Journal of Behavioral Decision Making, *J. Behav. Dec. Making*, **30**: 807–818 (2017)
Published online 8 March 2017 in Wiley Online Library (wileyonlinelibrary.com) **DOI:** 10.1002/bdm.2006

The Influence of Time Estimation and Time-Saving Preferences on Learning to Make Temporally Dependent Decisions from Experience

NATHANIEL J. S. ASHBY[1]* and CLEOTILDE GONZALEZ[2]

[1] *Technion–Israel Institute of Technology, Haifa, Israel*

[2] *Dynamic Decision Making Laboratory, Carnegie Mellon University, Pittsburgh, PA USA*

ABSTRACT

In this paper, we merge research related to experiential learning, temporal perception, and the value of time and money by examining decisions where the timing of action (response) determines the outcome received. We predicted that time-saving preferences and impatience would decrease maximization (i.e., taking action when it returned the largest reward), and that the constraints of temporal perception would compound their effects. Across three studies, participants undershot on average (i.e., responded earlier than the period of time during which a response would return the maximal reward) showed a preference for shorter-delay options and often did not find the maximal reward. In addition, participants' reliance on temporal perception increased undershooting, increased preferences for shorter-delay options, and reduced maximization. Nevertheless, participants who found the maximal reward continued to maximize at a high rate rather than opting for shorter delays and smaller rewards. Thus, while most participants appeared to have a preference for saving time, most behaved as reward maximizers rather than temporal discounters. Copyright © 2017 John Wiley & Sons, Ltd.

KEY WORDS decisions-from-experience; temporal perception; learning; temporal discounting; decision strategy

Decisions abound where one must decide whether to wait or take action, and where acting early or late can lead to poor outcomes. We must decide when to leave to account for traffic delays, when to buy or sell a stock, and when to cross a busy street. Such decisions rely heavily on previous experiences and are influenced by time estimation and time-saving preferences. Examining the role that time-saving preferences play in experiential learning (learning the value of a given action by taking action and seeing what happens) is therefore of great importance.

In this paper, we examine (1) individuals' ability to learn from experience when to take action to receive the largest (maximal) reward, (2) the impact of increased delays (i.e., whether a longer or shorter delay is required), and (3) the effect of temporal perception constraints on learning. This research draws from three lines of research: experiential learning (Rakow & Newell, 2010), the perception of time (Grondin, 2010), and the subjective value of time and money (Loewenstein & Prelec, 1992). In the following sections, we highlight findings from each of these areas that have implications for the current investigation. We then generalize those findings to inform our novel investigation into how time-saving preferences influence decision strategies and performance in repeated decisions from experience.

Learning to make decisions from experience

While not a new topic (Skinner, 1938), there has been a renewed interest in how decisions are made from experience (Erev et al., 2010; Rakow & Newell, 2010). In simple binary-choice paradigms of *decisions-from-experience*, where explicit information about potential outcomes and probabilities is hidden, individuals learn the values of options by repeatedly selecting from them and observing their outcomes (Barron & Erev, 2003; Hertwig & Erev, 2009). In decisions-from-experience, individuals tend to maximize (make more choices for the option of highest expected value) more with experience (Ashby & Rakow, 2016; Jessup, Bishara, & Busemeyer, 2008). However, when the probability of receiving a reward is highly variable or small, increased maximization does not always occur (Barron & Erev, 2003; Mehlhorn, Ben-Asher, Dutt, & Gonzalez, 2014). Interestingly, Ashby and Rakow (2016) reported that in a *decisions-from-feedback* paradigm (where repeated consequential choices with feedback are made), attention to outcomes diminished with experience. This finding indicates that decision makers sought to minimize their cognitive investment in the task. In the *decisions-from-samples* paradigm (Hertwig, Barron, Weber, & Erev, 2004), where individuals are free to sample options (simulate playing them) before making a consequential decision, individuals tend to rely on small sample sizes (Ashby & Rakow, 2014; Hertwig et al., 2004; Rakow, Demes, & Newell, 2008). Thus, even when exploration costs are low, decision makers show an aversion to prolonged search, presumably valuing the time saved more than the benefits of additional experience. Given that decision makers appear to under-explore and reduce engagement in decisions-from-experience, we might expect that such time-saving and effort-saving strategies would lead to earlier responses during exploration of temporally dependent outcomes. These decision strategies would lead to subpar outcomes when a delay is required.

Perception of time

A great deal of research has sought to understand how time is perceived (Block, 2014; Block & Gruber, 2014; Block, Zakay, & Hancock, 1999; Forster & Brown, 2011; Meck,

*Correspondence to: Nathaniel J. S. Ashby, Faculty of Industrial Engineering and Management, Technion–Israel Institute of Technology, Technion City, Haifa 32000, Israel. E-mail nathaniel.js.ashby@gmail.com

Copyright © 2017 John Wiley & Sons, Ltd.

