Craving for Money? Empirical Evidence from the Laboratory and the Field*

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Abstract

In a series of controlled laboratory experiments, we provide evidence for "Craving by Design" (CbD) hypothesis, where people knowingly expose themselves to negative tail risk due to craving for monetary gains. We then document the "cheap call selling anomaly:" selling calls priced below $1 has consistently delivered negative long-term returns and negative skew, which is puzzling when viewed from the prevailing body of knowledge alone, though expected when the latter is augmented with CbD hypothesis. These findings bring novel insights into the topic of limited self-control, the issue of problem gambling in recreational gamblers, and the motivations underlying investor decisions. (C91, D87, G41)

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As long as the music is playing, you've got to get up and dance.
— Charles O. Prince (Citigroup's CEO from 2003 to 2007) on Citigroup's continued engagement in leveraged buy-out deals despite fears of reduced liquidity because of the ongoing subprime meltdown.

Would you sell a \$1 lottery ticket that pays \$101 to the winner with a winning probability of 1%? By doing so, you would be engaging in a negatively-skewed gamble with negative expected value (SKEW<0, EV<0). Continued exposure to gambles of this kind is not worth the risks in a purely financial sense (EV<0). Yet, it appears to be a strange behavioral pattern in the financial industry where it has been dubbed "*picking up pennies in front of a steamroller*" (Taleb, 2004). One famous example is the continued involvement of CDO owners in the residential mortgage-backed (RMBS) CDO market 'in front of the steamroller' of the looming subprime crisis, until they eventually "blew up" in 2008.[1]

It seems clear that the origin of this behavior is not that people seek SKEW<0, inasmuch as it is well-known—at least since Menezes et al. (1980)—that people are generally averse to downside risk.[2] What makes them behave like this then?

The most immediate explanation for this behavior—henceforth, "the picking pennies bias"—relates to faulty cognition or, in the language of psychologists, "*miswanting*" (Winkielman and Berridge, 2003): being deluded that EV is positive. This comes from diverse sources, including many people's difficulty in grasping the payoff structure of complex financial products,[3] interpreting very small probability events,[4] and recognizing tail risk under model uncertainty.[5] In this paper, we provide evidence for a complementary explanation, namely "*irrational wanting*" (Winkielman and Berridge, 2003): people know what to do, yet they cannot help doing the opposite, and this can be tied to "craving" for monetary gains, in the same way as people sometimes happen to crave for foods and other kinds of rewards such as drugs and sex—the evidence suggests that the brain treats these different rewards

[1] For example, Crouhy et al. (2008) and Zuckerman (2010).

[2] For recent empirical evidence, see Huber and Huber (2019), Schneider (2019), and Holzmeister et al. (2020).

[3] For example, Brunnermeier and Oehmke (2009), Carlin and Manso (2011), and Oehmke and Zawadowski (2019).

[4] Evidence suggests that people tend to underestimate very low probabilities and treat them as if they are ignorable. For example, Kunreuther et al. (2001), Hertwig et al. (2004), Kunreuther and Pauly (2006), and Laury et al. (2009).

[5] When faced with fat-tailed outcome distributions, people sometimes fail to realize that the outcomes are not normally distributed. For example, Taleb (2004), Donnelly and Embrechts (2010), and Payzan-LeNestour (2018).

similarly (we elaborate in Section 1 of the paper).

In Section 1, we develop the idea of irrational wanting related to "craving," which we borrow from the field of affective neurosciences. The basic idea is that due to the way the brain is wired, the repeated exposure to monetary gains makes people susceptible to craving for money. We call this "*Craving by Design*" (CbD), in reference to recent anthropological work suggesting that any recreational gambler is susceptible to being *"addicted by design"* if repeatedly exposed to modern electronic gaming machines (Schull, 2014).

In Section 2 of the paper, we document findings consistent with CbD hypothesis in a series of controlled laboratory experiments. We consistently observe the picking pennies bias in participants in a gambling task across different experimental conditions used to control for the miswanting/faulty cognition factor, along with other potential explanations for the bias. These explanations include "probability matching" (matching the choice frequency for a given action with the probability of success of the action),[6] risk seeking, limited liability (not being exposed to significant losses in case of bad performance in the task), and the 'thrill of gambling' (getting utility from the pleasure of taking risks irrespective of whether this improves current wealth; see Conlisk (1993)). We find that except for when task participants are offered a "self-binding" commitment device so they can "tie their hands" (Elster, 1979), they consistently feature the picking pennies bias across experimental conditions, and this however much they are aware of the odds of winning and losing in the task. When task participants are offered a commitment device, the latter is widely used and the prevalence of the picking pennies bias among task participants is significantly reduced.

These experimental findings raise new questions about the motivations underlying investor behavior. For they suggest that there might be a significant number of investors who, in order to satisfy craving needs, engage in trades that are "Craving Prone": delivering good returns almost surely, and a disaster outcome with tiny likelihood. According to CbD hypothesis, the craving elicited by Craving-Prone trades could be strong enough to exert a pressure on equilibrium asset price that offsets countervailing forces from the other side of the trade, resulting in a negative long-run Expected Value (EV<0) for the "penny-pickers" engaged in the trade. Notwithstanding the negative EV, penny-pickers may choose to engage in Craving-Prone trades to satisfy their craving needs, like investors engage in negative EV 'lottery-trades' in order to satisfy gambling needs/preferences—their liking of SKEW>0.[7]

[6] For example, Vulcan (2000), Shanks et al. (2002), and Lo (2017).

[7] For example, Kumar (2008), Barberis (2011), and Eraker and Ready (2015). One insight from these studies is that the positive skewness of "lottery-like" returns caters to gambling needs, thus gamblers accept

In Section 3 of the paper, we document empirical evidence for this idea, using asset price and transaction-level data. The data support the idea that investors knowingly engage in EV<0, negatively-skewed (SKEW<0) trades due to a behavioral factor possibly tied to investor craving for monetary gains. They further support the idea that the EV<0 feature of these trades reflects the strength of investor craving—the force it exerts on the equilibrium price of Craving-Prone assets.

To control for the faulty cognition factor in the field as we do in the lab, we take several steps. These include focusing on the option markets, the selling side in particular, and analyzing in detail the nature and origin of the sell transactions. We reason that compared to other investors, option sellers are expected to be aware of the long-run EV of their trades.[8] So an option seller who consistently gets EV<0 from a given trade is likely to be aware of its negative value, especially if this seller comes from a firm rather than being a retail investor.

The core of our analysis focuses on options for which, according to CbD hypothesis, craving-driven selling pressures could dominate demand-based pressures related to the gambling and insurance motives (in short, "supply>demand"). One does not expect to observe this with put options given the strong demand for insurance against downside risk underlying put buying and corollary strong volatility premium embedded in puts—a well-established fact.[9] The volatility premium/demand for insurance is however lower for call options, so we focus on call options (rather than pooling put and call options as is commonly done in the literature). We further narrow our focus to call options priced below \$1—the so-called *"cheap calls"*, for which the foregoing Craving-Prone return property is particularly pronounced for the sellers, in the sense that relative to the other options, the cheap calls deliver bigger median returns for the sellers, with a higher likelihood of finishing out of the money (in other words, they deliver bigger 'pennies' with a higher likelihood of getting them; see Section 3).

We find that cheap call selling has consistently delivered negative long-run EV over time, and this is a signature of the cheap calls (not observed with the other options). This finding presents itself consistently across volatility and delta groups and after controlling for fixed effects related to firm factors and option specific characteristics. We further find that the

to pay a premium to get the positive skew, thereby driving up the price of lottery-like assets.

[8] Option trading requires constant performance monitoring (e.g., Pan and Poteshman (2006)), resulting in option prices containing more information and reacting more quickly to new information relative to other asset categories (e.g., Doran et al. (2007), Cremers et al. (2008a), and Baltussen et al. (2012)). Within the option markets, sellers have the reputation of being more sophisticated than buyers on average, consistent with recent empirical findings (e.g., Doran et al. (2013)).

[9] For example, Carr and Wu (2008), Bondarenko (2014), Bakshi and Kapadia (2015), and Bhansali and Harris (2018).

more Craving Prone the asset is for the seller, the more negative EV is, that is, the larger the discount the seller is incurring; and the discount is also more pronounced during low-yield periods, when Craving-Prone payoffs are harder to find. Our data also suggest that the demand for the cheap calls is no different from that for the other calls (if anything, it is higher), and the sellers of the cheap calls often come from firms.

Furthermore, and importantly, the data suggest there is "nothing special" about the cheap calls except for the Craving-Prone property of their returns for sellers (the fact that they deliver bigger pennies with a higher likelihood of getting them): we find the selling anomaly likewise prevails for puts priced below $1 *defined on negative beta assets* (the "cheap put selling anomaly"), whose returns feature similar Craving Proneness.

Relation to the literature This paper pertains to several strands of literature. Recent behavioral finance studies suggest that the behavioral anomaly documented here, which consists of exposing oneself to EV<0, SKEW<0 outcomes, is not isolated to options. For example, Henderson and Pearson (2011) show that retail structured products provide negative expected returns that are hard to explain with tax, liquidity, or other traditional risk premia, but can however be tied to investor sentiment and behavioral factors (Henderson et al., 2020). The anomaly may also concern households. For example, Chapman et al. (2018) show that a sample of the U.S. population is *"loss tolerant"* even when faced with large negative expected outcomes. Duffy and Orland (2020) show that savers faced with potential bankruptcy and an inability to smooth consumption through borrowing do not seek to reduce the likelihood of bankruptcy through increased savings.

Our empirical analysis of the cheap calls draws on prior work documenting how demand-based pressures can drive up asset price; see, e.g., Garleanu et al. (2009) and Eraker and Ready (2015). Echoing this literature, we posit that seller craving can drive down the price of Craving-Prone assets, having in mind symmetrical *supply*-based pressures. Garleanu et al. (2009) and Eraker and Ready (2015), together with consumer behavior studies showing that a $1 price cutoff separates what buyers see as "good deals" from the rest (Anderson and Simester, 2003),[10] further inspired us to use a $1 cutoff in our definition of the cheap calls. For these studies point to the cheap calls being more attractive to buyers than the other call options are, all other things being equal, because buyers see them as "good deals."[11]

[10]The commercial success of the "99 Cents Only Stores" across the U.S, and the success of iTunes' 0.99c songs, are two illustrations of this trait of consumer psychology.

[11]Eraker and Ready (2015) indeed report that "pink sheet stocks" [stocks whose price has fallen so low

The data reported in Section 3 are consistent with this idea, which is important to rule out the possibility that the pattern of EV<0 from cheap call selling reflects depressed demand. Rather, the evidence suggests that the EV<0 pattern occurs *despite* the demand for the cheap calls being strong.

To our best knowledge, this is the first study documenting the anomalous return property of cheap call selling, which is characterized by the combination of EV<0 and SKEW<0. Such a combination constitutes an anomaly viewed from the prevailing body of knowledge in finance, which predicts either the combination of EV<0 and SKEW>0, or EV>0 and SKEW<0 (for example, Kumar (2008), Cremers et al. (2008b), Bakshi and Kapadia (2015), and Cremers et al. (2015)). One key insight from the existing literature is indeed that both the gambling and insurance motives lead option buyers to accept to pay a premium, resulting in EV<0 and SKEW>0 from option buying. Option sellers get compensated for incurring crash risk and accordingly returns from option selling feature EV>0 and SKEW<0. We show that these predictions hold true for all options except for the most Craving Prone ones (namely, the cheap calls and the cheap puts for negative beta assets).

What led us to uncover the cheap calls anomaly is our focus on calls specifically, which contrasts with the common practice consisting of pooling put and call options.[12] What is an anomaly viewed from the existing body of work is however *"a matter of course"* (in the epistemological sense of the term; see, e.g., Burch (2018)) when this body of work is augmented with CbD hypothesis.

The current study also provides insights into gambling and self-control in economic decision-making. The fact that investors seek positively-skewed (lottery-like) asset returns and drive up the price of positively-skewed assets has long been appreciated both on the theoretical and empirical sides (see the above references). In contrast, how people behave in the face of negative skewness is not well understood (Barberis, 2013). It is seemingly puzzling that investors may knowingly expose themselves to EV<0, SKEW<0 monetary prospects since they dislike negative skewness, as stressed above. CbD hypothesis provides one explanation for this apparent paradox.[13]

that they have become delisted from the exchange] attract investors looking for a "cheap" deal. Garleanu et al. (2009) document similar "good deal effect" with low priced OTM puts.

[12]Pooling call and put options is natural when the aim is to model the underlying price process of option markets, which is largely driven by puts (for example, Bates (2015) and Heston (2015)). Of note, call options represent a significant portion of option markets. Relative to puts they have similar type of open interest and option volume (Doran et al., 2011). The average daily volume CBOE put/call ratio is 0.94 from Nov 2006 through July 2019.

[13]Note that exposure to both positive and negative skewness in the same individual is not a surprising

Our finding that offering a commitment device is effective at reducing the prevalence of the picking pennies bias in the laboratory echoes Elster (1979) and Ameriks et al. (2007) where people choose to commit when they value the cost of missing their target action more than the flexibility of adjusting their plans. Notably, prior studies on limited self-control chiefly focused on the temptation to consume. The present study complements those studies by shedding light on the temptation to take excessive risks. The idea that, under certain circumstances, people knowingly engage in EV<0 gambles because they cannot help doing so echoes Shiller (2000)'s conjecture that when people decide to participate in the stock market at the peak of a speculative bubble, "deep down, *they know* that the market is likely overpriced, and they are uncomfortable about this fact".[14]

1 Craving by Design Hypothesis

1.1 At the behavioral level

Consider an agent who is risk averse, loss averse, and dislikes negative skewness. Further assume that these risk preferences are fixed (they do not change over time), and the agent makes no mistakes (just for the sake of the argument here). From these assumptions it is clear that the agent always rejects any one-shot gamble featuring SKEW<0, EV<0.

Now bring this agent into the context of a recurrent choice between a sure monetary gain and a SKEW<0, EV<0 gamble yielding a good outcome most of the time and a big loss occasionally. The agent knows the statistics of the gamble. After each choice, she sees the outcome from both her chosen option and the other choice (the counterfactual outcome). CbD hypothesis posits that in this context, the agent will initially reject the gamble but after some time she may pursue it. She may do it either consistently or just a few times (we characterize the pattern in Section 2; see in particular Figure 5, p.25). The key point to make is that the agent behaves as if her risk preferences had changed, although they have not by definition: the agent features the same risk preferences as before and if asked, she

pattern under the existing gambling literature augmented with CbD hypothesis. For example, someone could both invest in Craving-Prone assets and buy lottery tickets.

[14]See Shiller (2000), p.14. Eminent theories attributed "irrational exuberance" either to mistaken beliefs—for example, see Part 3 of Shiller (2000), Shefrin (2009), and Ubel (2009)—or to "greed" fueled by aggressive bank lending—for example, see pp.54-56 of Shiller (2000), and Kindleberger and Alibert (2005). The idea of miswanting as defined in this paper relates to the former (mistaken beliefs); the one of irrational wanting, to the latter ("greed").

still systematically rejects any SKEW<0, EV<0 gamble, except for the present gamble to which she has just been repeatedly exposed. Her behavior is thus "*context dependent*".

1.2 Underlying bio mechanism

Why would our perfectly-informed agent reject the present gamble when it's a one-shot gamble but start choosing it after repeated exposure to it? A long-standing body of work in affective neuroscience points to the agent's "reward system" [the part of her brain where her desires originate (Panksepp, 2004)] as being to blame. In short,[15] the repeated exposure to the good outcome associated with the gamble most of the time makes the agent's reward system "*sensitized*": it responds more powerfully to the prospect of winning with the gamble every time the gamble is offered for choice, in the form of dopamine boosts—which are best understood as neurochemical "reward signals" (e.g., Winkielman and Berridge (2003), Steketee and Kalivas (2011), and Wolf (2016)). Such boosts are automatically triggered by the reward system; they do *not* reflect expected value (e.g., Wyvell and Berridge (2000) and Dickinson and Balleine (2002)). As a result, the agent "wants" the gamble despite knowing that EV<0. In other words, the agent is not "fooled by randomness" (Taleb, 2004) (cf. the "miswanting" mentioned in the Introduction); rather, she is fooled by her brain. Neuroscientists call this phenomenon "*craving*" or "*irrational wanting*" (see Berridge and O'Doherty (2013) for a survey).

Prior findings suggest that two key contributors of the foregoing sensitization of the reward system following repeated exposure to a given reward are reward size (e.g., Fiorillo et al. (2003) and Pessiglione et al. (2006)) and intensity, or the frequency of exposure to the reward: high frequency causes the reward to be even more wanted (e.g., Steketee and Kalivas (2011) and Wolf (2016)). Classical instances of craving include the case of a drug cue prompting a former addict to crave drugs anew, craving for a lolly cake when the agent is in a satiated state or thinks it is unhealthy (Plassmann et al., 2008), and being jilted in pursuing a desired love target, which has been shown to simultaneously increase the motivation to pursue this target and *decrease* its actual appeal (Litt et al., 2010).

This body of evidence for craving across different kinds of rewards (drug, food, sex, etc.), together with the current view in affective neuroscience that the reward system does not distinguish between the different kinds of rewards and processes them similarly (using

[15]For more details and references from neuroscience, see Section 1 of the working paper version of this article, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3545804.

a "common currency"; see Grabenhorst and Rolls (2011) and Levy and Glimcher (2012) for a review), suggests that craving may well exist for monetary rewards as well, in the precise sense described above for our agent: The repeated exposure to the gamble leads the agent's reward system to automatically associate the gamble with its good outcome, and the ensuing dopamine boosts can tilt the agent toward the gamble, irrespective of EV (which in the present case is negative). Recent findings are consistent with this idea (e.g., Bossaerts and Murawski (2016) and Rutledge et al. (2016)); however direct evidence is missing.

2 Laboratory Experiments

2.1 Experimental design

2.1.1 Gambling task

To test the idea that the repeated exposure to monetary gambles can make one "crave for money" in the sense explained in Section 1, we ask undergraduate students from the *University of New South Wales* (UNSW) to perform at *UNSW Business School Experimental Laboratory* one run of a gambling task that builds on a recently developed gambling paradigm (Payzan-LeNestour, 2018). In it, at each trial t, a bowman is shooting at a target on a wall. The wall is represented by a line; the target corresponds to the zero mark on that line, and the shot realized, denoted by X_t, can be anywhere on the line. Participants must decide whether to bet that the coming shot will fall up to four meters away from the target on both sides (i.e., $X_t \in [-4; 4]$). A winning bet yields \$2; a losing bet ($X_t \notin [-4; 4]$) results in a loss of \$40. The alternative to betting is to "skip," which guarantees \$0. Immediately after deciding whether to bet or skip, participants see the realized shot, are explicitly told their outcome at the trial, and then proceed to the next trial (Figure 1).

Participants play 15 independent sessions comprising 20 trials each. Participant payoff consists of the participants' final net accumulated outcomes from all sessions, plus/minus a starting account balance. During the task instructions, the participants are told that the account balance can take any value between −\$500 and \$500 and that the value will be revealed after they have completed the task. They are further explained the rationale behind this feature, which is to avert wealth effects in participant behavior, since in each trial during the task, the participants do *not* know the current value of their wealth (their current net accumulated outcomes +/− the amount of the account balance).[16] The experimenter sets the amount of the account balance before the participants start performing the task by writing the amount on a sheet of paper and placing the sheet in an envelope in the middle of the lab room; all this is done in front of the task participants.[17]

Such a payment rule provides task participants with high monetary incentives in two key regards. First, it generates a bimodal payoff distribution. For example, in Experiment 1 documented below, 59 out of 124 task participants win more than \$100 (mean: \$63, std: \$42) vs. 40 end up with the show-up reward of \$5 (given independent of subject performance as per the lab protocol).[18] Such bimodality is stressed both in the recruitment email and the task instructions, both for ethical reasons, and to ensure that the task participants have strong incentives to perform well in the task.

The second incentivizing aspect of such a rule is that it pays for the outcome from all decisions made, thereby averting the issue of "*diluted incentives*" (Charness et al., 2016) arising with the alternative "pay one" approach (paying for the outcome of only a subset of the choices made). However, the "pay all" rule potentially presents the issue of giving rise to wealth effects. The account balance feature is to address this problem, as explained above.

If the participants do not answer within the imparted time (5s; elapsed time is indicated by a timer, see Figure 1), they lose \$1, and do not see the hit realized at the trial. In practice there is only 3 missed trials across all experiments, and participants reply well before the imparted time (highest response time: 4.94s, average 0.63s, see Table A6 in the Internet Appendix). So by design, there is high-frequency exposure of the participants to monetary gambles, in relation to the intensity factor mentioned in Section 1.

