detection. *Journal of Experimental Psychology: Human Learning and Memory, 7*, 344–354.

James, G., & Koehler, D. J. (2011). Banking on a bad bet: Probability matching in risky choice is linked to expectation generation. *Psychological Science, 22*, 707–711.

Jefferson, S., & Nicki, R. (2003). A new instrument to measure cognitive distortions in video lottery terminal users: The informational biases scale (IBS). *Journal of Gambling Studies, 19*, 387–403.

Joukhador, J., Blaszczynski, A., & MacCallum, F. (2004). Superstitious beliefs in gambling among problem and non-problem gamblers: Preliminary data. *Journal of Gambling Studies, 20*, 171–180.

Kareev, Y., & Trope, Y. (2011). Correct acceptance weighs more than correct rejection: A decision bias induced by question framing. *Psychonomic Bulletin and Review, 18*, 103–109.

Kessler, R. C., Hwang, I., LaBrie, R., Petukhova, M., Sampson, N. A., Winters, K. C., et al. (2008). DSM-IV pathological gambling in the National Comorbidity Survey Replication. *Psychological Medicine, 38*, 1351–1360.

Koehler, D. J., & James, G. (2009). Probability-matching in choice under uncertainty: Intuition versus deliberation. *Cognition, 113*, 123–127.

Koehler, D. J., & James, G. (2010). Probability matching and strategy availability. *Memory and Cognition, 38*, 667–676.

Lakey, C. E., Rose, P., Campbell, W. K., & Goodie, A. S. (2008). Probing the link between narcissism and gambling: The mediating role of judgment and decision-making biases. *Journal of Behavioral Decision Making, 21*, 113–137.

Lopes, L. L. (1982). Doing the impossible: A note on induction and the experience of randomness. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 8*, 626–636.

MacLaren, V. V., Fugelsang, J., Harrigan, K. A., & Dixon, M. J. (2011). The personality of pathological gamblers: A meta-analysis. *Clinical Psychology Review, 31*(6), 1057–1067.

MacLaren, V. V., Fugelsang, J. A., Harrigan, K. A., & Dixon, M. J. (2012). Effects of impulsivity, reinforcement sensitivity, and cognitive style on pathological gambling symptoms among frequent slot machine players. *Personality and Individual Differences, 52*, 390–394.

Marmurek, H. H. C., Switzer, J., & D'Alvise, J. (2015). Impulsivity, gambling cognitions and the gambler's fallacy in university students. *Journal of Gambling Studies, 31*, 197–210.