1996). Temporal judgments generally become more accurate with experience, even when monetary rewards are absent (Wright, Buonomano, Mahncke, & Merzenich, 1997) and in complex tasks involving risk (Balci, Freestone, & Gallistel, 2009). Several additional factors have been found to influence temporal perception (Matthews & Meck, 2014), the most important of which to the current investigation is the duration of the time period being estimated. In what is known as the *scalar variability effect*, estimates of time retain mean accuracy but become increasingly variable (variance is found to be distributed normally around the mean) as duration increases (Ekman, 1959; Gibbon, 1977). Rakitin et al. (1998) found that participants' estimates of various durations were accurate (i.e., the mean estimate was equal to the actual time elapsed), but as the durations increased, so too did the variability. Thus, when individuals are faced with longer waits and must rely on temporal perception, we should expect performance to decrease due to increased variability in estimation. Nevertheless, because the observed variance is predicted to be, on average, distributed equally around the correct timing, we should not expect an early or late bias in duration estimates.

The value of time and time's influence on value

Classic economic theory posits that time and money should be equivalent because one can equate the value of any increment of time to its opportunity costs (e.g., hourly wage; Becker, 1965; Graham, 1981). Others have argued that time is unique because it cannot be saved or transferred to others (Gross, 1987; Soman, 2001; Zauberman & Lynch, 2005). Chang, Chang, Chang, and Chien (2013) found decisions to save time were less popular than decisions to save money, while Okada and Hoch (2004) found that individuals were more willing to gamble with time than with money. These findings suggest that time is often perceived to have less value than money. However, when the equivalency between time and money are made salient (e.g., by instructing individuals to think about their hourly wage or with experience), many of these differences disappear (DeVoe & House, 2012; Munichor, Erev, & Lotem, 2006; Saini & Monga, 2008).

In contrast, when faced with the option of having less now or more later, many behave as if they are impatient, opting for a smaller earlier reward—a finding known collectively as *temporal discounting* (Fishburn & Rubinstein, 1982; Green, Fristoe, & Myerson, 1994; Kirby & Maraković, 1995; Loewenstein & Prelec, 1992). For example, Chapman and Elstein (1995) reported that in descriptive decisions involving outcomes relating to health and money, most people preferred immediate rather than delayed outcomes. It seems that simply waiting for an outcome can directly impact its subjective value. While a reward might be objectively larger if one waits, one's subjective value of that reward might be lower the longer the delay before it is received (Frederick, Loewenstein, & O'donoghue, 2002). Nevertheless, temporal discounting can vary depending on framing techniques or attribute focus (Lempert & Phelps, 2016). Furthermore, existing work on intertemporal choice has been largely built on this notion of temporal discounting, but generally in the context of decisions-from-description rather than experiential choice.

These somewhat incongruent findings reflect the uncertainty surrounding how trade-offs of time and money operate, particularly in decisions under uncertainty and in decisions based on experience rather than on explicit descriptive information. One possibility supported by the literature is that individuals would demonstrate a willingness to wait for increased earnings, valuing money over time. An equally supported possibility is that individuals would be impatient, preferring a more immediate, though decreased, reward. Alternatively, given that the salience of a delay minimizes differential valuing of time and money, we might expect time and money trade-offs to become increasingly interchangeable under time delays.

The present studies

Incentivized decisions involving time–money trade-offs where information is presented descriptively are often studied in the laboratory, while decisions reliant on time perception and experience are not. This leaves a gap in theory related to the naturalistic intersection of experiential value learning, temporal perception, and the subjective value of time and money. The present studies integrate these lines of research, providing novel insight into the roles of time perception, time-saving preferences, and impatience (temporal discounting) in an experiential learning context. Specifically, the studies involve repeated decisions to act where (1) the timing of action determines the payout received and (2) the delay before a maximizing response (responding when the largest outcome will be obtained) can be made varies. This framework is akin to motor skill learning (Schmidt, 1975) and Peak-Interval timing paradigms (Rakitin et al., 1998).

Our aim is to investigate how trade-offs of time and money are made in repeated decisions where response-outcome mappings must be gleaned from experience. Based on findings of limited exploration (Ashby & Rakow, 2014; Hertwig et al., 2004) and discounting of future outcomes (Fishburn & Rubinstein, 1982), we predict that as delays before the time of maximal reward is reached become longer decisions will lead to less maximization on average because: (1) limited initial exploration will interfere with the discovery of the maximizing response, and (2) the value of the maximal response might be discounted, making an earlier response seem as or even more rewarding. Furthermore, based on the scalar variability effect (Ekman, 1959), we expect longer delays to lead to increased variability in response (i.e., the timing of when an action is taken), further decreasing the rate of maximization when temporal perception is relied upon.