Before performing the task, participants are provided with the following information about the stochastic structure of the task. Each session has a different bowman which can be either a "master" or an "apprentice," with equal probability. The shots from a master bowman

[16]Participants are told: "For scientific purposes, it is important that you don't know where you stand during the game. For example, imagine you lost several times and your current net accumulated outcomes are say −\$78. You may think you're in the red but you don't know that: if for instance the account balance has been set to say \$100, your current wealth in the game is actually positive. Conversely, imagine you won a lot and your accumulated outcomes are \$78. This does not mean your current wealth is positive: what if the current balance is −\$100 for example; recall it can be anything between −\$500 and \$500. Morale of the story: just focus on making the right choice on each trial."

[17]The experimenter chooses the amount before each session based on participant behavior in the previous sessions, in such a way that the expected cost of the session per participant falls within the \$20-\$50 range as per the lab guidelines.

[18]The payoff gap between high and low task performers is even larger in the other experiments, Experiment 5 in particular, more below.

are normally distributed around the target (i.e., mean is 0), with a standard deviation that differs across bowmen. For each bowman, the value of the standard deviation is drawn from a uniform distribution [0.1,2]. For each possible value of the standard deviation, the expected value of betting when the bowman is a master is positive by design. In contrast, the shots from an apprentice bowman are Cauchy distributed with a dispersion parameter fixed to 1, so they have a fat-tailed distribution, and the expected value of betting when the bowman is an apprentice is highly negative by design (see Internet Appendix 5.2.1 for the numbers).

Participants are told the expected value with each kind of bowman before they start performing the task. Special task instructions are used to ensure that they grasp this information. Instead of using statistical concepts, the task instructions comprise animations or "distribution builders" showing 300 successive sample shots from master and apprentice bowmen, allowing the task participants to grasp the shot distributions from the different kinds of bowmen through directly sampling many times from those distributions.[19]

This aspect of the method is inspired to us by Gigerenzer et al. (1988) and Goldstein et al. (2006). It is motivated by ample evidence that people flounder with even the most elementary explicit probabilistic reasoning tasks[20] because the human brain is a "*Bayesian sampler*:" it is not adapted to interpret explicit probabilities, but can, however, grasp statistics through sampling from probability distributions (Sanborn and Chater, 2016), as the task participants do here.[21] Thus, all the participants can gather without having to engage in any explicit computation that EV is positive with any kind of master bowman and negative with an apprentice, even those unfamiliar with basic statistics concepts such as EV, probability, etc. For participants familiar with those concepts, a "FAQs" document [provided in the Internet Appendix; Section 6.6 of this draft] distributed to the task participants at the end of the instruction phase of the experimental session explicitly mentions the statistics of the task. The experimenter re-emphasizes the fact that EV is positive with any kind of master bowman and negative with an apprentice bowman when reviewing these FAQs with the task participants just before they start performing the task.

Without these special task instructions, there would be significant chances that task participants underestimate the probability of losing with an apprentice, given people's afore-

[19]These animations can be seen at `http://bowmangame.weebly.com/task-instructions.html`.

[20]For example, Tversky and Kahneman (1973), Tversky and Kahneman (1974), Charness and Levin (2005), Elqayam and Evans (2011).

[21]For example, Gigerenzer et al. (1988) allowed people to directly experience random sampling in Kahneman and Tversky (1973)'s classic Engineer-Lawyer problem, and as a result, the "base rate neglect" bias was markedly reduced.

mentioned tendency to ignore the possibility of small probability disasters in the field (Laury et al., 2009). It appears that task participants do not underestimate that probability but, if anything, *over*-estimate it (see the Internet Appendix, Section 5.1 of this draft), consistent both with salience theory (Bordalo et al., 2012)[22] and the data reported in Section 2.2 for each experiment (specifically, the fact that participants tend to systematically skip in the first trials of each session with an apprentice; they would not do so if they treated the loss probability as being neglectable).

Rationale for the bowman narrative From a statistical perspective, apprentice bowmen are akin to the EV<0, SKEW<0 "Craving-Prone" assets mentioned in the Introduction. The financial history over the past 40 years abounds with examples of assets of this kind. Classical examples include high-yield bonds in 1989 (e.g., Altman (1987) and Altman (1992)) and RMBS CDOs in 2007 (Crouhy et al., 2008). The cheap call options studied in Section 3 are another example. In contrast, the statistics with master bowmen mirror the return distributions of assets such as investment-grade bonds.

However the task is devoid of any financial undertone. Our use of the bowman metaphor, rather than framing the task as a financial decision-making problem, aims to ensure that anyone can readily grasp the principle of the task, including financially illiterate task participants—possibly a non negligible portion of the task participants given the importance of financial illiteracy among the general population (e.g., Bernheim (1995) and Lusardi and Mitchell (2007)).

The current task thus falls within the "neutral" category as defined in Alekseev et al. (2017): not evocative in any sense but also not abstract. Participants understand the task while not being drawn into thinking about a financial decision situation. Besides addressing the financial illiteracy point, this presents the advantage of making the current experimental paradigm generic, in the sense that it speaks to the issue of excessive risk-taking in domains other than financial investing—for instance, recreational gambling.

[22] In salience theory, unlikely events are overweighted when they are associated with salient payoffs. By design, the state in which participants lose is very salient since the difference in the payoffs of the two actions (betting versus skipping) is larger in that state than in the case of a winning state (using Bordalo et al. (2012)'s notations, the state payoffs are (-40,0) in the former case and (2,0) in the latter case).

2.1.2 Varying key factors across five experiments

Since by design EV is positive with any kind of master bowman and negative with an apprentice, optimal behavior consists of betting if the bowman is a master and skipping otherwise.[23] In this context, the picking pennies bias described in the Introduction manifests itself when the agent happens to choose to bet in a session with an apprentice bowman. Such a behavior is consistent with both CbD hypothesis (after seeing a series of good outcomes in a session, the agent is tempted to bet) and the aforementioned—not mutually exclusive—explanations, related to faulty cognition, probability matching, risk seeking, and the thrill of gambling.

To assess the relative importance of these potential explanations for the picking pennies bias, we run a series of five experiments, each using a different version of the task. Each experiment is approved by *UNSW Human Research Ethics Advisory Panel* and written consent is obtained from all task participants. The text of the task instructions used for each experiment is provided as supplementary information (Section 6 in this draft). The online task instructions, a demo of the experimental task, and the experimental data, are provided at http://bowmangame.weebly.com/. We first test the foregoing hypotheses related to faulty cognition, probability matching, risk seeking, the thrill of gambling, and CbD, through comparing participant behavior across the five experiments. Then we bring the results together in a regression framework accounting for multiple explanations and shared variances.

To study the relative importance of faulty cognition in the prevalence of the the picking pennies bias, we take two steps. First, we compare the prevalence rate of the bias in **Experiment 1**, where the task participants are not told—and hence have to learn—whether the bowman is a master or an apprentice in each session, and **Experiment 2**, where the task participants are told the nature of the bowman before each session begins, so the cognitive dimension is absent from the task by design (Figure 2). [The task instructions used for Experiment 2 stress that the "*no deception rule*" is in effect in the experiment, to ensure that the task participants believe the information provided to them about the bowman type (see the multiple-choice questionnaire in Supplementary Information, end of Section 6.2 in the present draft).] Second, we run **Experiment 3**, which augments the design of Experiment 1 by asking the task participants at the end of each session whether the bowman in the session is a master or an apprentice (Figure 3). A correct answer yields $10, and an incorrect answer

[23] This is for risk-neutral participants. Loss-averse participants skip in sessions with a master bowman when they deem betting too risky. See the Internet Appendix (Section 5.2.1 of this draft) for the formalization of loss aversion in the current paradigm.

results in a loss of $10. This rule is well emphasized in the task instructions to ensure that the task participants are provided with the right incentives. We compare the accuracy of the task participants that feature the picking pennies bias (henceforth, the "penny-pickers") to that of the other task participants.

The data from Experiments 1-3 also allow us to test the probability matching and risk seeking explanations for the picking pennies bias against CbD hypothesis. For the former explanations predict the pattern of betting early on in each session whereas CbD hypothesis predicts the opposite—since by nature, craving-induced betting is only observed after a series of good outcomes.

To study the thrill of gambling explanation for the bias, we run **Experiment 4**, which augments the design of Experiment 1 by giving task participants the option to bind their decisions ("tie their hands") in each trial of each session by committing to either bet in all remaining trials of the session or skip in all remaining trials of the session (Figure 4). The rule is that once participants exercise the option, they are not allowed to change their mind thereafter, i.e., option use works like a commitment device. Assessing to what extent task participants use the commitment device, and comparing the prevalence rate of the picking pennies bias with the device (Experiment 4) and without (Experiments 1 & 3), constitutes a test of the thrill of gambling and CbD hypotheses against one another. For CbD hypothesis predicts that task participants use the commitment device and consequently there should be a reduced prevalence of the picking pennies bias in Experiment 4 relative to Experiments 1 & 3. The thrill of gambling hypothesis predicts that the commitment device is not used and there should be no change in the picking pennies bias across these experiments.

To avert "experimental demand effects" whereby participants in Experiment 4 may use the option feature merely because it is presented to them, the participants are told in the task instructions for Experiment 4 that using the option to bet/skip is not necessarily desirable, and that it is fine to choose to ignore that feature altogether. Furthermore, to avert that participants may use the option buttons merely to speed up the pace of the task, the instructions stress that using the option does *not* accelerate the pace of the task in any way. To prove this point, a demo of the task is shown to the participants at the end of the instruction phase.[24]

[24] Averting participant boredom is our main motivation for using the learning version of the task (the one used in Experiments 1 and 3) rather than the version in which no learning is involved (the one used in Experiment 2). With the latter, the optimal strategy would be completely obvious (use the 'skip in all' option at the first trial in a session with an apprentice) and participants would likely deviate from it merely as a result of feeling bored. It is also likely that some task participants would start imagining scenarios to

Last, to assess the importance of limited liability in the emergence of the picking pennies bias (the fact that in case of negative earnings from the task, participant payoff is the show-up reward of $5—the worst payoff that a participant can normally get as per the lab rules), we run **Experiment 5** which replicates the conditions of the original experiment except for that the foregoing payment rule is augmented with the following package: 1- Each participant comes to an office (not the lab) and receives a $100 monetary endowment two weeks before the experimental session. 2- The participants are told they are not to bring the endowment on the session day. 3- In case of negative earnings from the task, the participants have to pay off their debt to the experimenter up to $95. 4- The debt is to be paid within a week after the session date (by cash or banking transfer).

Features 3-4 imply that the participants in Experiment 5 are exposed to significant losses relative to their standard of living. Feature 4 makes it clear to the participants that not paying off their debt is not an option.[25] Comparing the prevalence rate of the picking pennies bias when participants are exposed to significant losses (Experiment 5) and when they are not (Experiments 1 & 3), provides information about the importance of the liability factor. (Finding a reduced prevalence rate of the bias in Experiment 5 would suggest that limited liability is a key factor here, while finding no significant decrease would suggest the opposite.)

To make sure that Features 3-4 do not conflict with *UNSW Human Research Ethics Committee* rules, we introduce the money endowment (Feature 1).[26] Feature 2 is to minimize the "house money effect" (Thaler and Johnson, 1990) and induce in the participants the feeling of playing with their own money. Not only the endowment is received several weeks before the session day (Feature 1); it is also not visible during the session since participants do not bring the cash (Feature 2). The idea is to make the endowment as intangible as possible

make the task more meaningful (e.g., "the task cannot be that simple, there is something the experimenter is not telling me").

[25] Participants are told that in case of misconduct, they will not be allowed to participate in any experiments in the lab in the future, and their main teacher will be informed of the misconduct. All of the participants who end up with negative earnings pay off their debt except for two participants whose data are therefore discarded.

[26] Myagkov and Plott (1997), Laury and Holt (2004), and Etchart-Vincent and l'Haridon (2011) used a similar feature to implement real losses in the lab. Our choice of the endowment amount of $100 corresponds to the maximal level achievable given budgetary constraints. Our motivation is to ensure that the amount is large enough to generate significant downside risk for the participants. For example, if the endowment was $50, the maximum possible loss from the task (to not infringe UNSW ethics rules) would be "only" $45. Setting it at $100 means that participants can lose up to $95 from the task. For the average undergraduate student, the prospect of losing $95 is significant relative to their conditions of living.

on the session day. This aspect of the design is inspired to us by Prelec and Simester (2001), which documented that the less tangible a payment is, the more people are willing to pay, which points to the existence of some kind of "money blindness" in people when the money is intangible (i.e., when it is not visible, when it was received a long time ago, etc.). In the same logic (making the endowment as intangible as possible on the session day), the participants are told in the task instructions that they will have to pay off the amount corresponding to their losses up to \$95; the endowment is not mentioned there (see Section 6.5).

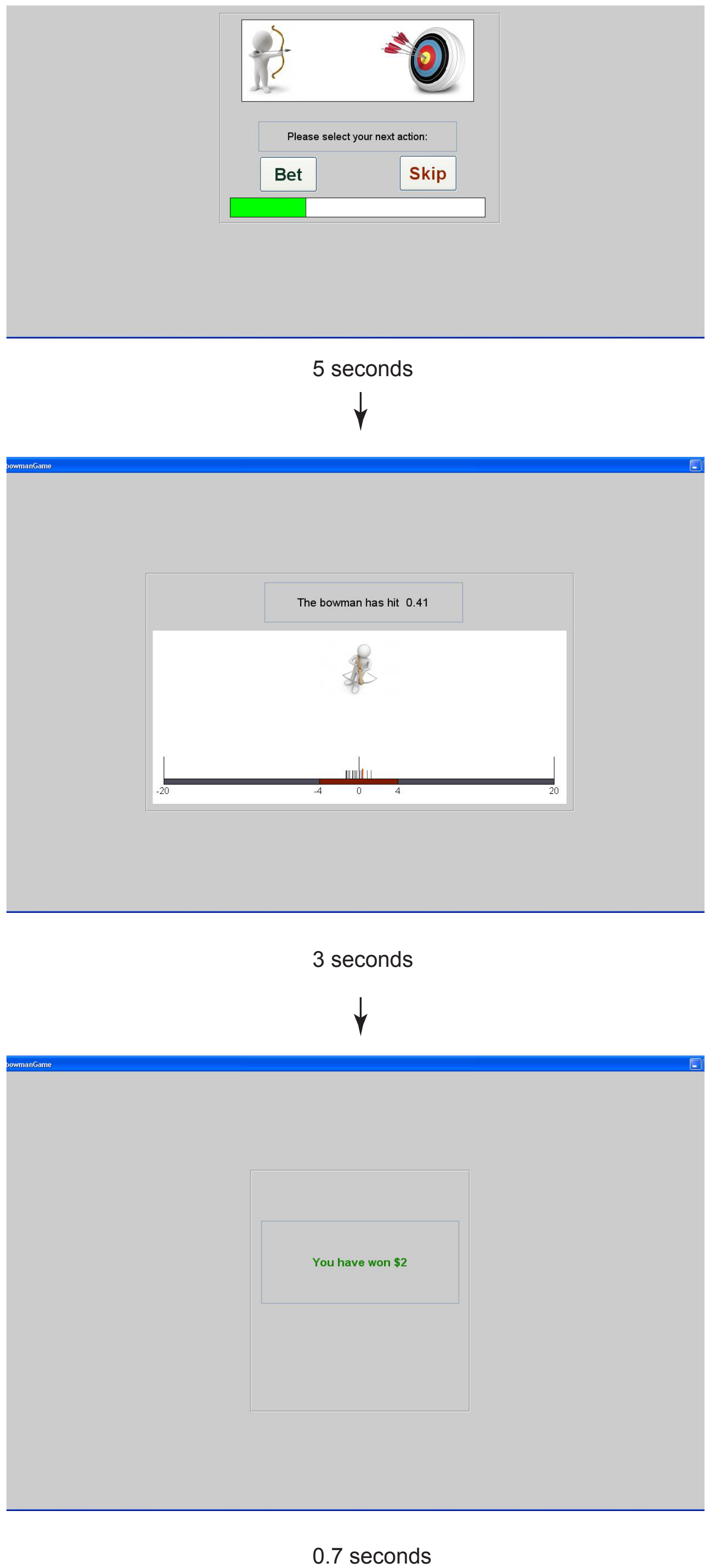

Figure 1: **Timeline of a trial of the task used in Experiment 1.**

Figure 2: **User interface of the task used in Experiment 2.** In Experiment 2, the nature of the bowman is revealed to the task participants before each session begins. Apart from that feature, the task is the same as the one used in Experiment 1, see Figure 1.

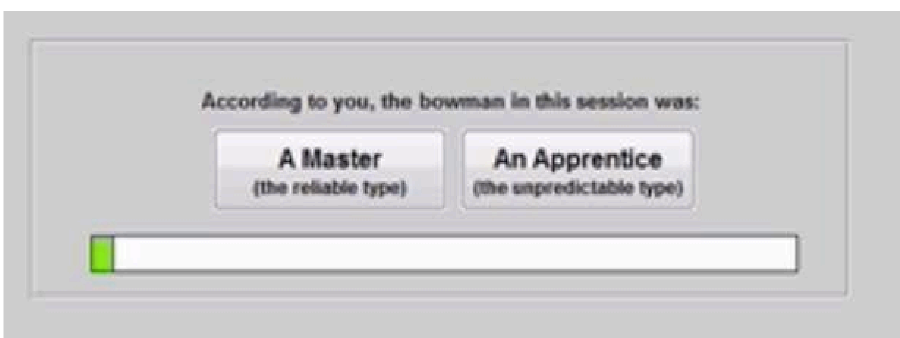

Figure 3: **User interface of the task used in Experiment 3.** The task used in Experiment 3 is an augmented version of the task used in Experiment 1 (see Figure 1) in which the task participants are further asked to report their belief about the bowman type at the end of each session.

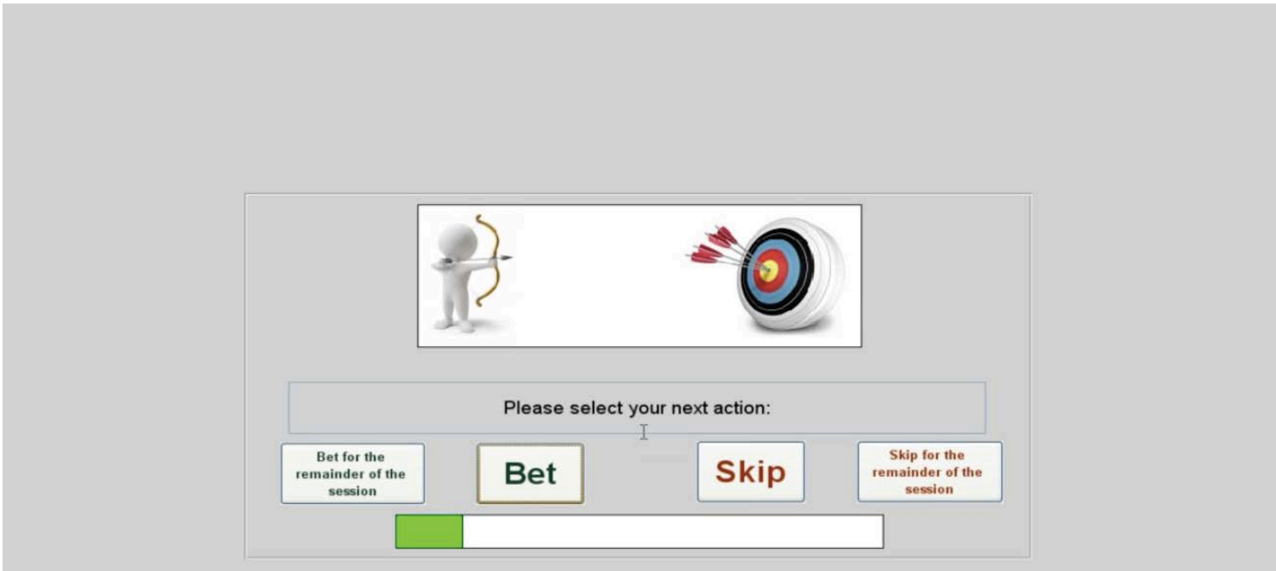

Figure 4: **User interface of the task used in Experiment 4.** In the task used in Experiment 4, in each trial, the task participants can exercise the option to bet/skip for all the remaining trials of the session by clicking on the "bet for the remainder of the session"/"skip for the remainder of the session" buttons situated next to the regular bet/skip buttons. Apart from that feature, the task is the same as the one used in Experiment 1, see Figure 1.