Mata, R., Schooler, L., & Rieskamp, J. (2007). The aging decision maker: Cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging, 22*, 796–810.
Michalczuk, R., Bowden-Jones, H., Verdejo-Garcia, A., & Clark, L. (2011). Impulsivity and cognitive distortions in pathological gamblers attending the UK National Problem Gambling Clinic: A preliminary report. *Psychological Medicine, 41*, 2625–2635.
Miedl, S. F., Buechel, C., & Peters, J. (2014). Cue-induced craving increases impulsivity via changes in striatal value signals in problem gamblers. *Journal of Neuroscience, 34*, 4750–4755.
Myers, J. L. (1976). Probability learning and sequence learning. In W. K. Estes (Ed.), *Handbook of learning and cognitive processes: Approaches to human learning and motivation* (pp. 171–205). Hillsdale, NJ: Erlbaum.
Navarette, G., Santamaria, C., & Froimovitch, D. (2015). Small samples in evolution: Did the law of small numbers arise as an adaptation to environmental challenges? *Frontiers in Evolutionary Psychology and Neuroscience, 6*, 1–3.
Newell, B. R., Koehler, D. J., James, G., Rakow, T., & van Ravenzwaaij, D. (2013). Probability matching in risky choice: The interplay of feedback and strategy availability. *Memory and Cognition, 41*, 329–338.
Newell, B. R., & Rakow, T. (2007). The role of experience in decisions from description. *Psychonomic Bulletin and Review, 14*, 1133–1139.
Otto, A. R., Taylor, E. G., & Markman, A. B. (2011). There are at least two kinds of probability matching: Evidence from a secondary task. *Cognition, 118*, 274–279.
Pennycook, G., Cheyne, J. A., Seli, P., Koehler, D. J., & Fugelsang, J. A. (2012). Analytic cognitive style predicts religious and paranormal belief. *Cognition, 123*, 335–346.
Rakow, T., Newell, B. R., & Zougkou, K. (2010). The role of working memory in information acquisition and decision making: Lessons from the binary prediction task. *Quarterly Journal of Experimental Psychology, 63*, 1335–1360.
Rogers, P. (1998). The cognitive psychology of lottery gambling: A theoretical review. *Journal of Gambling Studies, 14*, 111–134.
Scheibehenne, B., & Studer, B. (2014). A hierarchical Bayesian model of the influence of run length on sequential predictions. *Psychonomic Bulletin and Review, 20*, 211–217.
Scheibehenne, B., Wilke, A., & Todd, P. M. (2011). Expectations of clumpy resources influence predictions of sequential events. *Evolution and Human Behavior, 32*, 326–333.
Shaffer, H. J., Hall, M. N., & Bilt, J. V. (1997). *Estimating the prevalence of disordered gambling behavior in the United States and Canada: A meta-analysis*. Boston, MA: Harvard Medical School.
Shaffer, H. J., Peller, A. J., LaPlante, D. A., Nelson, S. E., & LaBrie, R. A. (2010). Toward a paradigm shift in internet gambling research: From opinion and self-report to actual behavior. *Addiction Research and Theory, 18*, 270–283.
Shanks, D. R., Tunney, R. J., & McCarthy, J. D. (2002). A re-examination of probability matching and rational choice. *Journal of Behavioral Decision Making, 15*, 233–250.
Shenhav, A., Rand, D. G., & Greene, J. D. (2012). Divine intuition: Cognitive style influences belief in god. *Journal of Experimental Psychology: General, 141*, 423–428.
Slutske, W. S., Moffitt, T. E., Poulton, R., & Caspi, A. (2012). Undercontrolled temperament at age 3 predicts disordered gambling at age 32: A longitudinal study of a complete birth cohort. *Psychological Science, 23*, 510–516.
Stinchfield, R. (2002). Reliability, validity, and classification accuracy of the South Oaks Gambling Screen (SOGS). *Addictive Behaviors, 27*, 1–19.
Studer, B., Limbrick-Oldfield, E. H., & Clark, L. (2014). "Put your money where your mouth is!" Effects of streaks on confidence and betting in a binary choice task. *Journal of Behavioral Decision Making*. doi:10.1002/bdm.1844.
Tombaugh, T. N. (2004). Trail making test A and B: Normative data stratified by age and education. *Archives of Clinical Neuropsycholology, 19*, 203–214.
Toplak, M. E., Liu, E., MacPherson, R., Toneatto, T., & Stanovich, K. E. (2007). The reasoning skills and thinking dispositions of problem gamblers: A dual-process taxonomy. *Journal of Behavioral Decision Making, 20*, 103–124.
Unturbe, J., & Corominas, J. (2007). Probability matching involves rule-generating ability: A neuropsychological mechanism dealing with probabilities. *Neuropsychology, 21*, 621–630.
Vulkan, N. (2000). An economist's perspective on probability matching. *Journal of Economic Surveys, 14*, 101–118.
West, R. F., & Stanovich, K. E. (2003). Is probability matching smart? Associations between probabilistic choices and cognitive ability. *Memory and Cognition, 31*, 243–251.
Wilke, A., & Barrett, H. C. (2009). The hot hand phenomenon as a cognitive adaptation to clumped resources. *Evolution and Human Behavior, 30*, 161–169.

Wilke, A., Scheibehenne, B., Gaissmaier, W., McCanney, P., & Barrett, H. C. (2014). Illusionary pattern detection in habitual gamblers. *Evolution and Human Behavior, 35*, 291–297.

Wilke, A., & Todd, P. M. (2012). The evolved foundations of decision making. In M. K. Dhami, A. Schlottmann, & M. Waldmann (Eds.), *Judgment and decision making as a skill: Learning, development and evolution* (pp. 3–27). Cambridge: Cambridge University Press.

Wolford, G., Miller, M. B., & Gazzaniga, M. (2000). The left hemisphere's role in hypothesis formation. *The Journal of Neuroscience, 20*(RC64), 1–4.

Wolford, G., Newman, S., Miller, M. B., & Wig, G. (2004). Searching for patterns in random sequences. *Canadian Journal of Experimental Psychology, 58*, 221–228.

Yellott, J. I, Jr. (1969). Probability learning with noncontingent success. *Journal of Mathematical Psychology, 6*, 541–575.

Zhao, J., Hahn, U., & Osherson, D. (2014). Perception and identification of random events. *Human Perception and Performance, 40*, 1358–1371.