STUDY 1: THE INFLUENCE OF TEMPORAL PERCEPTION

Method

Participants

Seventy participants (M_{age} = 28.29; 51% female) were recruited by using a human subject pool. They were paid

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

$4.00 for their participation and received bonus incentive payments based on their decisions. On average, participants took less than 30 minutes and earned $7.00 ($4.00 plus incentive payments).

Design and materials

In this experiment, participants were randomly assigned to one of two reward conditions and were given a choice between two reward actions (options). Of the two options, one provided a reward after a shorter delay (Short Option), while the other option provided a reward after a longer delay (Long Option). These options were randomly assigned to the labels "Action A" and "Action B" for each participant. The value of the reward, which was measured in points, depended upon which condition the participant was assigned: "Short-Better/Long-Worse" or "Long-Better/Short-Worse". In the "Short-Better" condition, choosing the short-delay option returned rewards that grew in 2-point increments, while choosing the long-delay option returned rewards that grew in 1-point increments (Figure 1). In the "Long-Better" condition, the assignment of the increments was reversed. The exact reward system for each option was as follows.

For the short-delay option, taking action in the first 1100 ms of a trial returned a reward of 0 points. From the first 1100 to 3100 ms, taking action returned a positive reward. The value of this reward increased by 1 point (or 2 points in the Short-Better condition) every 20 ms. After 3100 ms, the value of the reward remained unchanged for 300 ms. Thereafter, the value of the reward decreased by 1 point (2 points in the Short-Better condition) every 20 ms until reaching 0 points at the 5400 ms mark. Hence, the maximal reward could be attained by responding in between the first 1100 and 3400 ms.

For the long-delay option, taking action in the first 3100 seconds returned no reward. Thereafter, the value of the reward increased and decreased according to the same time increments as in the short-delay option: a 2-point increase (or a 1-point increase in the Short-Better condition) every 20 ms until the 5100 ms mark, where the reward value remained unchanged until the 5400 ms mark, and then a 2-point decrease every (or 1-point decrease in the Short-Better condition) 20 ms until reaching 0 points at the 7400 ms mark.

The program Inquisit by Millisecond Software was used to design the studies. As with any software, some imprecision in the timings of stimuli onset/offset and response latency existed. However, the software ensured minimal difference between the accuracy of presentation and response timings for experiments run in the laboratory and remotely (i.e., via Amazon Mechanical Turk) as both were run on a participant's computer rather than remotely.

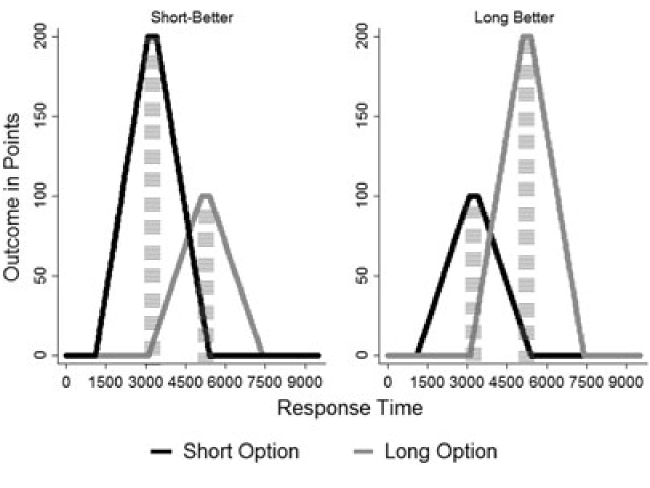

Figure 1. Response-outcome mappings with payouts (points) on the *y*-axis and time (from the presentation of the take action buttons) in milliseconds on the *x*-axis by option (Short or Long) and condition: Short-Better or Long-Better. The vertical dashed lines represent the period when response led to the greatest amount of points in an option (the maximal time window)

Procedure

After providing informed consent, participants were told that their task was to earn as many points as possible and that they would earn points by learning what action (option) and action timing led to the largest reward during a 9.5-second response window. Participants were then randomly assigned to the Short-Better condition ($n = 36$) or the Long-Better condition ($n = 34$) and underwent 120 trials (i.e., made a series of 120 decisions) between the two options, Action A and Action B. Participants responded by clicking on one of the options during the 9.5-second response window. Following each response, the resulting reward was shown for 500 ms and was followed by a blank screen for 150 ms before the next trial began (Figure 2). After participants made all 120 decisions, they were asked to describe how they had searched for the maximum outcome. Points were converted to dollars at a rate of 50 points = $0.01. Participants were then informed of their earnings and thanked for their time.