2.2 Main Findings

We choose the sample size in each of the five experiments to maximize power under budgetary constraints for all the main statistical tests reported below. For each test, a priori power calculations show that our chosen sample size gives us a minimum of 97% power to detect a medium effect size ($d = 0.5$) at the $\alpha = .05$ level.

2.2.1 Picking pennies bias

In **Experiment 1** (N= 124), optimal (Bayesian) behavior in each session consists of betting if and only if the evidence that the bowman is a master is above a given threshold (which increases with the degree of loss/risk aversion of the agent). Compared to the behavior of boundedly rational agents, the main Bayesian signatures in this setting consist of systematically skipping in the first trials of each session (boundedly rational agents tend to bet early), and betting despite losing in sessions with a master bowman if the evidence that the bowman is a master is sufficiently large (boundedly rational agents tend to systematically skip after a loss). The formal description of the Bayesian model is provided in the Internet Appendix (Section 5.2.1 in this draft). For simulations of the behaviors of the boundedly rational and Bayesian agents in the context of Experiment 1, see Payzan-LeNestour (2018).

The picking pennies bias manifests itself in a task participant when the participant bets after observing a "black swan," here defined as a shot falling more than 7 meters away from the target. The probability of seeing a shot of this kind is essentially null with any kind of master bowmen. (In the $56,560$ trials with a master across all participants and sessions, a shot more than 7 meters from target never occurs.) Therefore, seeing tail events of this kind makes it clear to the Bayesian model that the bowman is an apprentice, and hence the model systematically skips thereafter (since EV from betting when the bowman is an apprentice is known to be highly negative by design).

Note that from a purely statistical perspective, "the tails" start at 3σ, where σ denotes the standard deviation of the shots in a session with a master. That is, the tails start at 6 when $\sigma = 2$ (the maximal level of standard deviation possibly encountered in the task). Given this, it may seem natural to use a threshold value of 6 in our definition of a black swan. We set the threshold value to 7 instead to account for participant imprecision regarding where the tails of a given distribution start. We also refrain from counting single betting decisions as instances of penny picking to account for participant potential mistake or "trembling". Penny picking is thus defined as betting *at least twice* after observing a black swan in a session. (Importantly, all the main results reported next, as well as the regression results reported in Section 2.2.3, are robust to including single betting decisions in the count.)

The picking pennies bias is observed in seventy-four participants according to this measure of the bias (Table 2). The majority of the penny-pickers pick pennies in more than two sessions (Table 1). Penny picking thus appears to be a consistent behavioral pattern both across and within participants.

The penny-pickers do not see more black swans than the other task participants do (see Table A2 in the Internet Appendix and Section 2.2.3). The majority of them does not start picking pennies immediately after the occurrence of the black swan; rather, the penny-pickers typically skip in the aftermath of a black swan and bet later on in the session, as shown in Figure 5 (p.25). As a group, they fare poorly in the task, with average earnings around \$29 (vs. the other participants earn \$120 on average), and an earning standard deviation of \$120 (vs. \$58 for the other task participants), implying poor performance on both the mean and variance dimensions.

2.2.2 Potential explanations

Miswanting/faulty cognition The penny-pickers look like otherwise Bayesian agents with the picking pennies anomaly. Like the Bayesian model, they typically choose to skip in the first trials of each session (Figure 6, p.27, top graph). However, the Bayesian model always skips after a black swan, as stressed above. Could the picking pennies bias reflect impaired Bayesian learning caused by misunderstanding the nature of the tails of the shot distributions (and how they vary according to bowman type)? Penny-pickers could be deluded that an apprentice bowman is a master even after seeing a shot falling more than 7 meters away from the target, if they overlook that shots so far in the tails are a signature of the apprentice type. However this is unlikely to be among the root causes of the picking pennies bias in the experiment, inasmuch as when increasing the threshold used to define a black swan to 8 and 9 meters in two separate analyses, the percentage of penny-pickers remains high (53.2% and 52.4% respectively, see Table 2). The regression results documented in Section 2.2.3 confirm that the distance of the black swan to the target is not a predictor of penny picking.

Another potential source of impaired Bayesian learning is participant oversight (overlooking or forgetting the previous occurrence of a black swan event). However this is unlikely to be among the root causes of the penny picking bias in the experiment inasmuch as the percentage of penny-pickers remains qualitatively unchanged when we reassess the fraction of penny-pickers using only the subsample of black swan events associated with a $40 loss. We reason that those should be quite salient and memorable, given the magnitude of the loss outcome relative to the gain outcome ($40 vs $2).

To control for the two foregoing factors (participant confusion and oversight), we restrict the measure of the picking pennies bias to memorable black swan events (as just defined), and use a threshold value of 9 meters to identify black swan events. Even under this strict criterion to measure the prevalence of the picking pennies bias, the percentage of penny-pickers in Experiment 1 remains high at 37.1% (Table 1).

Table 1: **Prevalence of the picking pennies bias in each experiment.** The table shows the percentage of penny-pickers among the task participants and the percentage of penny-pickers that pick pennies in at least 2, 3, and 4 sessions, for each experiment. The mean number of sessions in which the penny-pickers pick pennies is also reported (as well as the standard deviation SD) for each experiment. For all experiments except for Experiment 2, the numbers reported in the table are those obtained with the strict criterion for penny picking proposed in the main text, i.e. penny picking is restricted to the instances when participants bet after a shot that fell at least 9 meters away from the target and lose $40 as a consequence ("memorable black swan events"). For Experiment 2, penny picking by definition encompasses all instances of betting in a session with an apprentice. This explains the higher percentage of penny-pickers recorded for Experiment 2. When using the more relaxed criterion mentioned in the main text to measure penny picking in the other experiments (betting after a shot that fell at least 7 meters away from target), the percentage of penny-pickers recorded for Experiment 2 is not higher than that for Experiment 1 (see Table 2 and Table A1 of the Internet Appendix, which is the tantamount of this table when using the more relaxed criterion).

		Penny picking frequency				
	Percentage of	Pick pennies in at least (%):			Mean	SD
	penny-pickers	2 sessions	3 sessions	4 sessions		
Experiment 1	37.1	63.0	26.1	8.7	1.8	0.9
Experiment 2	52.3	91.3	78.3	47.8	3.4	1.9
Experiment 3	36.8	78.9	57.9	42.1	2.9	1.8
Experiment 4	18.3	45.5	27.3	18.2	1.7	1.2
Experiment 5	31.9	66.7	46.7	26.7	2.1	1.3

Table 2: **Percentage of penny-pickers in each experiment for different criteria used to measure penny picking.** The criteria vary in the threshold value used to define a black swan (distance from target: 7 meters; 8 meters; 9 meters), and in whether all the instances of penny picking are included in the analysis ("All black swan events"), or only the instances when participants lose $40 as a consequence of betting ("Only memorable black swan events").

	All black swan events			Only memorable events		
	7m	8m	9m	7m	8m	9m
Experiment 1	59.7	53.2	52.4	43.5	37.1	37.1
Experiment 2	52.3	52.3	52.3	52.3	52.3	52.3
Experiment 3	44.6	44.6	44.6	38.7	36.8	36.8
Experiment 4	33.3	30.0	30.0	21.7	18.3	18.3
Experiment 5	51.1	48.9	48.9	34.0	31.9	31.9

A third possible source of impaired Bayesian learning in the experiment is the "*gambler's fallacy*" (for recent evidence of it, see Chen et al. (2016)): immediately after seeing a black swan, penny-pickers would mistakenly gather that "the disaster event has happened already, now a near miss is due so I shall bet." However, if the gambler's fallacy was among the root causes of the picking pennies bias, penny-pickers would choose to bet immediately after the occurrence of a black swan, and to skip after a prolonged series of near misses (mistakenly thinking that a tail event is then "due"). This is not the case. As stressed above, the penny-pickers typically behave like the Bayesian model except for the picking pennies anomaly, and only a minority of them (Type 1 in Figure 5) behaves in a way consistent with the gambler's fallacy. The regression results documented in Table 4 of Section 2.2.3 reinforce the conclusion that the gambler's fallacy is unlikely to underlie the picking pennies bias for the majority of the penny-pickers.[27]

[27]Confirming this collection of findings, the base Bayesian model fits the penny-pickers' behavior better than the model variant that incorporates the gambler's fallacy bias does (computational details can be found in the Internet Appendix—Sections 5.2.2 and 5.2.4 in this draft).

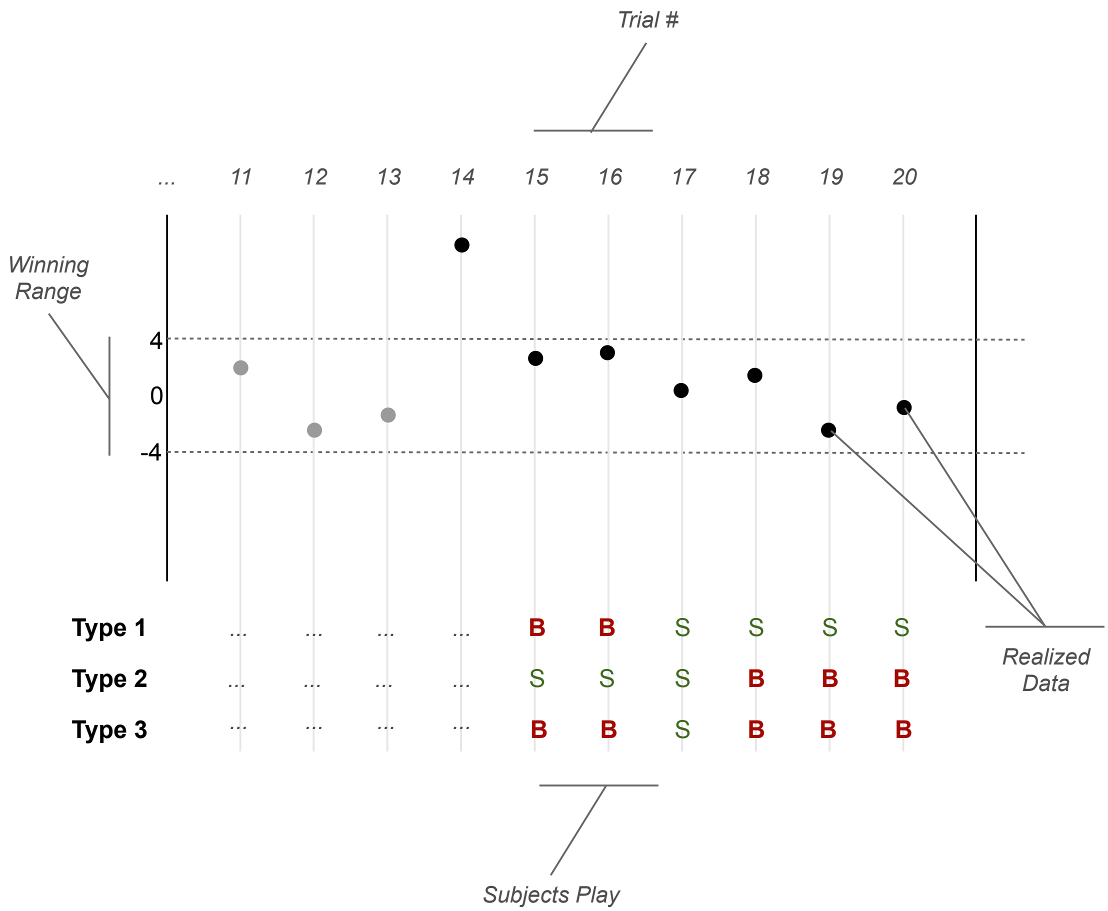

Figure 5: **Three types of penny-pickers, described using an exemplar session.** In this example, a "black swan" (as defined in the main text) occurs in trial 14 of the session, and behavior is described from that trial on. The first type of penny-picker bets immediately after seeing the black swan and skips after a few trials. The second type skips immediately after the black swan and returns to betting after a few trials. The third type bets on most of the trials following the occurrence of the black swan. The percentage of penny-pickers of Type 1, 2, and 3, is 29.4%, 60.9%, and 9.7%.

Taken together, the foregoing findings suggest that impaired Bayesian learning is not a major source of faulty cognition in the experiment. To investigate the possibility of other (non Bayesian) sources of faulty cognition, we study the behavior of the participants in **Experiment 2** (N=44; same cohort as in Experiment 1). More than half of them chooses to bet in at least one of the sessions with an apprentice bowman (Tables 1-2). We cannot reject the null hypothesis that the prevalence rate of the picking pennies bias is the same in Experiment 1 and Experiment 2 (χ^2 test for proportions: $\chi^2(1) = 2.49, 95\% \, CI = [-.33, .03], p = .11, V = .12$).

Thus, the prevalence rate of the picking pennies bias is not higher in Experiment 1 (where the cognitive factor is present) than in Experiment 2 (where it is absent). This suggests that faulty cognition—from all sources—is not among the root causes of the picking pennies bias in the current experimental setting. However, it could be that some of the penny-pickers in Experiment 2 question the information provided to them about the bowman type; i.e., after seeing a series of $2 outcomes in a session with an apprentice, some might imagine that the experimenter is deceiving them and the bowman is actually a master (although the no deception rule is well emphasized in the task instructions, as stressed above).

To account for this potential confound and further investigate the importance of faulty cognition in the emergence of the picking pennies bias, we study participant behavior in **Experiment 3** (N=52; same cohort as in the previous experiments). Participants behave like those of Experiment 1 for the prevalence rate of the picking pennies bias (Tables 1-2), along with other several key dimensions including the first time the participants start to bet in each session, betting rates, and earnings. The main finding is that there is no difference in accuracy between the penny-pickers and the other task participants (penny-pickers: 77.3%; others: 88.8%; $\beta(se) = -4.27(2.78), z = -1.53, p = .12$, more in Section 2.2.3).

Probability matching and risk seeking The penny-pickers typically skip in the first trials of each session, like the other participants; see the top graph of Figure 6 and the regression results documented in Section 2.2.3, Table 3. This suggests that neither probability matching nor risk seeking preferences underlie the picking pennies bias. In probability matching—a widespread behavioral tendency thought to be a product of evolution (Brennan and Lo, 2011), the frequency of choice of a given action matches the probability of success with that action (e.g., betting 80% of the time when the estimated probability of a winning bet is 0.8). Figure 6 compares the behavior of the actual penny-pickers to the one of the probability matching model in simulated runs of the task. The model predicts frequent

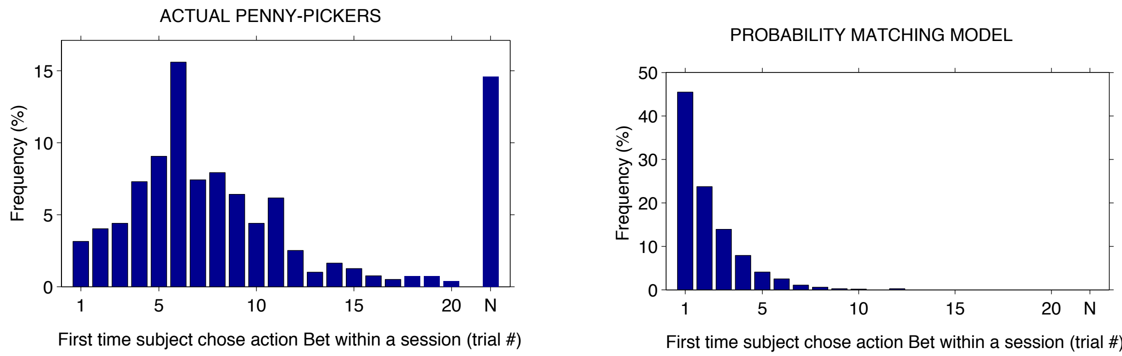

Figure 6: **Distribution of the first time the actual penny-pickers bet in the task (left graph) versus the first time the probability matching model bets in simulated runs of the task (right graph).** Left graph: the distribution is derived across all penny-pickers and sessions. Right graph: the distribution is derived across 100 simulated runs with the probability matching model. In each simulated run, the probability matching model bets 80% of the time (which roughly "matches" the probability of a winning bet in a session with an apprentice—see Internet Appendix 5.2.1). N: sessions in which the penny-pickers (left graph) and the probability matching model (right graph) choose to skip in all trials of the session. This behavior occurs in approximately 15% of the sessions with the penny-pickers but never occurs with the probability matching model.

betting, including in the first trials of each session, at odds with actual behavior. Likewise, risk-seeking agents start betting early in each session of Experiment 2.[28] This is at odds with the finding that in the large majority (93%) of the cases, betting never starts before the third trial of the sessions in Experiment 2.

This, along with the finding that sixty-six percent of the participants in Experiment 2 choose to skip when the standard deviation of the shots with a master bowman is above 1—consistent with the evidence of loss aversion previously documented for Experiment 1 (Payzan-LeNestour, 2018), suggests that the penny-pickers are not risk seekers in the way they approach the task. However, some of them could episodically increase their risk-taking after incurring losses. This may occur if they feel "in the red" (if some participants forget that their current net accumulated outcomes do *not* represent their current wealth level by

[28]This is also true for Experiments 1 and 3, except for participants—if any—that are prone to the so-called *"disjunction effect"* (for example, Tversky and Shafir (1992), Shafir and Tversky (1992), and Shafir (1994)). In Experiments 1 and 3, risk-seeking agents featuring the disjunction effect choose to bet both when they know that the bowman is an apprentice and when they know that the bowman is a master; however, they choose to skip when they do not know yet the type of the bowman (i.e., in the early stages of each session). However, the disjunction effect is ruled out by design in Experiment 2 (since there is no uncertainty about the bowman type from the beginning of each session).

design, see Section 2.1), or due to a shift in the reference point they use to encode outcomes (e.g., Kahneman and Tversky (1979) and Barkan and Busemeyer (1998)), or as a result of "emotional homeostasis" (participants seeking to suppress the negative emotion caused by losing through subsequent winning; for example, Andrade and Iyer (2009)).

The data suggest that neither of these three phenomena underlies the picking pennies bias here. First, the current net accumulated outcomes of the penny-pickers at the onset of picking pennies episodes are positive on average (centered around zero: one-sample t-test, $t(100) = -.83, p = .40, 95\%\, CI = [-18.83, 7.70], D = -.08$). Second, penny picking is highly prevalent in Experiment 2 despite the fact that it does *not* usually start in the aftermath of a loss by design. Third, and perhaps most importantly, the regression results reported in Section 2.2.3 show that the occurrence of the picking pennies bias is *not* more likely after bad outcomes (if anything it is less likely).

Thrill of gambling The majority of the participants in **Experiment 4** (48 subjects out of N=60; same cohort as in the previous experiments) use the option to bind their decisions, and the option to skip is predominantly used. Specifically, 26 subjects exclusively use the option to skip in all remaining trials of the session (henceforth, "skip-in-all") while only 2 participants exclusively use "bet-in-all." Among the 20 participants who use both options, skip-in-all is used 4.85 times on average (median, 5 times; mode, 3 times), whereas bet-in-all is used only 2.55 times on average (median, 2; mode, 1). Such asymmetry in option use rules out the possibility that participants use the options simply because they find it easier to commit to a given course of action rather than having to deliberate on each trial. For if they used the options chiefly for that reason, the frequency of choosing bet in all would not markedly differ from that for skip in all. The second key finding is that only 11 participants pick pennies in Experiment 4 (Tables 1-2). The proportion of penny-pickers is significantly smaller in Experiment 4 than that in Experiment 1 ($\chi^2(1) = 5.80, 95\%\, CI = [.06, 1.00], p = .007, V = .18$). These findings are at odds with the thrill of gambling hypothesis and in line with the idea that several participants use the option to skip as a commitment device to resist their craving urges, and the picking pennies bias is significantly reduced as a consequence.

Limited liability Could the high prevalence rate of the picking pennies bias in Experiments 1-3 be partly due to the fact that the task participants are not exposed to real monetary losses in case of bad performance in the task? This seems unlikely inasmuch as in **Experiment 5** ($N = 47$; same cohort as in the previous experiments), where the task participants are at risk of significant losses, the picking pennies bias prevails in 31.9% of the participants. The proportion of penny-pickers is similar to that in Experiments 1 & 3 ($\chi^2(1) = .21, 95\% \, CI = [-.11, .21]$, $p = .64, V = .03$).[29]

The finding that the prevalence rate of the picking pennies bias is unchanged when the task participants are at risk of significant losses (in Experiment 5) relative to when they are not (in the previous experiments), suggests that limited liability is not among the root causes of the picking pennies bias here. However the message is not that limited liability is not a significant factor in the field. On the contrary, we conjecture that limited liability, while not causing money craving, worsens its behavioral consequences (more in the Discussion).