Results

Maximization

The left panel of Figure 3 plots the proportion of participants making a maximizing response (picking the higher value

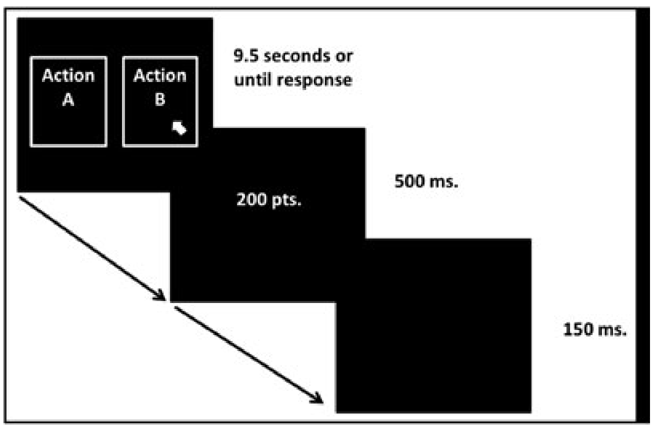

Figure 2. Example of the course of a trial in all studies. In Studies 2 and 3, wait times and actions were assigned by participants at the start of the trial by typing in a wait time for a given action

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

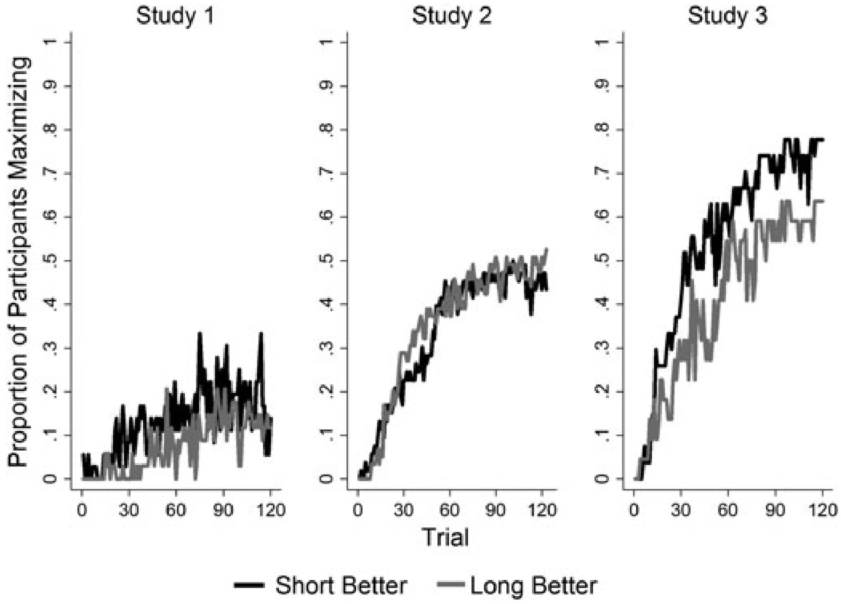

Figure 3. Proportion of participants taking action during the maximal response window in Study 1 (left panel), Study 2 (middle panel), and Study 3 (right panel), by condition

option at the time it provided its maximal reward of 200 points) across trials and condition. To examine how maximization developed over trials and whether there was any difference between conditions, we performed a logistic regression predicting whether action was taken during the maximal response window in the option providing the higher payout (e.g., the Short Option in the Short-Better condition) by trial number (entered linearly and centered), condition (coded 0 for Short-Better, 1 for Long-Better in this and the following analyses), and their interaction. In this and all the analyses that follow, we cluster on the level of the participant to correct for repeated measurement (Rogers, 1993). As expected, the likelihood of making a maximizing response increased with experience, odds ratio = 1.02 ($CI_{95\%}$ [1.01, 1.03]), $z = 6.05$, $p < .001$. Contrary to our hypothesis, neither the effect of condition nor its interaction with trial was significant, $ps = .09$.

Strategy

Those in the Short-Better condition discovered the maximal reward earlier ($M_{TrialNumber} = 33.87$; $CI_{95\%}$ [22.39, 45.35]) than those in the Long-Better condition ($M_{TrialNumber} = 49.44$; $CI_{95\%}$ [37.65, 61.24]). Furthermore, in both conditions, many participants (41%) never found the maximum reward. There was no evidence to suggest that the likelihood of finding the maximum reward differed between conditions. After participants found the maximum reward, the maximization rate ranged from 0 to 59% ($M = 24\%$; $CI_{95\%}$ [.19, .28]).

Figure 4 shows the mean error (distance between response and the maximal response time window) for individuals over trials and conditions and plotted separately by which option was selected. Negative numbers indicate a response *before* the maximal response time window for a given option (undershooting), while positive numbers indicate responses *after* it (overshooting). As the graph suggests, we found that participants undershot the maximal response window on average ($M = -1477.59$; $CI_{95\%}$ [−1819.45, −1135.73]).

To examine what influenced the direction of error, we regressed error on trial number; condition, which option was picked; and their interaction. Neither the effect of condition, $p = .84$, nor the effect of experience, $p = .16$, was significant. Which option was picked was significant with undershooting increasing when the Long Option was selected, $b = -2037.49$ ($CI_{95\%}$ [−2252.01, −1822.96]), $z = -18.62$, $p < .001$. The interaction between condition and trial was significant, indicating that undershooting decreased more in the Long-Better condition with experience ($b = 14.31$ ($CI_{95\%}$ [−7.33, 21.3]), $z = 4.01$, $p < .001$). Similarly, the interaction between the selected option and trial suggested that undershooting decreased more with experience when the Long Option was picked, $b = 4.06$ ($CI_{95\%}$ [1.45, 6.68]), $z = 3.05$, $p = .002$. Lastly, the three-way interaction indicated that undershooting remained higher in the Long-Better condition with experience when the Long Option was selected, $b = -6.01$ ($CI_{95\%}$ [−9.49, −2.53]), $z = -3.39$, $p = .001$.

Preference

The left panel of Figure 5 plots the average rate of picking the better option (irrespective of when action was taken) by condition (e.g., the Long Option in the Long-Better condition). While the rate of selecting the better option increased with experience, this effect appeared to be more pronounced in the Short-Better condition. To test whether this was the case, we performed a logistic regression predicting whether the better option was selected (coded 0 if it was not, 1 otherwise) by trial, condition, and their interaction. As expected, the likelihood of selecting the better

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

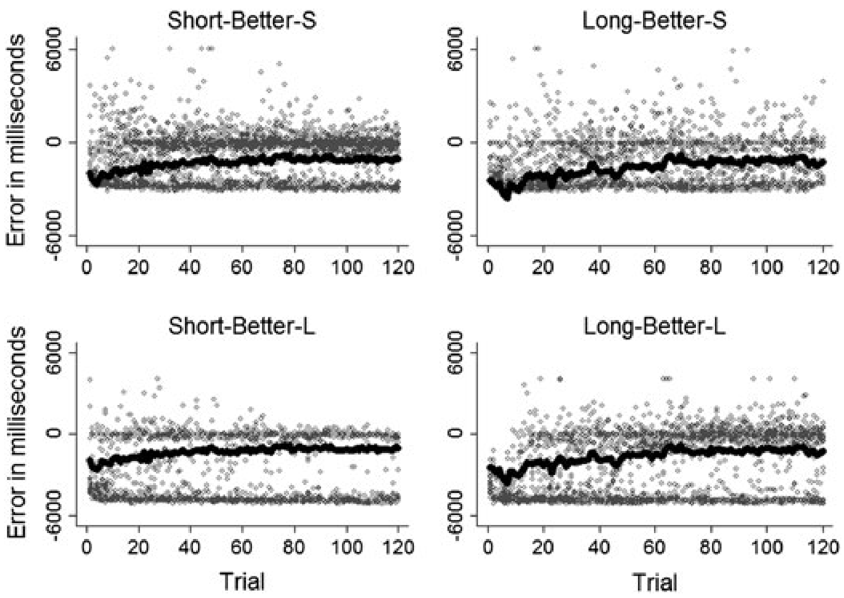

Figure 4. Error rates and response times in Study 1. The black lines represent the average error rate, while the grey points represent the individual response times, plotted over trials separately by condition (Short-Better or Long-Better) and which option was selected: Short (S) or Long (L). Points above (below) zero on the *y*-axis indicate overshooting (undershooting)