2.2.3 Regression results

We run a logistic regression predicting the picking pennies bias in all five experiments (Table 3). The independent variables include dummy codes for Experiments 1-5, the total number of black swans seen throughout the experiment, and whether the participant is more likely to start betting early, late, or never in a session. We run three models, each using a different threshold value to define a black swan event (7 meters, 8 meters, and 9 meters from target). This is to account for participant imprecision as discussed in Section 2.2.2, "Miswanting/faulty cognition."

It appears that the participants are less likely to pick pennies in Experiment 4 compared to Experiment 1, confirming the findings documented in Section 2.2.2. There is no effect of the total number of black swans seen, which confirms that the penny-pickers see the same number of black swans as the other participants do on average. The penny-pickers are not more likely to bet early, suggesting they are not more risk seekers than the other task participants.

In a complementary logistic regression including the proportion of sessions in which participants correctly guess the bowman type in Experiments 3 and 5 ("accuracy"), we find no effect of accuracy except under the 7 meters criterion to measure penny picking (Table A2 in the Internet Appendix). This finding suggests that the penny-pickers as identified by the strict criterion used in the above analyses (9 meters threshold) are not more cognitively impaired than the other participants as a group. That is, it seems the strict criterion works at isolating participants who pick pennies for non cognitive reasons, whereas the more

[29] Participant behavior is also similar to that in the other experiments along several other dimensions, including the first time the participants start to bet in each session, betting rates, and earnings. These descriptive statistics are not shown here to conserve space but they are available on request.

Table 3: **Logistic regression predicting the picking pennies bias.** The model uses as dependent variable participant type (0: Non penny-picker; 1: Penny-picker). The independent variables are predictors for Experiment [dummy to compare Experiment 1 (the reference) to Experiments 2-5], the (z-scored) total number of black swans seen by the participant ("Black swan number"), when the first bet decision most commonly occurs in the session [dummy coded "Early" = first 10 trials (reference), and "Late" = last 10 trials], and whether betting never occurs ("Never"). Here penny picking means betting after a memorable black swan as defined in the main text (the results are qualitatively unchanged when considering all black swan events). We run three regressions, each using a different threshold value to define a black swan event, as discussed in the main text (7 meters, 8 meters, and 9 meters from target). Due to small group sizes (e.g. few penny-pickers never bet), we use penalized log-likelihood estimation (Firth, 1993). * $<$ .10, ** $<$ .05, *** $<$ .01.

	7m	8m	9m
Intercept	0.357 (0.479)	0.361 (0.474)	0.333 (0.500)
Experiment 2	-0.192 (0.469)	0.216 (0.476)	-0.003 (0.474)
Experiment 3	0.195 (0.381)	0.448 (0.386)	0.423 (0.384)
Experiment 4	-0.864 (0.379)**	-0.758 (0.394)*	-0.833 (0.395)**
Experiment 5	0.036 (0.407)	0.300 (0.413)	0.239 (0.406)
Black swan number	-0.023 (0.036)	-0.058 (0.042)	-0.059 (0.048)
First bet (Late)	-0.955 (0.492)*	-0.707 (0.493)	-0.710 (0.494)
First bet (Never)	-3.067 (0.62)***	-2.907 (0.564)***	-2.857 (0.564)***
McFadden R^2	0.18	0.16	0.16
N	327	327	327

relaxed criterion (7 meters) includes participants for whom penny picking partly reflects faulty cognition, as conjectured above (see Section 2.2.2, "Miswanting/faulty cognition").

To further study the factors underlying penny picking, we run a logistic mixed effects model predicting betting in sessions with an apprentice after a black swan is seen (Table 4). The independent variables are the foregoing Experiment dummies, time from black swan occurrence ("First bet"), the decision in the previous trial, the current net accumulated outcomes ("wealth"), the mean outcome from the last 5 trials, session number, and how far in the tail the black swan is. We also run a complementary model using data from all participants and all sessions, to compare the behavior of the penny-pickers to that of the other task participants (Table 5). That model augments the previous mixed effects model with variables for bowman type, participant type (penny-pickers vs. others), and interaction terms for penny picking and the previous decision, wealth, the last 5 outcomes encountered, and session number. (The stepwise process of adding interaction terms can be found in Table A5 of the Internet Appendix.)

Table 4: **Logistic mixed effects model predicting penny picking.** The model uses as dependent variable betting after a black swan event (0: Skip; 1: Bet) in the penny-pickers, for all five experiments. The independent variables are dummy coded variables for experiment, to compare Experiment 1 (reference) to Experiments 2-5, "First bet" (0: penny picking starts in the first 2 trials after black swan occurrence; 1: it starts in the third trial or after), the nature of the previous decision (0: Skip, 1: Bet), the current net accumulated outcomes ("wealth"), the mean outcome from the previous 5 trials ("last 5 outcomes"; the results are qualitatively unchanged when using the previous outcome, last 3 outcomes, and last 10 outcomes instead), session number, and for the 7 meters version of the model, the distance of the black swan from target (0: between 7 and 8 meters; 1: beyond 8 meters). The criterion to measure penny picking is betting after a memorable black swan as defined in the main text (the results are qualitatively unchanged when considering all types of black swan events). We run three regressions, each using a different threshold value to define a black swan event, as discussed in the main text (7 meters, 8 meters, and 9 meters from target). As the split for 8 meters and 9 meters is identical, the results are combined into one column. Wealth, mean outcome for last 5 trials, and session number are z-scored to standardize betas. By-participant intercepts were used to control for subject-wise error rates. Due to small group sizes for some participants, fixed effects are initialized with Cauchy priors (Gelman et al., 2008). We assess conditional R2 following Nakagawa and Schielzeth (2013).

	7m	8-9m
Intercept	-1.278 (0.168)***	-1.029 (0.179)***
Experiment 2	-0.364 (0.327)	-0.412 (0.328)
Experiment 3	0.218 (0.218)	0.148 (0.225)
Experiment 4	0.563 (0.276)**	0.605 (0.296)**
Experiment 5	-0.145 (0.241)	-0.195 (0.252)
First bet (Late)	-0.074 (0.116)	-0.153 (0.125)
Previous decision (bet)	1.499 (0.098)***	1.346 (0.106)***
Wealth	0.066 (0.066)	0.041 (0.071)
Last 5 outcomes	0.178 (0.049)***	0.200 (0.053)***
Session number	-0.245 (0.051)***	-0.257 (0.055)***
Black swan distance (> 8m)	0.176 (0.144)	
Conditional R^2	0.27	0.26
N	2969	2397

It appears that betting at time $t-1$ increases the chance of betting at time t (Table

Table 5: **Logistic mixed effects model predicting betting for all participants in all trials.** The independent variables include dummy coded variables for experiment [dummy to compare Experiment 1 (the reference) to Experiments 2-5], bowman type (0: Master; 1: Apprentice), participant type (0: Non penny-picker, 1: Penny-picker), the previous decision, session number, "wealth" and "last 5 outcomes" (see Table 4 for the definitions), and interaction terms between penny picking and previous decision, wealth, last 5 outcomes, and session number. By-participant intercepts were used to control for subject-wise error rates. Due to small group sizes for some participants, fixed effects are initialized with Cauchy priors (Gelman et al., 2008). We assess conditional R2 following Nakagawa and Schielzeth (2013).

	7m	8-9m
Intercept	-1.804 (0.049)***	-1.734 (0.048)***
Experiment 2	0.151 (0.081)*	0.093 (0.083)
Experiment 3	0.092 (0.073)	0.056 (0.075)
Experiment 4	-0.055 (0.070)	-0.077 (0.072)
Experiment 5	-0.135 (0.076)*	-0.169 (0.078)**
Bowman (apprentice)	-1.814 (0.024)***	-1.820 (0.024)***
Penny picking (PP)	1.304 (0.057)***	1.318 (0.060)***
Previous decision (bet)	3.921 (0.031)***	3.892 (0.030)***
Wealth	0.080 (0.033)**	0.091 (0.031)***
Last 5 outcomes	0.322 (0.020)***	0.300 (0.018)***
Session number	-0.191 (0.021)***	-0.211 (0.020)***
PP × Previous decision	-1.076 (0.044)***	-1.109 (0.044)***
PP × Wealth	-0.004 (0.039)	-0.005 (0.038)
PP × Last 5 outcomes	-0.266 (0.022)***	-0.254 (0.021)***
PP × Session number	0.016 (0.259)	0.062 (0.025)**
Conditional R^2	0.65	0.65
N	99640	99640

4); however, the effect is not specific to the penny-pickers and is actually stronger in the other task participants (Table 5). These findings suggest that although "choice stickiness" [the tendency to persevere in a given course of action; e.g., Feltovich (2000)] might influence participant behavior, it is unlikely to be a major factor underlying penny picking.

The regression results documented in Table 4 also confirm that the gambler's fallacy is unlikely to be among the root causes of the picking pennies bias. Indeed, if it was, the coefficient of the variable "First bet" would be significantly negative since an agent susceptible to the gambler's fallacy bets immediately after the occurrence of the black swan and is less likely to bet as time from black swan occurrence passes. As shown above, this behavioral pattern is only observed in a minority of the penny-pickers (Figure 5, p.25).

The regression results further add to the evidence documented in Section 2.2.2 that the average penny-picker does not pick pennies because they "feel in the red". Table 4 indeed shows no effect of wealth on penny picking. Table 5 documents an overall *positive* effect of wealth, with no interaction effect, which suggests that on average participants choose to bet when they have *higher* net accumulated outcomes, and the effect prevails in the penny-pickers and the other participants alike.

The idea of increased risk-taking in the aftermath of losses (due to a change in reference point or emotional homeostasis, as proposed above) is likewise falsified: betting appears to be more likely if the last few trials had a *positive* outcome (Table 4). This finding is however in line with CbD hypothesis according to which prior winnings make the decision maker want to bet more.[30]

Last, we run an augmented version of our mixed effects model with response time added and modelled separately on the sessions with an apprentice bowman vs. a master (see Table A4 in the Internet Appendix). We find higher response times for penny picking decisions, i.e., when the participant chooses to bet after a black swan is seen. In contrast, betting decisions are made more quickly than decisions to skip in sessions with a master bowman. These findings are consistent with the idea that penny-pickers hesitate in the trials when they pick pennies as they know that their behavior is sub-optimal but they cannot help behaving that way.[31]

2.2.4 Modelling of money craving

The collection of findings thus suggests that neither faulty cognition, probability matching, risk seeking, the thrill of gambling, limited liability, or all the other explanations considered above, are among the root causes of the picking pennies bias here. The findings are however consistent with CbD hypothesis—the idea that task participants are tempted to bet after seeing a series of good outcomes. A parsimonious way to formalize this idea in the context of

[30] Table 4 further shows that the penny-pickers are more likely to bet in Experiment 4 than in Experiment 1, perhaps not surprisingly since the penny-pickers in Experiment 4 pick pennies despite the presence of the commitment device, whereas the group of penny-pickers in Experiment 1 includes "mild cases" who may have used the commitment device if offered the opportunity. Therefore, if anything one would expect the group of the penny-pickers in Experiment 4 to be more irrational than those in Experiment 1.

[31] The findings cannot be attributed to a learning effect (higher response time possibly reflecting learning) inasmuch as they still obtain when we restrict the analysis to the data from Experiment 2, in which learning is absent by design.

the current experimental paradigm consists of modifying the definition of the utility function in the base behavioral model: in the "craving" variant of the model, the \$2 outcome is encoded as $\$2 + DA$, with $DA \geq 0$. DA (which stands for "dopamine") captures the craving phenomenon described in Section 1: mesolimbic sensitization "inflates" reward value encoded by the system—metaphorically, it makes the agent "greedy".[32] This model variant fits the penny-pickers' behavior significantly better than the base model does (computational details are provided in the Internet Appendix, Sections 5.2.3 and 5.2.4 in this draft).

3 Cheap Call Selling Anomaly

3.1 Replication of well-established findings

The food craving phenomenon—an intense desire for specific foods—appears to be a fairly common issue in people. The foregoing provides laboratory evidence that the same may well be true for money. Could money craving lead investors to knowingly engage in EV<0, SKEW<0 trades? A natural place to test the idea is the option market (for the reasons explained in the Introduction). We thus use all options in the Optionmetrics database from 1996 to June 2019. The sample for a given day contains all traded options with a non-zero bid price, a bid-ask spread between 0 and all 25%,[33] and a maturity less than 60 days.[34] For each option i in the sample, we compute both the standard return metric:

$$\text{MID}_{i,t} = \frac{\text{Mid Price}_{i,T} - \text{Mid Price}_{i,t}}{\text{Mid Price}_{i,t}}, \tag{1}$$

where Mid Price$_i$ denotes the mid-point price of option i (the average of the bid- and ask-price) and T is the close of the last day of trading ($T > t$), and the following "corrected" returns that incorporate transaction costs:

$$\text{SELL}_{i,t} = \frac{\text{Ask Price}_{i,T} - \text{Bid Price}_{i,t}}{\text{Bid Price}_{i,t}}, \tag{2}$$

$$\text{BUY}_{i,t} = \frac{\text{Bid Price}_{i,T} - \text{Ask Price}_{i,t}}{\text{Ask Price}_{i,t}}, \tag{3}$$

[32]We thank Pietro Ortoleva for suggesting this specification of the model to capture CbD hypothesis.

[33]Removing negative and wide bid-ask spreads is to account for potential data errors and unreasonable (non tradable) prices.

[34]We analyze options with a maturity above 60 days separately and all the results reported below also hold with that sample (those results are not shown to conserve space but they are available on request).

where Ask Price_i and Bid Price_i denote option i ask price and bid price respectively. To account for the possibility that the percent returns be driven by outliers, we also compute the dollar return metrics Mid $\text{Price}_{i,T}$ − Mid $\text{Price}_{i,t}$, Ask $\text{Price}_{i,T}$ − Ask $\text{Price}_{i,t}$, and Bid $\text{Price}_{i,T}$ − Bid $\text{Price}_{i,t}$, for respectively MID, SELL, and BUY dollar returns. One can think of the MID return as reflecting the balance of supply and demand prior to execution, and the SELL (resp. BUY) return as reflecting the price at which sellers (resp. buyers) are willing to trade the option. Overall there are $183,983,273$ option observations in the sample, $17,071,406$ unique options, and $9,723$ unique firms.

Table 6 shows descriptive statistics of returns from a long position in the option (MID and BUY returns) and from a short position (SELL returns), both for all options pooled together, and for the call options only.[35] For all options pooled together, the average and median MID returns are −8.76% and −68.43% respectively. The average MID dollar return is −\$0.97, and SKEW>0. These findings confirm the well-established knowledge that option buying (resp. selling) provides EV<0 (resp. EV>0) and SKEW>0 (resp. SKEW<0). See, e.g., Kumar (2008), Cremers et al. (2008b), Bakshi and Kapadia (2015), and Cremers et al. (2015). In our data, this remains true after incorporating transaction costs: BUY (resp. SELL) returns are significantly negative (resp. positive) with SKEW>0 (resp. SKEW<0).

3.2 Cheap call selling anomaly

The picture is very different when focusing on the call options (Table 6, right-hand columns): the average SELL returns of the cheap calls are negative (−23.81%) and negatively-skewed (SKEW =−13.32), consistent with CbD hypothesis. Strikingly, even without incorporating transaction costs, cheap call selling results in EV<0 (the average MID returns are indeed 7.41%, implying *negative* average returns from shorting these options).[36] The pattern of $EV < 0$ from cheap call selling also appears to be consistent over time (Figure 7), which suggests that the sellers are aware of it (more on this in Section 3.6).

Table 6 further suggests that cheap call selling is “Craving Prone” in the sense that it is particularly attractive to penny-pickers: Selling cheap calls indeed yields bigger pennies than selling calls above \$1 (median returns: 88% vs. only 44% from selling calls above \$1) and ends up profiting the seller more often (70.4% of the time vs. 40.2% of the time with

[35]The results for the put options are qualitatively similar to those for all options (not shown here to conserve space but available on request).

[36]Note that the average BUY returns of the cheap calls are also negative, implying that once transaction costs are incorporated, cheap call trading results in an average expected loss for *both* buyers and sellers.

the other call options). This, together with the pattern of $EV < 0$ from cheap call selling, points to some possible craving-induced selling pressure on cheap call price—an idea we flesh out next.

Table 6: **Summary statistics of option returns** The table shows the MID, BUY, and SELL returns for all options, cheap calls ("Calls $<$ \$1"), and the other calls ("Calls $\geq$ \$1"). Both percent returns and dollar returns are shown (to highlight that the percent returns are not driven by outliers in the current sample). The table also reports median returns (Median), standard deviation (SD), the proportion of options that expire out-of-the-money (OTM), which is when the call sellers win money, the number of unique options in the sample (Unique N), and the total number of options in the sample (N).

		All Options			Calls < \$1			Calls ≥ \$1		
		MID	BUY	SELL	MID	BUY	SELL	MID	BUY	SELL
Average	%	-0.088	-0.169	0.005	0.074	-0.067	-0.238	-0.007	-0.077	0.071
	\$	-0.967	-1.209	0.724	0.042	-0.035	-0.118	-0.756	-1.060	0.452
Median	%	-0.684	-0.734	0.633	-0.947	-1.000	0.886	-0.494	-0.547	0.442
	\$	-1.014	-1.166	0.868	-0.354	-0.406	0.300	-1.090	-1.285	0.904
SD	%	1.777	1.661	1.917	3.244	2.981	3.566	1.582	1.494	1.686
	\$	9.120	9.134	9.113	1.640	1.610	1.675	11.494	11.500	11.495
Skew	%	7.371	7.318	-7.431	13.107	12.931	-13.325	6.583	6.546	-6.639
	\$	0.497	0.430	-0.552	9.913	10.151	-9.636	-0.365	-0.527	0.206
OTM (in %)		50.90			70.44			40.23		
Unique N		17,071,406			5,256,144			7,124,416		
N		183,983,273			22,121,539			79,203,260		

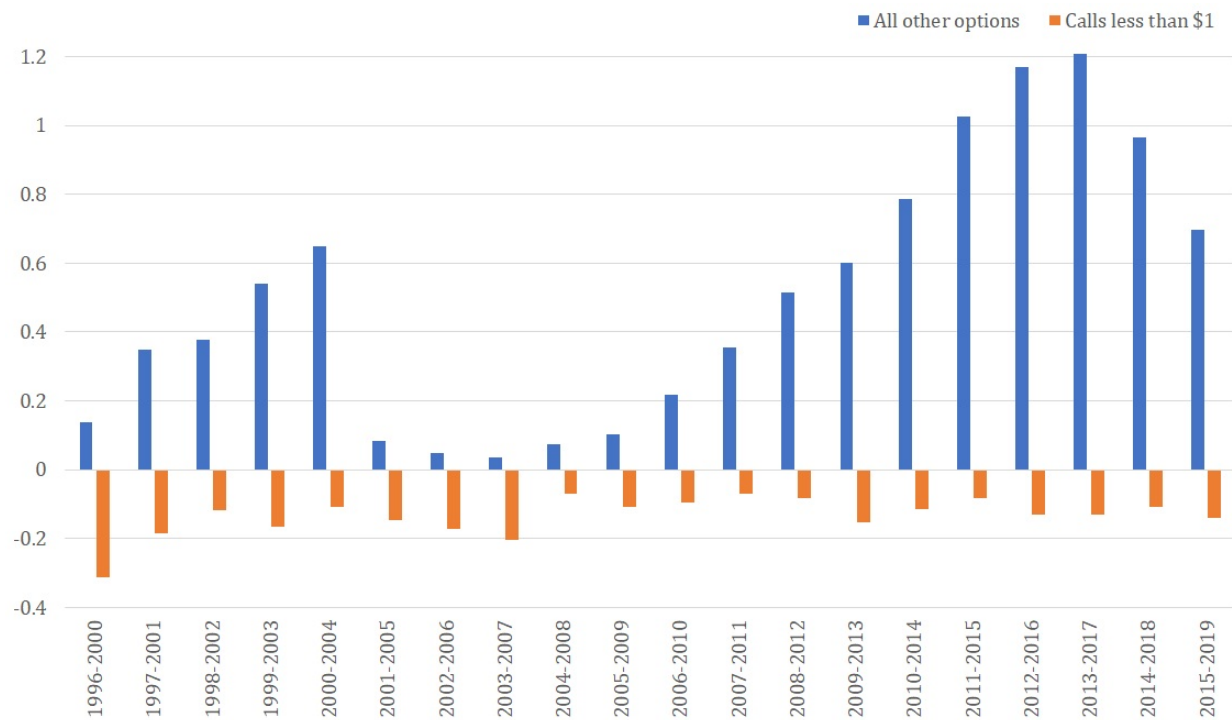

Figure 7: **Five-year rolling average dollar returns from cheap call selling (orange) versus from selling all other options (blue).**

3.3 Evidence of selling pressure caused by craving

We sort options into delta and volatility baskets and compare the returns of the cheap calls to the returns of the other calls. Strikingly, cheap call selling consistently delivers EV<0 even without incorporating transaction costs: the MID returns of the cheap calls are indeed positive across *all* volatility levels except for the top level (Table 7, Panel A), and across *all* delta levels, in contrast to that with the other calls, for which the MID returns are negative across all delta levels (Table 7, Panel B).[37]

That the MID returns of the cheap calls are positive across all volatility levels except for the top level points to the presence of some supply-based pressure dominating the volatility premium/demand-for-insurance effect on cheap call price, except for the top volatility level, for which the demand for insurance is expected to be the highest.[38]

Now turning to the fact that across all delta levels, the MID returns are positive in the case of the cheap calls, and negative in the case of the other calls: This fact suggests that in the case of the cheap calls, the aforementioned selling pressure systematically dominates the countervailing buying pressure coming from the gambling motive, whereas in the case of the other calls, the gambling force systematically dominates. The delta of a given option is indeed a proxy for the degree of attractiveness of the option to both gamblers on the demand side (lower delta options have lower cost and higher potential returns if the option finishes in the money) and penny-pickers on the supply side (lower delta options have lower probability of finishing in the money and higher average median returns: 90.3% on average for the options in two lowest delta deciles vs. 0.05% for the two highest delta deciles).