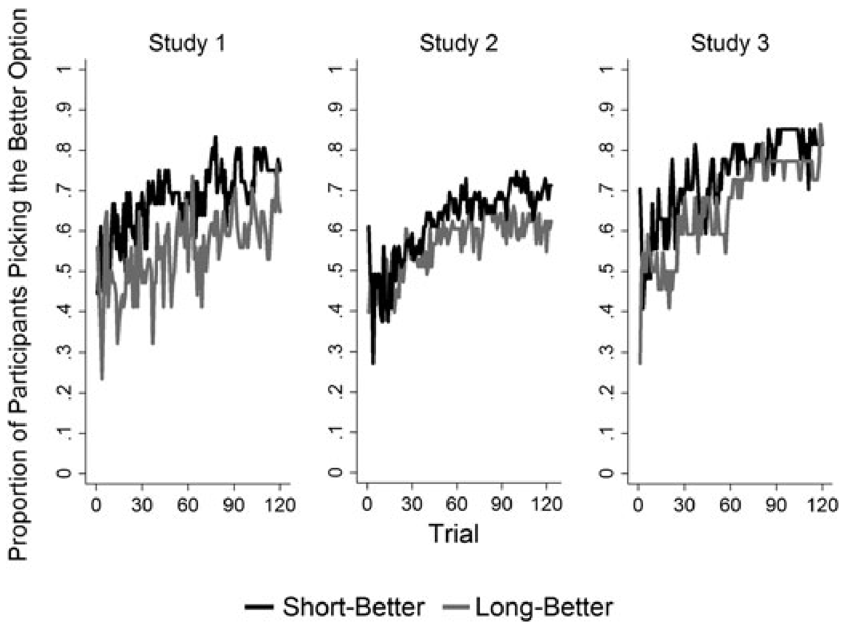

Figure 5. Proportion of participants selecting the better option when the Short Option was better (Short-Better) and when the Long Option was better (Long-Better) across trials in Study 1 (left panel), Study 2 (middle panel), and Study 3 (right panel)

option increased with experience, odds ratio = 1.03 ($CI_{95\%}$ [1.02, 1.04]), $z = 4.56$, $p < .001$. In line with our predictions, condition was significant, indicating that the better option was selected less frequently in the Long-Better condition, odds ratio = .34 ($CI_{95\%}$ [.13, .94]), $z = -2.09$, $p = .04$. However, its interaction with trial was not significant, $p = .12$. To see if there was a general preference for the Short Option, we examined the average rate of selecting the Short Option across conditions and trials. In line with our predictions, we found a significant preference (relative to 50%) for the Short Option (57%; $CI_{95\%}$ [.56, .58]), indicating that participants preferred quicker rather than longer waits.

Stated exploration strategy

Participants employed a variety of exploration strategies. First, 37% of participants indicated that they alternated between options (picked a different option on each trial), testing similar response times (starting off with quick responses and then adding delay) for each option and comparing outcomes. Second, 24% of participants indicated that they selected one option, starting off with a quick response and adding delay, until they found the option's maximum reward, and then explored the next option in a similar fashion. Four percent of participants reported using a variety of the first strategy, and 7% of participants

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

reported using a variety of the second strategy. In both strategies, the variation involved waiting until the end of the possible response window and then making quicker responses. A random search strategy was reported by 10% of participants. Thus, in line with their behavior, 61% of participants reported conscious exploration strategies that involved initially responding quickly (a stair climbing strategy; Busemeyer & Myung, 1987) and demonstrated a preference for minimizing wait during exploration.

Discussion

The fact that the majority of participants used time-saving decision strategies (i.e., consistently undershot) supports our hypotheses. This preference for saving time appears to have reduced/delayed finding the maximizing response, particularly when a longer delay was required. In addition, there was a general bias for the shorter-delay option. Together, these findings suggest that even when delays are short and experienced preferences for saving time at the cost of reward are still observed. These results are in agreement with observations of temporal choice in decisions from description (Loewenstein & Prelec, 1992).

One finding of interest relevant to research on temporal perception is that mean accuracy did not align with the maximal respond window but instead showed an early response bias. This pattern of results contrasts with what is typically found in Peak Interval Tasks—fairly accurate mean response times even with increasing variability (Rakitin et al., 1998). Thus, while individuals can accurately judge a period of time, when rewards lead to a trade-off between wait and reward, individuals' preferences for shorter waits appear to introduce an early response bias.

STUDY 2: REMOVING TEMPORAL PERCEPTION

While the previous findings support our hypothesis that individuals employ time-saving decision strategies, it is unclear to what degree imprecision in temporal perception played a role. For example, participants may have grown increasingly frustrated trying to estimate the best time to take action, which dissuaded them from delaying action. Therefore, in Study 2, to clarify whether the preferences for the shorter-delay option and undershooting are robust, we removed reliance on temporal estimation by having participants enter the time they wished to wait at the start of each trial.

Participants

One-hundred and twelve participants ($M_{age} = 37.05$; 46% female) were recruited by using Amazon Mechanical Turk. They were paid $0.75 for their participation and received incentive payments based on their decisions as in the previous study. There was an attention check (clicking an invisible box instead of continue on the instruction page), and participants who failed it were not able to take part in the study. The study lasted under 20 minutes on average with participants earning around $2.00 ($0.75 plus incentive payments).

Design and procedure

The design and procedure were identical to those employed in Study 1 except for one critical change. Rather than clicking at a point in time to take action, participants indicated ahead of time what action they wanted to take (Action A or Action B) and when. Participants were randomly assigned to the Short-Better condition ($n = 53$) or the Long-Better condition ($n = 59$), and on each trial, they indicated which action (option) they wanted to take and at what point in the 9.5-second response window they wanted to take it by entering a time between 1 and 9500 ms. After waiting for the duration they entered, they were shown the outcome of their decision. Points were converted at a rate of 120 points to $0.01.

Results

Maximization

The middle panel of Figure 3 plots the proportion of participants making a maximizing response across trials and conditions. We performed a logistic regression to predict whether action was taken during the maximizing response window. As in the previous study, we found that the likelihood of making a maximizing response increased with experience, odds ratio = 1.02 ($CI_{95\%}$ [1.01, 1.02]), $z = 7.47$, $p < .001$. As before, and counter to our predictions, the effect of condition was not significant nor was its interaction with trial, $p\text{s} > .79$.

Strategy

Those in the Short-Better condition ($M_{TrialNumber} = 29.35$; $CI_{95\%}$ [20.82, 37.89]) discovered the maximizing time window earlier than those in the Long-Better condition ($M_{TrialNumber} = 31.74$; $CI_{95\%}$ [24.62, 38.85]), although the difference was not significant, $p = .08$. As in the previous study, many participants (42%) never found the maximum reward. The likelihood of finding the maximum reward did not differ significantly between conditions. After finding the maximum reward, the rate of maximization was higher than in the previous study, ranging from 0 to 100% across participants ($M = 77\%$; $CI_{95\%}$ [.76, .79]). To see how participants' decisions diverged from the maximization response after finding the maximum reward, we created a variable indicating whether a response was taken before (coded 0) or after (coded 1) the maximizing time window. On average, divergences involved shorter rather than longer delays ($M = 57\%$; $CI_{95\%}$ [.54, .59]). This finding suggests that after participants found the maximal reward, they either sought to shorten their wait by finding the lower bound of the maximizing response window or preferred to minimize their wait on some trials even when it reduced their reward.

Figure 6 shows the average error by which option was selected across trials and conditions. In line with the previous study, participants responded earlier than the maximizing

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

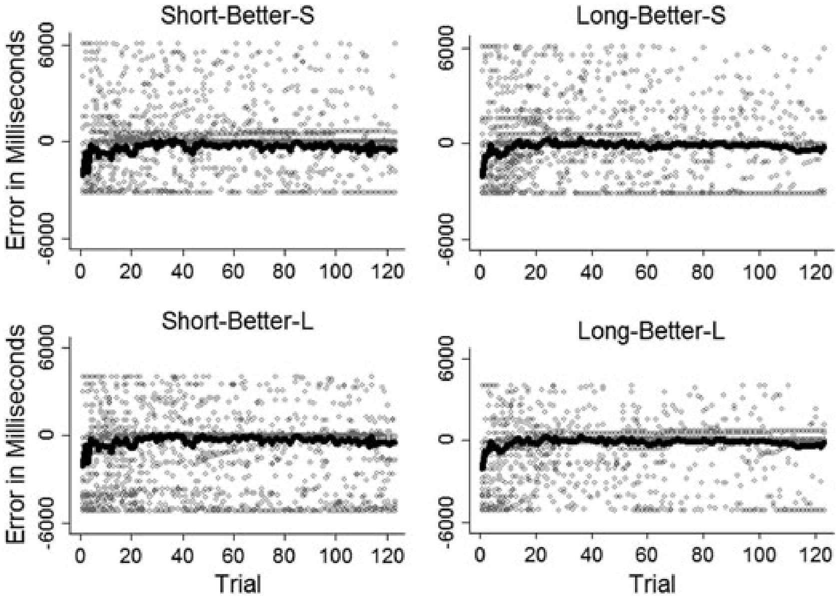

Figure 6. Error rates and response times in Study 2. The black lines represent the average error rate, while the grey points represent the individual response times, plotted over trials separately by condition (Short-Better or Long-Better) and the delay option selected: Short (S) or Long (L). Points above zero on the *y*-axis indicate overshooting; points below, undershooting

response window ($M = -237.22$; $CI_{95\%}$ [−265.16, −209.29]), but notably, less error was present than when decisions relied on temporal perception. Neither condition nor experience had any significant effect on the direction of error; $p = .81$, $p = .29$, respectively. In contrast to the previous study, their interaction was not significant either, $p = .44$. Selecting the Long Option predicted a significant increase in undershooting, $b = -820.49$ ($CI_{95\%}$ [−1220.03, −420.95]), $z = -4.07$, $p < .001$. The interaction between condition and selected option was significant, with undershooting decreasing when the Long Option was selected and provided the larger reward, $b = 566.22$ ($CI_{95\%}$ [85.46, 1046.97]), $z = -4.07$, $p < .001$. The interaction between selected option and trial was not significant, $p = .10$, nor was the three-way interaction, $p = .34$.