We find further evidence of a selling pressure on cheap call price through computing the difference between SELL and MID returns, which has been used in prior work to measure the average selling pressure (for example, George and Longstaff (1993) and Muravyev (2016)). The difference is -31.22% (or -16c) for the cheap calls vs. 7.78% for the other calls (Table 6), which points to the presence of a selling pressure producing 31.22% more negative returns from cheap call selling, and an absence of selling pressure in the case of the other calls.

The data further support the idea that this selling pressure is caused by craving among the sellers of the cheap calls, inasmuch as for the cheap calls and for them only (not observed

[37] A fortiori, the SELL returns of the cheap calls (resp. other calls) are negative (resp. positive) across all delta levels.

[38] Table 7, Panel A further shows that the SELL return difference between the highest and lowest volatility quintiles is significantly positive both for the cheap calls and the other calls, consistent with the idea that the demand for insurance/volatility premium is equally present for both call categories. The regression results below confirm this.

with the other calls), the foregoing average selling pressure metric is higher for the two lowest delta deciles than for the two highest deciles (Table 7, Panel B). This differential selling pressure comes as no surprise viewed from CbD hypothesis: selling cheap calls from the two highest delta deciles is not Craving Prone (median returns: 0%) relative to selling those from the two lowest delta deciles (median returns: 90.8%). The other calls feature a smaller gap in median returns (low delta median returns: 82.5%; high delta: −1.6%; two-sample Mann-Whitney test to compare the gap in median returns for the cheap calls vs. the other calls: $Z = -140.3, p < 0.0001$).

The data therefore suggest that the negative EV from cheap call selling may reflect a selling pressure caused by craving among the sellers of the cheap calls. Could the negative EV also reflect depressed demand for the cheap calls on the buying side? This is unlikely inasmuch as the difference between BUY and MID returns, which can be used as a measure of the average buying pressure, is −14.09% for the cheap calls vs. −6.31% for the other calls (Table 6), pointing to a *higher* buying pressure for the cheap calls—possibly related to the "good deal effect" mentioned in the Introduction as well as a higher gambling motive for the cheap calls (more on this in Section 3.6).

Table 7: **Difference in mean option returns sorted into implied volatility quintiles and delta deciles.** "Diff" denotes the difference in mean returns between the cheap calls and the calls priced above one dollar. Returns are sorted into implied volatility (IV) quintiles (Panel A) and delta (Δ) deciles (Panel B). Robust t-statistics are given in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: IV Groups

	SELL			MID			SELL Skew	SELL Skew
	Call <\$1	Call ≥\$1	Diff	Call<\$1	Call ≥\$1	Diff	for calls <\$1	for calls ≥\$1
IV< 0.20	-0.40***	-0.19***	-0.21***	0.26***	0.12	0.14**	-9.97	-3.85
	(5.38)	(4.58)	(2.74)	(1.95)	(1.22)	(2.19)		
0.20≤IV<0.35	-0.24***	-0.10***	-0.14***	0.08***	0.03	0.05**	-7.94	-6.29
	(5.38)	(4.58)	(2.74)	(1.95)	(1.22)	(2.19)		
0.35≤IV<0.50	-0.20***	-0.08***	-0.13***	0.05	0.0	0.05**	-12.47	-6.87
	(4.60)	(3.41)	(2.57)	(1.13)	(0.01)	(2.00)		
0.50≤IV<0.65	-0.12***	-0.04***	-0.09***	-0.03	-0.04***	0.01	-9.01	-6.09
	(3.05)	(1.74)	(1.86)	(0.73)	(1.83)	(0.22)		
0.65≤IV	-0.02	0.03	-0.04	-0.14***	-0.10***	-0.04	-13.90	-15.37
	(0.45)	(1.53)	(1.07)	(3.75)	(5.71)	(0.91)		
H-L	0.39***	0.22***	0.17***	-0.40***	-0.22***	-0.18***		
	(6.29)	(7.58)	(3.22)	(6.56)	(7.60)	(3.50)		

Panel B: Delta Groups

	SELL			MID			SELL Skew	SELL Skew
	Call <\$1	Call ≥\$1	Diff	Call <\$1	Call≥ \$1	Diff	for calls <\$1	for calls ≥\$1
Δ<0.10	-0.19***	0.08	-0.27***	0.13	-0.17***	0.20***	-63.41	-20.88
	(3.07)	(1.64)	(3.43)	(0.53)	(3.52)	(2.58)		
0.10≤ Δ <0.20	-0.26***	-0.07**	-0.19***	0.15***	-0.02***	0.13***	-21.99	-10.90
	(6.94)	(2.07)	(3.63)	(3.11)	(0.52)	(2.62)		
0.20≤ Δ<0.30	-0.26***	-0.11***	-0.15***	0.12***	0.02	0.10**	-12.90	-6.61
	(8.47)	(3.73)	(3.56)	(3.82)	(0.62)	(2.33)		
0.30≤ Δ<0.40	-0.25***	-0.11***	-0.14***	0.10***	0.02	0.08**	-11.81	-4.67
	(9.19)	(4.46)	(3.64)	(3.85)	(0.97)	(2.12)		
0.40≤ Δ<0.50	-0.23***	-0.10***	-0.13***	0.08***	0.02	0.06**	-9.51	-3.45
	(9.52)	(4.52)	(3.84)	(3.45)	(0.76)	(1.98)		
0.50≤ Δ<0.60	-0.22***	-0.08***	-0.13***	0.07***	0.003	0.07**	-10.27	-3.27
	(10.06)	(4.14)	(4.58)	(3.33)	(0.15)	(2.33)		
0.60≤ Δ<0.70	-0.19***	-0.07***	-0.13***	0.05***	-0.005	0.06**	-9.07	-3.13
	(10.28)	(3.93)	(4.87)	(2.72)	(0.30)	(2.19)		
0.70≤ Δ<0.80	-0.17***	-0.06***	-0.11***	0.03*	-0.01	0.04*	-6.53	-6.71
	(10.68)	(4.22)	(4.95)	(1.90)	(0.46)	(1.69)		
0.80≤ Δ<0.90	-0.15***	-0.06***	-0.09***	0.01	-0.01	0.02	-6.21	-5.41
	(12.11)	(4.91)	(5.44)	(1.12)	(0.63)	(1.25)		
0.90≤ Δ<1.00	-0.14***	-0.05***	-0.09***	0.02*	0.002	0.01	-9.29	-5.15
	(14.65)	(6.95)	(7.26)	(1.72)	(0.24)	(1.19)		
$H_{10,9} - L_{1,2}$	0.082*	-0.058***	0.14***	-0.159	0.091**	-0.251***		
	(1.79)	(1.46)	(3.08)	(1.33)	(2.33)	(3.38)		

The findings so far thus support the idea that **1)** there is a systematic pattern of negative EV from cheap call selling that is distinctive to the cheap calls; **2)** this pattern reflects the fact that cheap call selling is particularly Craving Prone for the sellers (more Craving Prone than selling the other calls), resulting in a selling pressure on the equilibrium price of the cheap calls. To strengthen the evidence for **1)** & **2)**, we run fixed effects regressions, controlling for firm specific variables and option specific characteristics (following the methodology proposed in Doran et al. (2013)):

$$\begin{aligned} \mathrm{R}_{i,t} = \alpha_{i,t} + \beta_1 \mathrm{MP}_{i,t} + \beta_2 \Delta_{i,t} + \beta_3 \mathrm{IV}_{i,t} + \beta_4 \mathrm{Mat}_{i,t} + \beta_5 \{\mathrm{MP} < 1\}_{i,t} \\ + \beta_6 \mathrm{BM}_{i,t} + \beta_7 \mathrm{Size}_{i,t} + \beta_8 1\mathrm{YR}_{i,t} + \beta_9 \mathrm{SP}_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $\mathrm{R}_{i,t}$ is either of $\mathrm{MID}_{i,t}$, $\mathrm{SELL}_{i,t}$, and $\mathrm{BUY}_{i,t}$ (we run three separate regressions). The variables $\mathrm{MP}_{i,t}$, $\Delta_{i,t}$, and $\mathrm{IV}_{i,t}$ respectively denote the price, delta, and implied volatility of option i on day t. $\mathrm{Mat}_{i,t}$, $1\mathrm{YR}_{i,t}$, $\mathrm{BM}_{i,t}$ and $\mathrm{Size}_{i,t}$ denote remaining time to maturity, the prior 1 year (52-week) return, book-to-market ratio, and firm size. $\mathrm{SP}_{i,t}$ denotes the bid-ask spread (an important control here as the bid-ask spread directly affects selling profitability). $\{\mathrm{MP} < 1\}_{i,t}$, our main variable of interest, is a dichotomous variable that equals 1 if the price of option i is less than one dollar, and equals 0 otherwise. CbD hypothesis predicts a positive (resp. negative) coefficient on this variable in the specification that uses the MID (resp. SELL) returns as dependent variable. This is precisely what we find (Table 8, regression (2), Panel A and Panel B).[39] We further find that the average predicted MID returns of the cheap calls are positive, and that relative to selling the other calls, cheap call selling results in a 31% worse returns (Table 8, Panel A). The results from the SELL specification reinforce the message that the pattern of negative EV from cheap call selling is specific to the cheap calls and presents itself consistently even after adding all the necessary control variables: the average predicted SELL returns are indeed negative for the cheap calls whereas they are positive for the other calls (Table 8, Panel B).

3.4 Time variation in craving

Next, we test a prediction of CbD hypothesis that relates to how craving for the cheap calls should vary over time: it should be maximal (resp. minimal) when other craving opportunities are scarce (resp. abundant). For example, during high-yield periods (when the spread

[39] CbD hypothesis further predicts an insignificant coefficient in the specification that uses the BUY returns. This is what we find too (the results are not shown to conserve space but are available on request).

on corporate bonds is high relative to treasury bonds), there are ample yield enhancement strategies delivering Craving-Prone payoffs as defined above. Conversely, during low-yield periods, cheap call selling is more valuable to penny-pickers as strategies yielding Craving-Prone payoffs are harder to find; therefore, the discount that penny-pickers are willing to incur to be able to satisfy their craving needs through selling the cheap calls is bigger, i.e., EV from cheap call selling is *more negative*. CbD hypothesis thus predicts more negative average SELL returns—and more positive MID returns—of the cheap calls during low-yield periods relative to high-yield periods.

To test this prediction, we run the foregoing fixed effects regression augmented with a dummy variable to capture the time variation in craving opportunities in the logic just explained [1: periods when the Bloomberg/Barclays US Corporate High Yield Index minus the yield on US Treasury bonds is below its long term average ("low yield"); 0: the index is above its long term average ("high yield")]. We further add a dummy variable to control for time variation in market volatility [1: periods when the VIX index is below its long term average ("low volatility"); 0: periods when VIX is above its long term average ("high volatility")]. Adding these dummies hardly changes the coefficient on {MP<1}, and the coefficient on the low yield dummy is significantly positive (0.074) in the MID specification and significantly negative (−0.076) in the SELL specification, as predicted (Table 8, regression (3), Panel A and Panel B). Also consistent with CbD hypothesis is the finding that the effect of the low yield dummy is more pronounced for the cheap calls than for the other calls (more in Section 3.7).

Table 8: **Fixed effects call returns.** Regressions corresponding to Equation (4) in the main text, without (regression (1)) and with (regression (2)) the dummy MP < 1 included. The model underlying regression (3) is Equation (4) augmented with the variables $1_{\text{Low Yield}}$ and $1_{\text{Low VIX}}$ as defined in Section 3.4 of the main text. The dependent variable is the MID returns (Panel A) and the SELL returns (Panel B) of the call options. Clustered and heteroskedasticity robust t-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. As predicted by CbD hypothesis, the coefficients on the main variables of interest MP < 1 and $1_{\text{Low Yield}}$ are positive in Panel A and negative in Panel B, and the average predicted MID (resp. SELL) returns of the cheap calls are positive (resp. negative). These average predicted returns are computed from the coefficients on the independent variables reported in the table, and the average values $\overline{MP} = 4.08, \overline{SIZE} = 699M, \overline{1YR} = 2.94, \overline{BM} = 0.39, \overline{\Delta} = 0.54, \overline{IV} = 0.47, \overline{Mat} = 25.46, \overline{SP} = 0.33$.

	Panel A: MID Returns			Panel B: SELL Returns		
	(1)	(2)	(3)	(1)	(2)	(3)
MP	-0.006**	-0.008***	-0.008***	0.006**	0.008***	0.008***
	(2.51)	(2.91)	(2.93)	(2.51)	(2.94)	(2.96)
SIZE	-0.002***	-0.002***	-0.002***	0.002***	0.002***	0.002***
	(3.10)	(2.85)	(2.77)	(3.14)	(2.86)	(2.78)
1YR	-0.033	-0.031	-0.029	0.034	0.031	0.029
	(1.14)	(1.08)	(1.02)	(1.16)	(1.09)	(1.02)
BM	0.146***	0.131***	0.123***	-0.152***	-0.135***	-0.127***
	(2.90)	(2.81)	(2.76)	(2.90)	(2.80)	(2.75)
Δ	0.113*	0.45***	0.433***	0.017	-0.366***	-0.349***
	(1.83)	(6.62)	(6.21)	(0.27)	(5.33)	(4.96)
IV	-0.067	-0.068	-0.108	0.066	0.068	0.11
	(0.81)	(0.84)	(1.08)	(0.78)	(0.82)	(1.09)
Mat	0.085***	0.11***	0.105***	-0.077***	-0.105***	-0.1***
	(8.36)	(10.32)	(10.04)	(7.48)	(9.79)	(9.48)
SP	-0.324***	-0.322***	-0.308***	0.304***	0.303***	0.287***
	(12.28)	(11.56)	(11.11)	(11.64)	(10.88)	(10.40)
$1_{\text{Low Yield}}$			0.074***			-0.076***
			(8.88)			(9.05)
$1_{\text{Low VIX}}$			-0.02***			0.021***
			(7.76)			(7.92)
MP < 1		0.333***	0.325***		-0.378***	-0.37***
		(13.53)	(13.89)		(15.11)	(15.54)
α	0.094*	-0.166***	-0.148***	-0.248***	0.048	0.03
	(1.66)	(3.25)	(2.76)	(4.31)	(0.92)	(0.55)
Firms		5,830			5,830	
Observations		31,288,565			31,288,565	

3.5 Variation in "Craving Proneness" in the cross section

The analysis reported in Section 3.4 exploits the time variation in "craving opportunities" (the idea that Craving-Prone payoffs are harder to find during low yield periods). In this section, we seek to exploit variations in "Craving Proneness" in the cross section. As explained above, the Craving Proneness of a given asset is the extent to which the asset is attractive to penny-pickers: the bigger the pennies and the higher the likelihood of getting them, the more Craving Prone. The foregoing findings along with CbD hypothesis suggest that in the cross section, the more Craving Prone a given trade is, the bigger the EV reduction that penny-pickers are willing to incur to engage in the trade. Figure 8 provides direct evidence for such a relationship between the degree of Craving Proneness of a call for sellers, and the size of the discount on this call. Calls priced below \$1 are more Craving Prone than calls priced above \$2, and the size of the discount is also higher for them (in fact, calls above \$2 are not discounted at all—the EV from selling them is positive); calls priced between \$1 and \$1.5 and those priced between \$1.5 and \$2 are somewhere in between. Strikingly, the relationship between degree of Craving Proneness and discount size in the cross section appears to be almost linear.

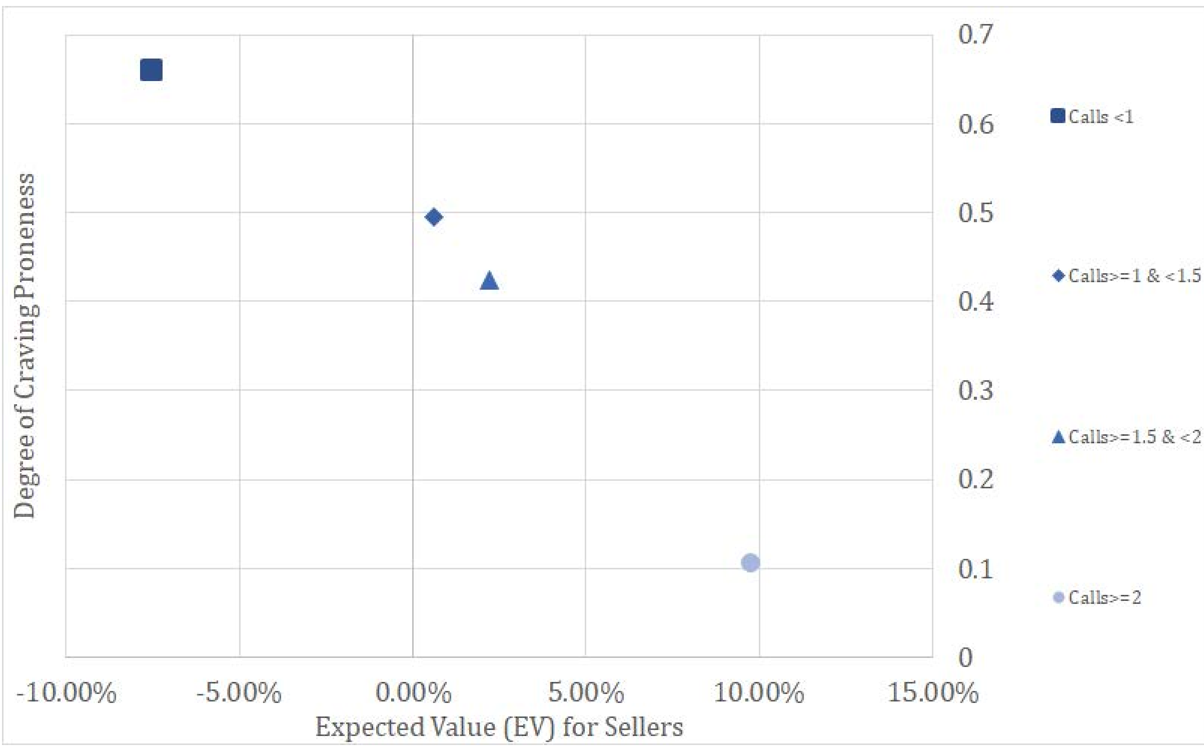

Figure 8: **Relationship between discount size and degree of "Craving Proneness" in the cross section.** X-axis: Expected Value (EV) from selling the option. A negative value indicates the option is discounted. Y-axis: Degree of Craving Proneness, measured by the median returns × the percentage of the options finishing out of the money.

3.6 Who are the sellers?

In the final stage of analysis, we examine who are the sellers of the cheap calls and the nature of the transactions underlying the cheap call selling anomaly, using the data provided by the *International Securities Exchange* (ISE) from May 2005 to 2019. There are four types of transactions, open buy, closing buy, open sell, and closing sell. It is important to distinguish between the four types as only open sell transactions may reflect the craving motive (closing sell transactions do not); likewise, only open buy (not closing buy) transactions can be tied to the gambling motive. We have access to the daily volume of each transaction type for all individual options, separated by trader class. This allows us to examine if cheap call open sell transactions come more from the class of *"customers"*, which encompasses both retail investors and sophisticated traders such as hedge funds, or from the class of *"firms"*, which only includes sophisticated traders (institutional or proprietary).

We reason that finding that most cheap call sellers are from the customer class would point to investor unsophistication as possibly being among the key factors underling the cheap call selling anomaly. Finding that cheap call sellers are relatively more represented in the firm class would suggest the opposite. This is what we find: firms engage more in cheap call open sell transactions than customers do; and for firms, the volume of open sell transactions is larger than the volume of open buy transactions, whereas the reverse is true for customers (see Table A11 in the Internet Appendix).

The evidence that the cheap call selling anomaly comes more from firms than from customers is strengthened when regressing the volume of open sell and open buy call transactions on all the independent variables used in Table 8, regression (3), for customers and firms separately. It appears that among the new open sell positions initiated by firms, there are 54 additional positions for the cheap calls relative to the other calls (see Table 9, coefficient of the {MP<1} dummy); the corresponding number for customers (11 additional positions) is significantly lower ($\chi^2(1) = 97.5, p < 0.0001$). Moreover, the coefficient of the low yield variable in the regression of open sell volume is significantly larger for firms than for customers ($\chi^2(1) = 100.08, p < 0.0001$), which further supports the idea that firms are behind the cheap call selling anomaly to an even greater extent than customers are.

Table 9 further shows that traders from the customer class engage significantly more in open buy transactions of the cheap calls relative to the other calls. Given the evidence of gambling in retail investors from prior work, and the fact that the gambling motive leads to initiate new open buy positions, this finding reinforces the foregoing idea that demand is not lower for the cheap calls than for the other calls (if anything, it may be higher).

Last (but not least), the ISE data fully confirm the existence of the cheap call selling anomaly: the MID returns (resp. SELL returns) for open sell transactions are positive (resp. negative) for the cheap calls and negative (resp. positive) for all other options (see Table A12 in the Internet Appendix).

Table 9: **Firm fixed effects regression on call volume by trader class.** The dependent variable is either the volume of an open buy or an open sell transaction for firms (left) and customers (right) as defined by the *International Securities Exchange*. The independent variables are the same as those used in Table 8, regression (3). Clustered and heteroskedasticity robust t-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Firms		Customers	
	Open Sell	Open Buy	Open Sell	Open Buy
MP	-1.73**	-1.84***	-0.937***	-1.286***
	(1.97)	(3.26)	(3.89)	(4.98)
SIZE	-0.001***	-0.001***	-0.001***	-0.001***
	(6.81)	(4.50)	(2.96)	(4.65)
1YR	-0.043	0.035	0.003	-0.006
	(1.20)	(1.00)	(0.48)	(0.54)
BM	39.302*	14.311	-1.095	-0.971
	(1.86)	(1.29)	(1.13)	(0.41)
Δ	-14.69***	-0.999	3.722***	-1.922***
	(3.69)	(0.32)	(6.37)	-(1.00)
IV	76.496***	85.229***	52.091***	85.925***
	(6.77)	(7.32)	(9.28)	(12.32)
Mat	0.455***	0.221***	-0.097***	-0.179***
	(7.29)	(4.75)	(6.19)	(6.87)
SP	-43.926***	-12.896*	-12.077***	-19.6**
	(3.34)	(1.82)	(2.19)	(2.26)
$1_{\text{Low Yield}}$	24.265***	59.17***	16.091***	14.939***
	(3.07)	(7.77)	(6.90)	(4.39)
$1_{\text{Low VIX}}$	9.188	6.653	0.055	7.01***
	(0.97)	(1.13)	(0.03)	(2.73)
MP < 1	54.879***	13.436	11.423***	34.108***
	(7.75)	(1.62)	(5.86)	(9.68)
α	118.074***	114.386***	44.139***	55.318***
	(7.00)	(8.08)	(9.40)	(9.21)
Firms	3,101	3,162	3,308	3,315
Observations	600,574	703,266	4,257,236	3,744,950

3.7 Robustness checks

We conduct many robustness checks and supplementary tests of CbD hypothesis, which are documented in the Internet Appendix and include the following.

Supplementary fixed effects regressions. We run the above fixed effects regressions without {MP$<$1} included and on all options pooled (in reference to the existing literature), the cheap calls, and the other calls, in three separate regressions (Table A8). The results for all options fully replicate the existing body of knowledge; those for the cheap calls and the other calls fully confirm that the cheap call selling anomaly—the positive MID returns and negative SELL returns of the cheap calls—is distinctive to the cheap calls. Table A8 further shows that the coefficient of our key low yield dummy (cf. Section 3.4) is more significant for the cheap calls than for the other calls.

Moreover, and importantly, we replicate all the foregoing findings in regressions of our full model (Table 8, regression (3)) augmented with option specific characteristics directly tied to the volatility premium and unhedgeable risk—the so-called *"Greeks"* (Table A9).

Systematic underperformance of covered call strategy based on cheap call selling. Figure A1 shows that the widely used covered call strategy [which consists of being long a stock while selling a call based on this stock] based on cheap call selling has consistently underperformed just owning the underlying stock, contrary to that with the other calls. This finding suggests that traders engaged in cheap call selling cannot ignore the negative value of this selling if it is part of a covered call strategy, as is likely often the case. As such, this finding strengthens the foregoing evidence that cheap call sellers are likely aware of the negative EV of cheap call selling, and yet undertake it to satisfy their craving needs or, in the language of finance practitioners, *"to get the yield."*

"Cheap put selling anomaly" for options defined on negative beta assets. Table A10 provides evidence that the negative EV pattern of cheap call selling cannot be explained by some hidden (unobservable) characteristics of the cheap calls and that it is their foregoing Craving-Prone property *per se* that underlies the pattern. To establish this, we focus on options defined on negative beta assets—assets whose returns are negatively correlated to the equity markets (for example VIX, VXX, and inverse SPX instruments). These options have a payoff structure that is opposite to that with traditional options, meaning that cheap *put* selling delivers Craving-Prone payoffs in this case; therefore, according to CbD hypothesis, there should be a "cheap *put* selling anomaly" in this case. This is precisely what Table A9 documents. These findings auggest that there is "nothing special" about the foregoing cheap calls except for the Craving-Prone property of their returns for sellers.

4 Discussion

To summarize, the evidence from the laboratory and the existence of the cheap call selling anomaly—and symmetrical cheap put selling anomaly for negative beta assets—together support the idea that under repeated exposure to monetary gains (actually experienced or counterfactual), people knowingly engage in EV<0, SKEW<0 gambles due to a behavioral factor possibly tied to 'money craving'. That is, in the same way that gamblers accept EV<0 to satisfy their gambling needs (get SKEW>0), penny-pickers would accept EV<0 to satisfy their craving needs. This idea implies that even the most savvy agents are susceptible to the picking pennies bias. Consequently, policy solutions solely aimed at increasing investor awareness of the risks they are taking are bound to be insufficient. They should be complemented by nudging—e.g., offering investors commitment devices so they can protect themselves against their craving urges, in the vein of what Experiment 4 implements. Beyond the financial industry, such nudging could also benefit recreational gamblers, inasmuch as the current findings support the idea that modern gaming machines leave all recreational gamblers vulnerable to money craving by design—an idea recently developed by Schull (2014).

Back to finance, while the cheap calls only make up 19.3% of the option volume traded over the sample period, this still translates to 10.7 billion contracts traded and a dollar value of $510 billion. Therefore, the cheap call selling anomaly has a significant dollar impact.

In a sense, our findings are not particularly surprising in light of the current consensus in neuroscience that the brain treats different kinds of rewards (food, sex, money etc.) in the same way, as explained in Section 1. Given that the craving phenomenon is well-known to occur for primary rewards such as foods, from a neuroscientific perspective there is reason to expect the same to be true for money.

That said, one may legitimately wonder if the cheap call selling anomaly could have a rational origin, rather than reflecting craving for money as we propose here. It is very possible that market makers engage in cheap call selling and offset the risk through dynamic replication and delta/vega hedging (using the underlying instrument and other options).

However, the anomaly documented in this paper *cannot* reflect this: we did remove market makers from the ISE data for all the analyses reported in the paper. What about non market markets? The key point to make here is that for non market makers, the cost of dynamic replication and delta hedging cheap calls is excessively costly, due to the bid-ask spreads and the gamma risk from a move when the option goes into the money. To be more specific, the daily cost of delta rebalancing far exceeds the benefit of selling a cheap call. The average ratio of delta to price is .48 for the cheap calls vs. for all other options, it is .01. Therefore, it is highly unlikely that the cheap call selling anomaly documented in this paper be rational in the sense just described.

Could cheap call selling come from firms that are providing liquidity across a range of options and are willing to give up some returns from selling the cheap calls to gain volume in other options? While such liquidity motive may well exist, it fails to explain i) why the anomaly is particularly pronounced during low-yield periods (Section 3.4), inasmuch as in our data, liquidity needs do not appear to be higher during low-yield periods (the volume of traded options is similar to that during high-yield periods); ii) why the size of the anomaly correlates with the degree of Craving Proneness of the asset the way it does (Section 3.5). It should also be noted that the liquidity motive only concerns firms; hence it cannot explain the cheap call selling by customers documented in Section 3.6.

That said, it is worth emphasizing certain limitations of our study. One important limitation is that our analysis does not enable us to say how money craving combines with limited liability in the case of financial investing. The experimental findings only enable us to say that the absence of losses for task participants in Experiments 1-4 is not among the key factors underlying the picking pennies bias in these experiments, inasmuch as task participants feature the bias to the same extent when they are exposed to significant losses (in Experiment 5). While this finding supports the idea of "*loss tolerance*" proposed by Chapman et al. (2018), we caution against concluding that limited liability does not matter. On the contrary, we suspect that limited liability is an important institutional factor interacting with money craving. To be more specific, we think it is possible that high degrees of liability work like a commitment device in helping partially "neutralize" craving impulses in investors. This could be one explanation for why the evidence for CbD hypothesis documented here appears to be even more pronounced for firms than for customers (Section 3.6), inasmuch as firms face limited liability. This question is left for future empirical research.

The current findings raise many other interrogations for future research. For example, it would be interesting to determine how often the anomaly documented in this paper, which consists of trading negatively skewed assets with negative expected value, reflects purely behavioral explanations such as money craving, how often it reflects faulty cognition, and how often it reflects a mix of behavioral and cognitive factors.

It will also be important to study interindividual differences in the propensity for money craving. For example, are older individuals less susceptible to money craving, as recent studies indirectly suggest (e.g., Ameriks et al. (2007), Bossaerts and Murawski (2016), and Rutledge et al. (2016))? To begin investigating this question, we have 42 professional MBA students from the Australian Graduate School of Management perform one run of the task used in Experiment 1. (These supplementary data are provided as part of the submission material along with the main data.) The mean age of these participants is 33.3 years old vs. it is 21 for the undergraduate participants. We do not find a decreased prevalence rate of the picking pennies bias in the MBA participants relative to the younger cohort. However absence of evidence is not 'evidence of absence,' and further research is needed to test whether the propensity for money craving changes with age.

Future work could also examine whether education helps protect people against money craving (if, for example, education positively impacts self-control capability), and whether there are country fixed-effects in the prevalence of money craving. Having in mind these two questions, it is worth noting that the present findings were fully replicated in a separate study that involved running Experiment 3 with eighty three undergraduates from *Brown University*, which is a top American university. (These supplementary data are provided as part of the submission material.) Further work is needed to examine the relevance of individual characteristics such as nationality and educational profile to help predict the occurrence of money craving in people.

As noted in the Introduction, the cheap call selling anomaly is reminiscent of behavioral patterns that have been recently identified by other scholars, in particular Henderson and Pearson (2011), Chapman et al. (2018), and Duffy and Orland (2020). Together with the current findings, these studies suggest that the anomaly consisting of exposing oneself to negative expected value, negatively skewed prospects, prevails in different economic situations and concerns different kinds of actors. It would be interesting to delineate its scope in future work.

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5 Internet Appendix

5.1 Participant estimates of the probability of a losing bet under negative tail risk in Experiments 1-5

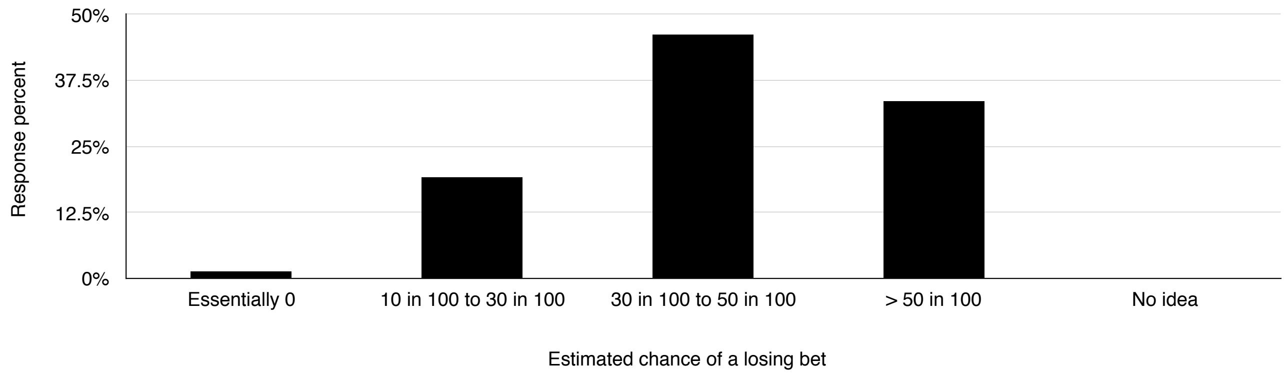


Figure 9: **Participants' estimated chance of a losing bet under negative tail risk in Experiments 1-5.** The graph shows the distribution of the estimated probability of a losing bet with an apprentice bowman reported by the participants in a debriefing questionnaire filled out at the end of the experimental session. X-axis: Estimated chance of a losing bet in a session with an apprentice. Y-axis: Response percent. The mode estimate across participants is in the 30%-50% range; the true statistic is approximately 15% (see Appendix 5.2).

5.2 Modelling

5.2.1 Bayesian model

At each trial t of a given session, the agent compares the likelihood of the two possible models of the world (M_1 vs M_2) given the data available until (included) trial t $\underline{X_t} = (X_1, X_2, \cdots, X_t)$:

- If the bowman is a master (M_1), the data $\underline{X_t}$ have density $f_1(\underline{X_t} \mid \sigma)$:

$$f_1(\underline{X_t} \mid \sigma) = \prod_{k=1}^{t} \frac{1}{\sqrt{(2\pi)}\sigma} \exp\{\frac{-X_k^2}{2\sigma^2}\},$$

  where σ is uniformly distributed between 0.1 and 2 by design.

- If the bowman is an apprentice (M_2), the data $\underline{X_t}$ have density $f_2(\underline{X_t})$:

$$f_2(\underline{X_t}) = \prod_{k=1}^{t} \frac{1}{\pi(X_k^2 + 1)}.$$

During each trial, the agent assesses how likely it is that the session has a master bowman versus an apprentice bowman in light of the available data $\underline{X_t}$. The metric used is the "marginal or predictive density" (Berger and Pericchi, 2001) of $\underline{X_t}$ under each model (M_1 and M_2):

$$\begin{aligned} m_1(\underline{X_t}) &= \int_{0.1}^{2} f_1(\underline{X_t}|\sigma) \times \pi(\sigma) d\sigma, \\ m_2(\underline{X_t}) &= f_2(\underline{X_t}), \end{aligned}$$

where, $\pi(\sigma)$, the prior used for σ, reflects the fact that σ is uniformly distributed between 0.1 and 2: $\pi(\sigma) = \frac{1}{2-0.1}$. The posterior probability of each model given the data $\underline{X_t}$ is:

$$P(M_1 \mid \underline{X_t}) = \frac{P(M_1)\, m_1(\underline{X_t})}{P(M_1)\, m_1(\underline{X_t}) + P(M_2)\, m_2(\underline{X_t})},$$
$$P(M_2 \mid \underline{X_t}) = \frac{P(M_2)\, m_2(\underline{X_t})}{P(M_1)\, m_1(\underline{X_t}) + P(M_2)\, m_2(\underline{X_t})},$$

where $P(M_1)$ and $P(M_2)$ denote the prior probability of being in a session with a master and an apprentice, respectively. $P(M_1) = P(M_2) = 1/2$ by design (the agent knows that there are equal chances of facing an apprentice or a master in each session).

The expected value of Action Bet at trial t, which is denoted by V_t, is:

$$V_t = P(M_1 \mid \underline{X_{t-1}}) \ \Big[p_g \times 2 - (1 - p_g) \times 40\Big] + P(M_2 \mid \underline{X_{t-1}}) \ \Big[p_c \times 2 - (1 - p_c) \times 40\Big], \quad (5)$$

where p_g (resp. p_c) denotes the probability of a winning bet in a session with a master bowman (resp. apprentice bowman).

The behavior consists of betting in trial $t + 1$ if and only if $V_t > 0$ and choosing to skip otherwise. Note that this rule assumes risk-neutrality, for parsimony. Importantly, the *Prospect Theory* version of the Bayesian model behaves qualitatively the same. The expected value of action bet for the Prospect Theory agent is

$$\begin{aligned} V_t = P(M_1 \mid \underline{X_{t-1}}) \ \Big[w(p_g) \times 2^{\alpha_1} - \lambda\, w(1 - p_g) \times 40^{\alpha_2}\Big] \\ +P(M_2 \mid \underline{X_{t-1}}) \ \Big[w(p_c) \times 2^{\alpha_1} - \lambda\, w(1 - p_c) \times 40^{\alpha_2}\Big], \end{aligned} \quad (6)$$

where α_1 and α_2 govern the shape of the value function, λ is the loss-aversion parameter, and $w(.)$ is the probability-weighting function introduced by Prelec (1998): $w(p) = \exp\{-(-ln\, p)^{\alpha_3}\}$. α_1, α_2, α_3 and λ are free parameters in the model comparison analysis (see Appendix 5.2.4).

The main findings reported in Appendix 5.2.4 hold under either specification of the Bayesian model (risk neutral and Prospect Theory). Also for robustness purposes, we consider a softmax (logit) decision rule in place of the foregoing deterministic rule. Under the logit rule, the probability to bet at trial $t + 1$ is

$$P^{\text{Bet}}(t + 1) = \frac{\exp \beta V_t}{1 + \exp \beta V_t}, \quad (7)$$

where β, the noise parameter, is inversely proportional to the degree of randomness in participant behavior ($\beta \geq 0$). The main results mentioned below in section 5.2.4 hold under either choice rule (deterministic and logit).

To compute p_g, the agent first derives the standard deviation estimate $\widetilde{\sigma}(t) = \sqrt{\frac{1}{t}\sum_{k=1}^{t} {X_k}^2}$. Using this estimate, the agent assesses the likelihood of a winning bet in a session with a master bowman to be

$$p_g \equiv p_g(t) \quad = \quad 1 - 2\left(1\text{-}\Phi\left(\frac{4}{\widetilde{\sigma}(t)}\right)\right).$$

.

In the base behavioral model, the probability of a winning bet in a session with an apprentice bowman is (using the definition of the Cauchy density):

$$p_c \quad = \quad \frac{1}{\pi}\int_{-4}^{4} \frac{1}{x^2+1}dx = \frac{1}{\pi}\ \left[tan^{-1}(4) - tan^{-1}(-4)\right] = 0.844.$$

5.2.2 Formalization of the "gambler's fallacy" hypothesis

We consider a variant of the Bayesian model in which the agent is prone to the gambler's fallacy. In that variant, the probability of a winning bet in a session with an apprentice bowman is:

$$p_c \equiv p_c(t) \quad = \quad \frac{n_t}{100-t},$$

where $n_t = n_{t-1} - I(X_t \in [-4;4])$.[40] $n_0 = 95$. The agent thinks of the stochastic structure of the task as an urn containing initially 95% white balls and 5% black balls. In each trial, a ball is drawn without replacement. The drawing of a white (resp. black) ball corresponds to the occurrence of a near miss (resp. a shot outside of the winning range). Such a mistaken view of the stochastic structure of the task causes the agent to bet after seeing a black swan and to skip after a long series of realizations within the winning range. Note that such contrarian behavior is in sharp contrast to the behavior of the base model (which never bets after seeing a black swan and most often bets after a long series of realizations within the winning range).

[40] $I(X_t \in [-4;4]) = 1$ if $X_t \in [-4;4]$ and 0 otherwise.

5.2.3 Formalization of CbD hypothesis

A parsimonious way to capture CbD in the current paradigm is to augment the base model with the following feature: in the computation of the V metric (Equation (5)), the \$2 outcome is encoded as $\$2 + DA$, with $DA \geq 0$ (DA is a free parameter, more below). We also consider the multiplicative version of the model where the \$2 outcome is encoded as $DA \times \$2$, with $DA \geq 1$. The additive version fits the data better than the multiplicative variant does in the following model comparison analysis.

5.2.4 Model comparison analysis

We fit the base behavioral model (Section 5.2.1) and both foregoing variants—the one augmented with the gambler's fallacy feature (Section 5.2.2) and the one augmented with CbD (Section 5.2.3)—to each task participant's choices in Experiments 1 & 3 and then compare their prediction accuracy (the percentage of trials in which the model successfully predicts the participant's choice). In the benchmark analysis, we assume risk neutrality so there are no free parameters except for the craving parameter DA for the CbD model described in Appendix 5.2.3. As a robustness check, we also assess the prediction accuracy of the Prospect Theory versions of each model (base model, gambler's fallacy, and CbD); and we further run the foregoing model comparison for both the deterministic version of the models and the logit version (Equation (6)). The randomness parameter β is treated as a free parameter in the procedure.

To measure the goodness-of-fit of a given model, we use the cross-validation procedure proposed by Payzan-LeNestour (2018), which takes two steps, an in-sample estimation followed by an out-of-sample validation test. In the estimation step, the free parameters of the model—if any—are optimized by minimizing the total squared prediction error compounded over the set of trials for the first eight sessions. The ensuing parameter estimates are then used to predict the choices in the last seven sessions (out-of-sample validation). The success rate of the model is measured by the percentage of trials in which the model successfully predicts the subject's choice in the last seven sessions.

For the large majority of the penny-pickers, the base behavioral model described in Appendix 5.2.1 fits participant behavior better than the variant that incorporates the gambler's fallacy (the one described in Section 5.2.2) does. The goodness-of-fit of the base model is unambiguously better according to a paired t-test (the null hypothesis that the fits of the two models are equal is rejected with a p value close to null). Making the parameter n_0 free in the gambler's fallacy model (rather than fixing it to 95 like in the description in Appendix 5.2.2) does not improve the goodness-of-fit of the model.

In contrast, for the majority of the penny-pickers, the Bayesian model augmented with CbD (see Section 5.2.3) fits participant behavior better than the base Bayesian model does. Its goodness-of-fit is unambiguously better according to a paired t-test (the null hypothesis that the fits of the two models are equal is rejected; p value: 0.007).

6 Supplementary Information: Task Instructions (Not for Publication)

The following pages show the text and static pictures used in the task instructions. The animations that constituted a core aspect of the instructions for all the experiments (as explained in the main text) can be seen at http://bowmangame.weebly.com/task-instructions.html.

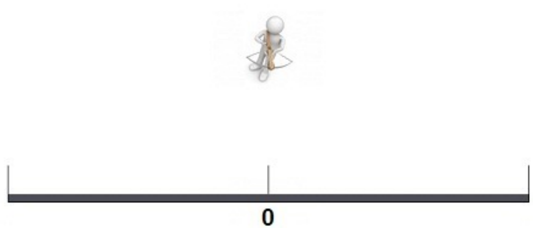
6.1 Task instructions used in Experiment 1

The following instructions explain the nature of the Bowman Game.

Please read them carefully.

The principle of the game is that on each trial, a bowman is going to shoot an arrow towards a target on a wall (See Pic 1A: the wall is represented by the gray line; 0 represents the target).

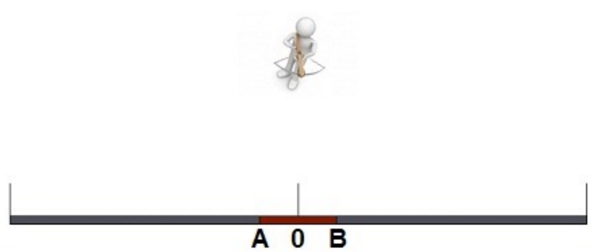
Picture 1A



Before the bowman shoots each arrow, you will have the opportunity to bet on whether the arrow will be close to the target or not. At each trial, before the bowman shoots the arrow, your task will be to choose between two actions, **Bet** and **Skip**:

- By selecting **Bet** you will earn $2 if the arrow hits the wall up to four meters away from the target on the left or on the right (i.e., if the hit is anywhere within the segment [AB] on Pic. 1B), and you will lose $40 otherwise.

Picture 1B



- By selecting **Skip** you do not lose nor earn anything no matter where the arrow hits: you always get $0.

Once you have indicated your choice, the bowman shoots and you see where the arrow hits. You'll then move to the next trial, in which you'll choose again between Bet and Skip, and then see the realized hit at that trial.

A play of the game is divided into 15 sessions of 20 trials each. For each session, a new bowman is doing the shooting for the entirety of the session.

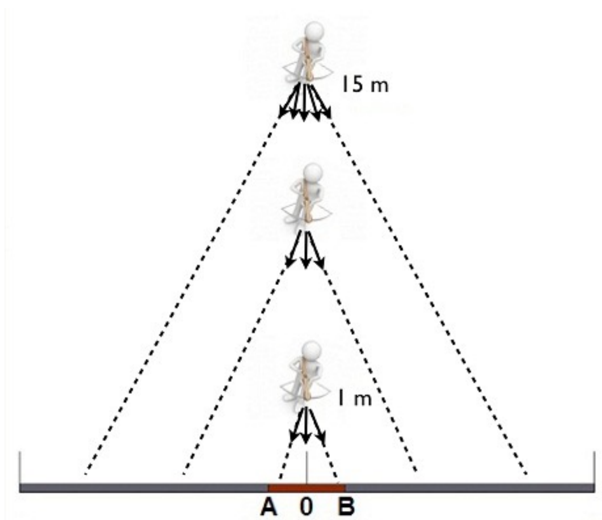
Each bowman is either a Master Bowman or an Apprentice Bowman, and has a specific shooting style corresponding to its skill level. We describe next the shooting style of the Master Bowman and then the Apprentice Bowman.

The Master Bowman

The hits of a Master Bowman are normally distributed around the target.

The dispersion of the hits from the target (the standard deviation) increases with the shooting distance of the bowman. The shooting distance differs across bowmen (see Pic. 2) but it is never changing within a session.

Picture 2



The standard deviation of the hits of a given bowman is unknown. It is uniformly distributed between 0.1 and 2 (i.e., all numbers within [0.1; 2] are equally likely).

The following interactive animation illustrates how the hits of the Master Bowman are distributed around the target, for different shooting distances (i.e., for different values of the standard deviation):

[show animation—distribution builders for Normal distributions here]

The Apprentice Bowman

The distribution of the hits of an Apprentice Bowman is bell shaped and symmetric around the target, like the one of the Master Bowman. But it's NOT NORMAL: with an Apprentice Bowman, you should not expect any particular hit to happen, because the hits can potentially be anywhere on the wall.

Apprentice Bowmen always shoot at the same distance from the target. The dispersion of their hits always equals 1, which implies that their hits are distributed around the target as follows:

[show animation—distribution builder for Cauchy distribution here]

<u>Please note</u>

Whether the bowman for a session is a Master Bowman or an Apprentice Bowman is not told

<u>Also note</u>

The distance of the bowman to the wall will vary from session to session, but the distance you'll see on the screen will appear to be the same at each trial (again, this is NOT the real distance; the real distance varies from session to session).

This game is very hard, so you will need to be very concentrated to be successful. Your payment will be extremely sensitive to your performance during the game. Specifically, your payment will be the addition of:

- the fixed show-up reward of $5
- an account balance allocated to each participant at the start of the game (more on this below)
- all your accumulated earnings and losses during the entire game

The account balance is the same for all participants and has been fixed before the game begins. Its amount, which can be any number between -500 and +500, will be revealed at the end of the game only. This is because we don't want you to be influenced by it during the game.

Your accumulated earnings and losses can be negative of course. In that case, the negative amount will be deducted from the money allocated to you at the start. If it goes below $5, you will still receive $5 as the show-up fee. If you are very good at the game, your final amount as calculated by the formula above might be more than $110. In that case, your payment will be capped at $110, as we simply can't afford to pay each of you more than that. It may be challenging to reach this score though!

Good luck!

Just a quick reminder that on each trial during the game:

- by selecting Bet,

You earn $2 if the arrow hits the wall up to four meters away from the target.
You lose $40 if the arrow hits the wall beyond four meters away from the target.

- by selecting Skip,

You do not lose nor earn anything no matter where the arrow hits: you always get $0.

One more thing: If you don't answer within the imparted time (indicated by a timer), you lose $1, and you don't see the hit realized at the trial, so try to keep the pace!

Please fill out the following multiple-choice questionnaire. This is to check your understanding of the rules of the game before you start to play. Thanks for your attention!

[multiple-choice questionnaire; for each question computer tells the subject whether answer is correct]

<u>Multiple-Choice Questionnaire</u>

1. By playing Bet on a trial you earn $2 if the arrow shot by the bowman at the trial hits the wall up to four meters away from the target on the left or on the right, and you lose $40 otherwise (i.e., if the arrow hits the wall beyond four meters away).

True/False

2. On each trial, the bowman doing the shooting can see, just before he shoots the arrow, whether you chose Bet.

True/False

3. The sessions are completely independent: facing a Master Bowman in the current session does not make it more likely to face a Master Bowman on the following session. The chances to face a Master Bowman vs. an Apprentice Bowman are always 50-50.

True/False

4. The dispersion (standard deviation) of the hits of a Master Bowman can be any number between 0.1 and 2. Before a session with a master begins, you are not told this number; it is fixed (will not change) throughout the session.

True/False

5. The bowman doing the shooting will remain the same throughout a given session.

True/False

6. The account balance that is allocated to you at the beginning of the game can be anything, any number between $-500 to $500.

True/False

6.2 Task instructions used in Experiment 2

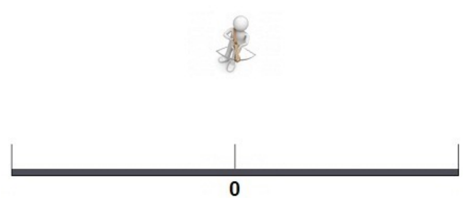
Psychology students are excluded from the pool of potential participants in Experiment 2 because they would be potentially biased if deceived in prior psychology experiments (psychologists commonly use deception in their experiments).

The following instructions explain the nature of the Bowman Game.

Please read them carefully.

The principle of the game is that on each trial, a bowman is going to shoot an arrow towards a target on a wall (See Pic 1A: the wall is represented by the gray line; 0 represents the target).

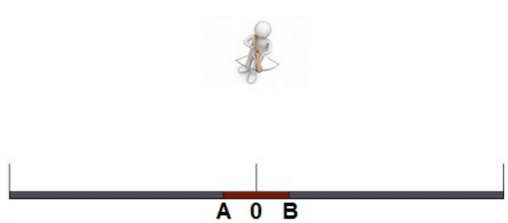
Picture 1A



Before the bowman shoots each arrow, you will have the opportunity to bet on whether the arrow will be close to the target or not. At each trial, before the bowman shoots the arrow, your task will be to choose between two actions, **Bet** and **Skip**:

- By selecting **Bet** you will earn $2 if the arrow hits the wall up to four meters away from the target on the left or on the right (i.e., if the hit is anywhere within the segment [AB] on Pic. 1B), and you will lose $40 otherwise.

Picture 1B



- By selecting **Skip** you do not lose nor earn anything no matter where the arrow hits: you always get $0.

Once you have indicated your choice, the bowman shoots and you see where the arrow hits. You'll then move to the next trial, in which you'll choose again between Bet and Skip, and then see the realized hit at that trial.

A play of the game is divided into 15 sessions of 20 trials each. For each session, a new bowman is doing the shooting for the entirety of the session.

Each bowman is either a Master Bowman or an Apprentice Bowman, and has a specific shooting style corresponding to its skill level. You will be notified at the start of each session as to the skill level of the bowman for that session.

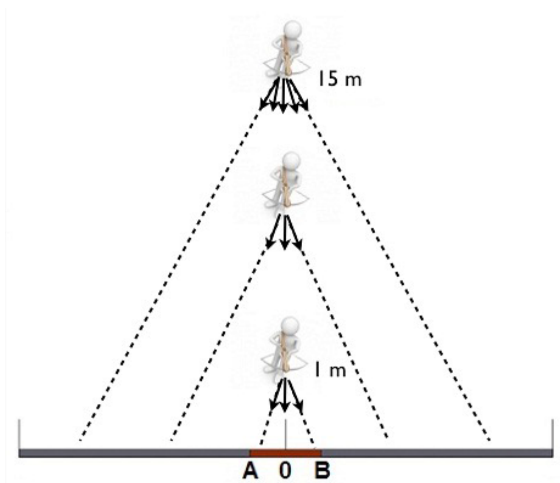
We describe next the shooting style of the Master Bowman and then the Apprentice Bowman.

The Master Bowman

The hits of a Master Bowman are normally distributed around the target.

The dispersion of the hits from the target (the standard deviation) increases with the shooting distance of the bowman. The shooting distance differs across bowmen (see Pic. 2) but it is never changing within a session.

Picture 2



The standard deviation of the hits of a given master bowman can be any number between 0.1 and 2. You will be notified of that number before the session begins.

The following interactive animation illustrates how the hits of the Master Bowman are distributed around the target, for different shooting distances (i.e., for different values of the standard deviation):

[show animation—distribution builders for Normal distributions here]

The Apprentice Bowman

The distribution of the hits of an Apprentice Bowman is bell shaped and symmetric around the target, like the one of the Master Bowman. But it’s NOT NORMAL: with an Apprentice Bowman, you should not expect any particular hit to happen, because the hits can potentially be anywhere on the wall.

Apprentice Bowmen always shoot at the same distance from the target. The dispersion of their hits always equals 1, which implies that their hits are distributed around the target as follows:

[show animation—distribution builder for Cauchy distribution here]

This game is hard, so you will need to be very concentrated to be successful. Your payment will be extremely sensitive to your performance during the game. Specifically, your payment will be the addition of:

- the fixed show-up reward of $5
- an account balance allocated to each participant at the start of the game (more on this below)
- all your accumulated earnings and losses during the entire game

The account balance is the same for all participants and has been fixed before the game begins. Its amount, which can be any number between -500 and +500, will be revealed at the end of the game only. This is because we don't want you to be influenced by it during the game.

Your accumulated earnings and losses can be negative of course. In that case, the negative amount will be deducted from the money allocated to you at the start. If it goes below $5, you will still receive $5 as the show-up fee. If you are very good at the game, your final amount as calculated by the formula above might be more than $110. In that case, your payment will be capped at $110, as we simply can't afford to pay each of you more than that. It may be challenging to reach this score though!

Good luck!

Just a quick reminder that on each trial during the game:

- by selecting Bet,

You earn $2 if the arrow hits the wall up to four meters away from the target.
You lose $40 if the arrow hits the wall beyond four meters away from the target.

- by selecting Skip,

You do not lose nor earn anything no matter where the arrow hits: you always get $0.

One more thing: If you don't answer within the imparted time (indicated by a timer), you lose $1, and you don't see the hit realized at the trial, so try to keep the pace!

Please fill out the following multiple-choice questionnaire. This is to check your understanding of the rules of the game before you start to play. Thanks for your attention!

[multiple-choice questionnaire; for each question computer tells the subject whether answer is correct]

<u>Multiple-Choice Questionnaire</u>

1. By playing Bet on a trial you earn $2 if the arrow shot by the bowman at the trial hits the wall up to four meters away from the target on the left or on the right, and you lose $40 otherwise (i.e., if the arrow hits the wall beyond four meters away).

True/False

2. On each trial, the bowman doing the shooting can see, just before he shoots the arrow, whether you chose Bet.

True/False

3. At the beginning of each session you are told the nature of the bowman doing the shooting for that session, but that piece of information might be wrong.

True/False

4. The dispersion (standard deviation) of the hits of a Master Bowman can be any number between 0.1 and 2. Before a session with a master begins, you are not told this number; it is fixed (will not change) throughout the session.

True/False

5. The bowman doing the shooting will remain the same throughout a given session.

True/False

6. The account balance that is allocated to you at the beginning of the game can be anything, any number between $-500 to $500.

True/False

6.3 Task instructions used in Experiment 3

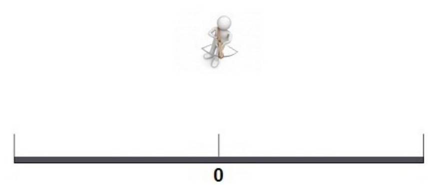
Highlighted in blue below (not highlighted in the instructions that the subjects read) are the parts of the instructions that were added to the instructions used in Experiment 1 (the rest was common across the two experiments).

The following instructions explain the nature of the Bowman Game.

Please read them carefully.

The principle of the game is that on each trial, a bowman is going to shoot an arrow towards a target on a wall (See Pic 1A: the wall is represented by the gray line; 0 represents the target).

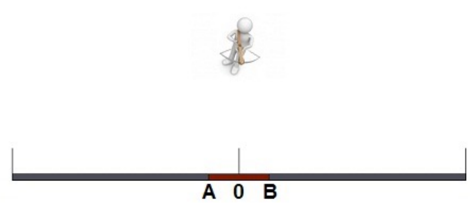
Picture 1A



Before the bowman shoots each arrow, you will have the opportunity to bet on whether the arrow will be close to the target or not. At each trial, before the bowman shoots the arrow, your task will be to choose between two actions, **Bet** and **Skip**:

- By selecting **Bet** you will earn $2 if the arrow hits the wall up to four meters away from the target on the left or on the right (i.e., if the hit is anywhere within the segment [AB] on Pic. 1B), and you will lose $40 otherwise.

Picture 1B



- By selecting **Skip** you do not lose nor earn anything no matter where the arrow hits: you always get $0.

Once you have indicated your choice, the bowman shoots and you see where the arrow hits. You'll then move to the next trial, in which you'll choose again between Bet and Skip, and then see the realized hit at that trial.

A play of the game is divided into 15 sessions of 20 trials each. For each session, a new bowman is doing the shooting for the entirety of the session.

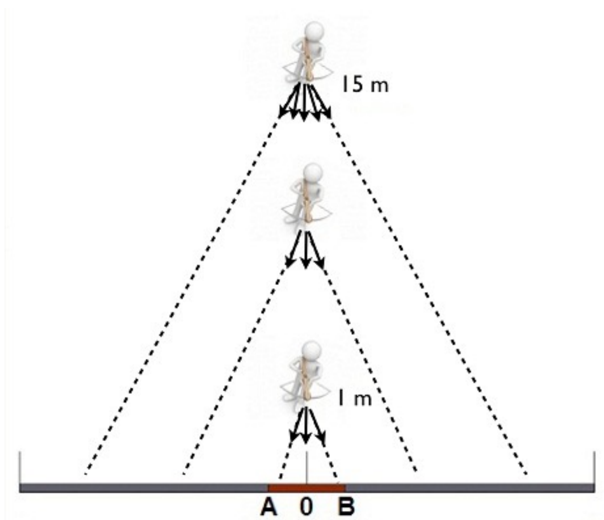
Each bowman is either a Master Bowman or an Apprentice Bowman, and has a specific shooting style corresponding to its skill level. We describe next the shooting style of the Master Bowman and then the Apprentice Bowman.

The Master Bowman

The hits of a Master Bowman are normally distributed around the target.

The dispersion of the hits from the target (the standard deviation) increases with the shooting distance of the bowman. The shooting distance differs across bowmen (see Pic. 2) but it is never changing within a session.

Picture 2



The standard deviation of the hits of a given bowman is unknown. It is uniformly distributed between 0.1 and 2 (i.e., all numbers within [0.1; 2] are equally likely).

The following interactive animation illustrates how the hits of the Master Bowman are distributed around the target, for different shooting distances (i.e., for different values of the standard deviation):

[show animation—distribution builders for Normal distributions here]

The Apprentice Bowman

The distribution of the hits of an Apprentice Bowman is bell shaped and symmetric around the target, like the one of the Master Bowman. But it's NOT NORMAL: with an Apprentice Bowman, you should not expect any particular hit to happen, because the hits can potentially be anywhere on the wall.

Apprentice Bowmen always shoot at the same distance from the target. The dispersion of their hits always equals 1, which implies that their hits are distributed around the target as follows:

[show animation—distribution builder for Cauchy distribution here]

<u>Please note</u>

Whether the bowman for a session is a Master Bowman or an Apprentice Bowman is not told

<u>Also note</u>

The distance of the bowman to the wall will vary from session to session, but the distance you'll see on the screen will appear to be the same at each trial (again, this is NOT the real distance; the real distance varies from session to session).

This game is very hard, so you will need to be very concentrated to be successful. Your payment will be extremely sensitive to your performance during the game. Specifically, your payment will be the addition of:
- the fixed show-up reward of $5
- an account balance allocated to each participant at the start of the game (more on this below)
- all your accumulated earnings and losses during the entire game

The account balance is the same for all participants and has been fixed before the game begins. Its amount, which can be any number between -500 and +500, will be revealed at the end of the game only. This is because we don't want you to be influenced by it during the game.

Your accumulated earnings and losses can be negative of course. In that case, the negative amount will be deducted from the money allocated to you at the start. If it goes below $5, you will still receive $5 as the show-up fee. If you are very good at the game, your final amount as calculated by the formula above might be more than $110. In that case, your payment will be capped at $110, as we simply can't afford to pay each of you more than that. It may be challenging to reach this score though!

Good luck!

<u>One more thing</u>

At the end of each session, you will be asked your opinion about the bowman you've faced in the session (whether he was a master or an apprentice).

A correct answer yields $10. An incorrect answer results in a loss of $10.

If you don't answer within the imparted time (20 sec), you'll lose $12.

Just a quick reminder that on each trial during the game:

- by selecting Bet,

You earn $2 if the arrow hits the wall up to four meters away from the target.
You lose $40 if the arrow hits the wall beyond four meters away from the target.

- by selecting Skip,

You do not lose nor earn anything no matter where the arrow hits: you always get $0.

One more thing: If you don't answer within the imparted time (indicated by a timer), you lose $1, and you don't see the hit realized at the trial, so try to keep the pace!

Please fill out the following multiple-choice questionnaire. This is to check your understanding of the rules of the game before you start to play. Thanks for your attention!

[multiple-choice questionnaire; for each question computer tells the subject whether answer is correct]

<u>Multiple-Choice Questionnaire</u>

1. By playing Bet on a trial you earn $2 if the arrow shot by the bowman at the trial hits the wall up to four meters away from the target on the left or on the right, and you lose $40 otherwise (i.e., if the arrow hits the wall beyond four meters away).

True/False

2. On each trial, the bowman doing the shooting can see, just before he shoots the arrow, whether you chose Bet.

True/False

3. The sessions are completely independent: facing a Master Bowman in the current session does not make it more likely to face a Master Bowman on the following session. The chances to face a Master Bowman vs. an Apprentice Bowman are always 50-50.

True/False

4. The dispersion (standard deviation) of the hits of a Master Bowman can be any number between 0.1 and 2. Before a session with a master begins, you are not told this number; it is fixed (will not change) throughout the session.

True/False

5. The bowman doing the shooting will remain the same throughout a given session.

True/False

6. The account balance that is allocated to you at the beginning of the game can be anything, any number between $-500 to $500.');

True/False

7. At the end of each session, you will be asked to give your guess about the nature of the bowman in the session. If you reply correctly you win $10, but if you reply incorrectly you lose $10. If you fail to reply, you lose $12.

True/False

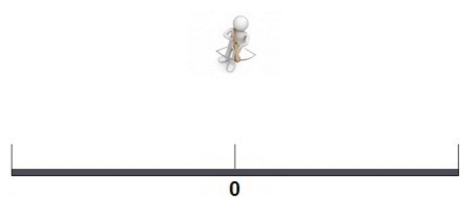
6.4 Task instructions used in Experiment 4

The following instructions explain the nature of the Bowman Game.

Please read them carefully.

The principle of the game is that on each trial, a bowman is going to shoot an arrow towards a target on a wall (See Pic 1A: the wall is represented by the gray line; 0 represents the target).

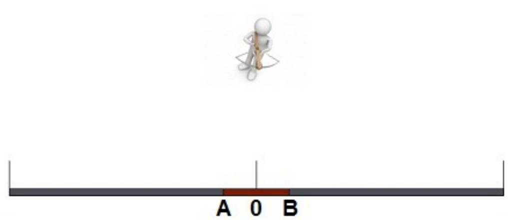
Picture 1A



Before the bowman shoots each arrow, you will have the opportunity to bet on whether the arrow will be close to the target or not. At each trial, before the bowman shoots the arrow, your task will be to choose between two actions, **Bet** and **Skip**:

- By selecting **Bet** you will earn $2 if the arrow hits the wall up to four meters away from the target on the left or on the right (i.e., if the hit is anywhere within the segment [AB] on Pic. 1B), and you will lose $40 otherwise.

Picture 1B



- By selecting **Skip** you do not lose nor earn anything no matter where the arrow hits: you always get $0.

Once you have indicated your choice, the bowman shoots and you see where the arrow hits. You'll then move to the next trial, in which you'll choose again between Bet and Skip, and then see the realized hit at that trial.

A play of the game is divided into 15 sessions of 20 trials each. For each session, a new bowman is doing the shooting for the entirety of the session.

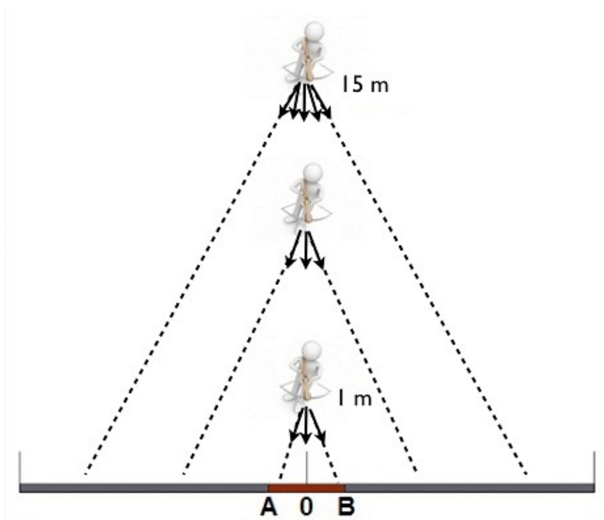
Each bowman is either a Master Bowman or an Apprentice Bowman, and has a specific shooting style corresponding to its skill level. We describe next the shooting style of the Master Bowman and then the Apprentice Bowman.

The Master Bowman

The hits of a Master Bowman are normally distributed around the target.

The dispersion of the hits from the target (the standard deviation) increases with the shooting distance of the bowman. The shooting distance differs across bowmen (see Pic. 2) but it is never changing within a session.

Picture 2



The standard deviation of the hits of a given bowman is unknown. It is uniformly distributed between 0.1 and 2 (i.e., all numbers within [0.1; 2] are equally likely).

The following interactive animation illustrates how the hits of the Master Bowman are distributed around the target, for different shooting distances (i.e., for different values of the standard deviation):

[show animation—distribution builders for Normal distributions here]

The Apprentice Bowman

The distribution of the hits of an Apprentice Bowman is bell shaped and symmetric around the target, like the one of the Master Bowman. But it's NOT NORMAL: with an Apprentice Bowman, you should not expect any particular hit to happen, because the hits can potentially be anywhere on the wall.

Apprentice Bowmen always shoot at the same distance from the target. The dispersion of their hits always equals 1, which implies that their hits are distributed around the target as follows:

[show animation—distribution builder for Cauchy distribution here]

Please note

1. Whether the bowman for a session is a Master Bowman or an Apprentice Bowman is not told

2. The distance of the bowman to the wall will vary from session to session, but the distance you'll see on the screen will appear to be the same at each trial (again, this is NOT the real distance; the real distance varies from session to session).

At anytime, the option to bind your choices for the remainder of the session

At each trial during the game, you'll have the option to bind your choices for the remainder of the session, simply by pressing a button. Clicking on the button to Skip [resp. Bet] for the remaining trials means you'll play Skip [resp. Bet] at each of these trials.

Note:

1. Once you've confirmed your decision to use the option to Bet or Skip for the remainder of a session, you **cannot** change your mind later on during the session.

2. If you use the option, you will still see every individual trial and the result corresponding to your choice to Skip [resp. Bet]

One more thing…

The length of the experiment is constant and is not affected by how (let alone how quickly) you respond. In other words, responding quickly won't get you out of here faster!

This game is very hard, so you will need to be very concentrated to be successful. Your payment will be extremely sensitive to your performance during the game. Specifically, your payment will be the addition of:

- the fixed show-up reward of $5
- an account balance allocated to each participant at the start of the game (more on this below)
- all your accumulated earnings and losses during the entire game

The account balance is the same for all participants and has been fixed before the game begins. Its amount, which can be any number between -500 and +500, will be revealed at the end of the game only. This is because we don't want you to be influenced by it during the game.

Your accumulated earnings and losses can be negative of course. In that case, the negative amount will be deducted from the money allocated to you at the start. If it goes below $5, you will still receive $5 as the show-up fee. If you are very good at the game, your final amount as calculated by the formula above might be more than $110. In that case, your payment will be capped at $110, as we simply can't afford to pay each of you more than that. It may be challenging to reach this score though!

Good luck!

Just a quick reminder that on each trial during the game:

- by selecting Bet,

You earn $2 if the arrow hits the wall up to four meters away from the target.
You lose $40 if the arrow hits the wall beyond four meters away from the target.

- by selecting Skip,

You do not lose nor earn anything no matter where the arrow hits: you always get $0.

One more thing: If you don't answer within the imparted time (indicated by a timer), you lose $1, and you don't see the hit realized at the trial, so try to keep the pace!

Please fill out the following multiple-choice questionnaire. This is to check your understanding of the rules of the game before you start to play. Thanks for your attention!

[multiple-choice questionnaire; for each question computer tells the subject whether answer is correct]

<u>Multiple-Choice Questionnaire</u>

1. By playing Bet on a trial you earn $2 if the arrow shot by the bowman at the trial hits the wall up to four meters away from the target on the left or on the right, and you lose $40 otherwise (i.e., if the arrow hits the wall beyond four meters away).

True/False

2. On each trial, the bowman doing the shooting can see, just before he shoots the arrow, whether you chose Bet.

True/False

3. The sessions are completely independent: facing a Master Bowman in the current session does not make it more likely to face a Master Bowman on the following session. The chances to face a Master Bowman vs. an Apprentice Bowman are always 50-50.

True/False

4. The dispersion (standard deviation) of the hits of a Master Bowman can be any number between 0.1 and 2. Before a session with a master begins, you are not told this number; it is fixed (will not change) throughout the session.

True/False

5. The bowman doing the shooting will remain the same throughout a given session.

True/False

6. The account balance that is allocated to you at the beginning of the game can be anything, any number between $-500 to $500.

True/False

7. At any trial of a session, you can decide to bet (resp skip) for the remainder of the session, by simply pressing a button “Bet for the remainder of the session” (resp “Skip for the remainder of the session”.

True/False

8. When you decide to skip or bet for the remainder of a session, you do not jump straight away to the next session. You see the result corresponding to your decision at each of the remaining trials of the session. However, you cannot reverse your choice to skip or bet for the remainder of the session.

True/False

6.5 Task instructions used in Experiment 5

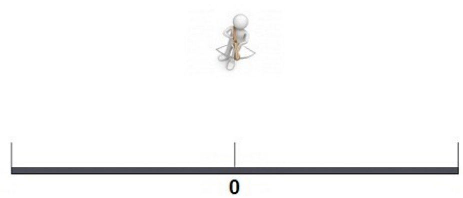
Highlighted in blue below (not highlighted in the instructions that the subjects read) is the part of the instructions that differed from the instructions used in Experiment 3.

The following instructions explain the nature of the Bowman Game.

Please read them carefully.

The principle of the game is that on each trial, a bowman is going to shoot an arrow towards a target on a wall (See Pic 1A: the wall is represented by the gray line; 0 represents the target).

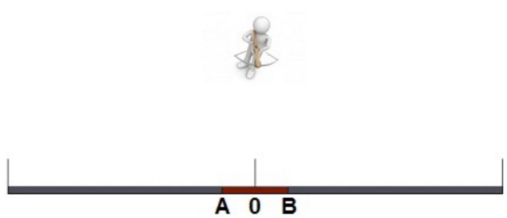
Picture 1A



Before the bowman shoots each arrow, you will have the opportunity to bet on whether the arrow will be close to the target or not. At each trial, before the bowman shoots the arrow, your task will be to choose between two actions, **Bet** and **Skip**:

- By selecting **Bet** you will earn $2 if the arrow hits the wall up to four meters away from the target on the left or on the right (i.e., if the hit is anywhere within the segment [AB] on Pic. 1B), and you will lose $40 otherwise.

Picture 1B



- By selecting **Skip** you do not lose nor earn anything no matter where the arrow hits: you always get $0.

Once you have indicated your choice, the bowman shoots and you see where the arrow hits. You'll then move to the next trial, in which you'll choose again between Bet and Skip, and then see the realized hit at that trial.

A play of the game is divided into 15 sessions of 20 trials each. For each session, a new bowman is doing the shooting for the entirety of the session.

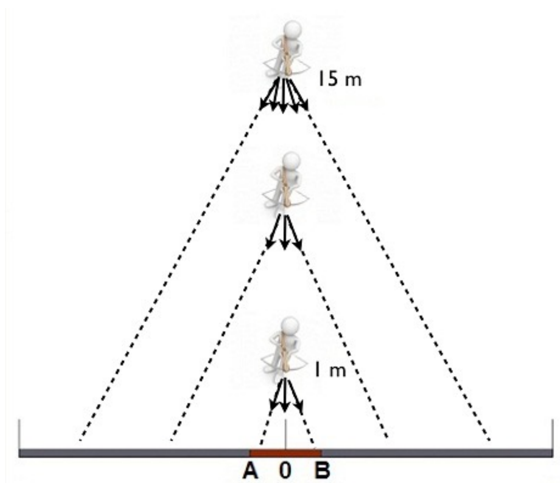
Each bowman is either a Master Bowman or an Apprentice Bowman, and has a specific shooting style corresponding to its skill level. We describe next the shooting style of the Master Bowman and then the Apprentice Bowman.

The Master Bowman

The hits of a Master Bowman are normally distributed around the target.

The dispersion of the hits from the target (the standard deviation) increases with the shooting distance of the bowman. The shooting distance differs across bowmen (see Pic. 2) but it is never changing within a session.

Picture 2



The standard deviation of the hits of a given bowman is unknown. It is uniformly distributed between 0.1 and 2 (i.e., all numbers within [0.1; 2] are equally likely).

The following interactive animation illustrates how the hits of the Master Bowman are distributed around the target, for different shooting distances (i.e., for different values of the standard deviation):

[show animation—distribution builders for Normal distributions here]

The Apprentice Bowman

The distribution of the hits of an Apprentice Bowman is bell shaped and symmetric around the target, like the one of the Master Bowman. But it's NOT NORMAL: with an Apprentice Bowman, you should not expect any particular hit to happen, because the hits can potentially be anywhere on the wall.

Apprentice Bowmen always shoot at the same distance from the target. The dispersion of their hits always equals 1, which implies that their hits are distributed around the target as follows:

[show animation—distribution builder for Cauchy distribution here]

Please note

Whether the bowman for a session is a Master Bowman or an Apprentice Bowman is not told

Also note

The distance of the bowman to the wall will vary from session to session, but the distance you'll see on the screen will appear to be the same at each trial (again, this is NOT the real distance; the real distance varies from session to session).

This game is very hard, so you will need to be very concentrated to be successful. Your payment will be extremely sensitive to your performance during the game. Specifically, your payment will be the addition of:

- the fixed show-up reward of $5
- an account balance allocated to each participant at the start of the game (more on this below)
- all your accumulated earnings and losses during the entire game

The account balance is the same for all participants and has been fixed before the game begins. Its amount, which can be positive or negative, will be revealed at the end of the game.

If your accumulated earnings and losses are negative at the end of the experiment, then you will have to pay the experimenter for your losses. Your payment is capped at $95 dollars though. For example, if the addition of the 3 elements indicated above ends up at -$20, then you will pay $20. If it's -$150, your payment is only $95 because of the cap.

If your accumulated earnings and losses are positive at the end of the experiment, then you will be paid by the experimenter for your gains. Your payment is capped at $110 dollars though. For example, if the addition of the 3 elements indicated above ends up at $20, then you will receive $20. If it's $150, your will receive only $110 because of the cap.

Good luck!

One more thing

At the end of each session, you will be asked your opinion about the bowman you've faced in the session (whether he was a master or an apprentice).

A correct answer yields $10. An incorrect answer results in a loss of $10.

If you don’t answer within the imparted time (20 sec), you’ll lose $12.

Just a quick reminder that on each trial during the game:

- by selecting Bet,

You earn $2 if the arrow hits the wall up to four meters away from the target.
You lose $40 if the arrow hits the wall beyond four meters away from the target.

- by selecting Skip,

You do not lose nor earn anything no matter where the arrow hits: you always get $0.

One more thing: If you don't answer within the imparted time (indicated by a timer), you lose $1, and you don't see the hit realized at the trial, so try to keep the pace!

Please fill out the following multiple-choice questionnaire. This is to check your understanding of the rules of the game before you start to play. Thanks for your attention!

[multiple-choice questionnaire; for each question computer tells the subject whether answer is correct]

<u>Multiple-Choice Questionnaire</u>

1. By playing Bet on a trial you earn $2 if the arrow shot by the bowman at the trial hits the wall up to four meters away from the target on the left or on the right, and you lose $40 otherwise (i.e., if the arrow hits the wall beyond four meters away).

True/False

2. On each trial, the bowman doing the shooting can see, just before he shoots the arrow, whether you chose Bet.

True/False

3. The sessions are completely independent: facing a Master Bowman in the current session does not make it more likely to face a Master Bowman on the following session. The chances to face a Master Bowman vs. an Apprentice Bowman are always 50-50.

True/False

4. The dispersion (standard deviation) of the hits of a Master Bowman can be any number between 0.1 and 2. Before a session with a master begins, you are not told this number; it is fixed (will not change) throughout the session.

True/False

5. The bowman doing the shooting will remain the same throughout a given session.

True/False

6. The account balance that is allocated to you at the beginning of the game can be anything, any number between $-500 to $500.

True/False

7. At the end of each session, you will be asked to give your guess about the nature of the bowman in the session. If you reply correctly you win $10, but if you reply incorrectly you lose $10. If you fail to reply, you lose $12.

True/False

6.6 FAQs

The following document was distributed to the task participants (printed format) after they went through the online task instructions, just before they started to perform the task. It was presented as "FAQs" and a final opportunity for participants to ask clarifying questions to the experimenter before starting to perform the task. Note Question 6 was only present in Experiments 3 and 5.

FAQS

1. Shall you expect the hits of a Master bowman to reach the target on average?

YES! The distribution of the hits of any master bowman is normally distributed around the target. It means that one expects the hits to reach the target on average; but of course this is not always the case for each individual hit. How far from the target the hits can be? The standard deviation tells you that:

- You saw in the simulations that if the std is 1 then the hits are all within -4 and +4
- If the std is 2 (the max that can happen) then there is a positive probability that the hits be outside [-4,+4], but this probability is quite small

2. What does the standard deviation have to do with the distance at which the bowman shoots?

You don’t care about the distance in itself. All you need to remember is that master bowmen differ in the distance at which they do the shooting hence the standard deviations of their hits differ. It can be any number between 0.1 and 2.

It’s just that if the guy shoots from very far away the standard deviation is bigger than if the guy shoots from nearby the target.

3. Should we expect the std for a given master bowman to be 0.1 or 2 or something else?

It is uniformly distributed between 0.1 and 2 meaning all values between 0.1 and 2 are equally likely.

4. **What about the distribution of the hits of an apprentice bowman? Is it normal too? The hits look pretty dispersed in the simulation so why is the dispersion only 1?**

The distribution of the hits of an apprentice is NOT normal.

It's bell-shaped and symmetric around the target, like the normal distribution, but it's much more unpredictable than a normal. It is a very unpredictable ("fat tail") distribution called *Cauchy.* Its dispersion parameter is 1. The simulation shows to you what it looks like exactly.

5. **Are the hits of an apprentice bowman and those of a master with a standard deviation of 2 pretty much the same?**

NO they're not!

The hits of the master bowman with a std of 2 are most often within -4 and +4 and on expectation they reach at the target. By contrast, anything is possible with the hits of an apprentice! They're completely unpredictable.

6. **Why am I asked at the end of each session the nature of the bowman I've just faced? Is it important for my final earnings that I answer the question correctly [i.e., if the bowman was an apprentice (resp. a master), I say my guess is that the bowman was an apprentice (resp. a master)]?**

You're asked that question because it is of interest for us (the experimenters) to know what you believe.

You should really try hard to reply correctly because **if you're wrong** (e.g., the bowman was an apprentice and you said you think it was a master), **you lose $10; if you're right you win 10 additional dollars.**