Preference

The middle panel of Figure 5 plots the average rate of picking the better option at any point during the trial by condition (e.g., the Long Option in the Long-Better condition). We performed a logistic regression as in the previous study and found that the likelihood of selecting the better option increased with experience, odds ratio = 1.01 ($CI_{95\%}$ [1.002, 1.011]), $z = 2.96$, $p = .003$. Counter to the previous study, condition was not significant, $p = .42$, nor was its interaction with trial number, $p = .36$. In contrast to the previous study, no significant preference for the Short option was found (47%; $CI_{95\%}$ [.39, .54]).

Discussion

In Study 2, we found that by removing the need to estimate wait times, participants undershot less and were able to maintain a maximizing response at a higher rate after finding the maximal reward. Thus, Study 2 suggests that a great deal of the deviation from maximization found in Study 1 was likely driven by the constraints of temporal perception. We did not observe a strong discounting of delayed rewards (i.e., most participants maintained high maximization rates once they found the maximal reward). This finding suggests that temporal discounting (impatience) in experiential learning tasks involving small amounts of money over short periods of time is not particularly robust. Nevertheless, participants were more likely to undershoot the maximizing response window after its discovery than to overshoot it, which suggests that they were attempting to minimize their wait. Additionally, many participants never found the maximizing response window. As such, it seems clear that participants do have preferences for saving time and effort, which lead to maladaptive strategies such as limited exploration.

STUDY 3: REMOVING THE BENEFITS OF EARLY RESPONSE

The previous studies show that both temporal perception and preferences for saving time play a role in how decisions involving wait evolve with experience. In Study 3, we aimed to see if removing incentives for responding quickly (e.g., being able to leave the experimental session sooner) would eliminate preferences for saving time. In other words, would time-saving preferences continue to exert a measurable influence when there was no benefit to waiting less in the task?

We included two tasks proposed to measure impatience in exploration and exploitation: intertemporal choice (Weber et al., 2007) and decisions-from-samples (Hertwig et al., 2004). We hypothesized that those who showed greater temporal discounting would also show a greater preference for saving time (e.g., a preference for the Short Option, increased undershooting, and decreased maximization after

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

finding the maximal response window). For the amount of samples drawn in the decisions-from-samples task, our predictions were split. On one hand, we expected that those who sampled little would also be impatient when choosing between shorter and longer delay rewards, both when described (the intertemporal choice task) and when learned from experience (the current task). On the other hand, we thought it possible for those who sampled extensively to be indecisive explorers. Such individuals would, after finding the best action and response time, continue to explore for something better (i.e., a different response time and/or option), dampening the effects of experience.

Participants

Fifty-seven participants (M_{age} = 25.21; 41% female) were recruited by using a different subject pool than Study 1. They were paid approximately \$6.25 for their participation and received additional payments based on their decisions. The conversion rate for points to real dollars was \$0.01 per 200 points. The experimental session time was fixed at 30 minutes.

Materials and design

The design was identical to Study 2 except for three changes. First, participants were instructed that they could not collect their earnings until 30 minutes had passed and were reminded of this fact several times. This manipulation was intended to remove any objective benefits of using a time-saving decision strategy during the task. Second, we included a standard decisions-from-samples task (Hertwig et al., 2004) where participants could sample up to 100 times each from two options before indicating which option they wanted to play once for real. The options in the first pair were \$0.25 with certainty or \$2.50 at a 10% chance and \$0.00 otherwise, while the options in the second pair were either \$2.25 with certainty or \$2.50 at a 90% chance and \$0.00 otherwise. Lastly, we included a task designed to measure intertemporal choice following Weber et al. (2007). Participants were asked if they would rather have \$25 today or a larger dollar amount 3 months later at increments of \$2.50 up to \$50. Participants were told that this decision would be carried out for one participant selected at random. Eight participants were excluded from all analyses because they expressed non-monotonic preferences (e.g., accepting a delay of 3 months for \$5 more but not \$15), suggesting that they had not understood the task. Five participants indicated that \$50 (an additional \$25) was insufficient incentive to wait 3 months. Because we could not calculate their exact discount rate, we created 12 groups of discounting: non-discounters (requiring no additional money to wait 3 months) to extreme discounters (requiring more than \$25.00) in steps of \$2.50. The final data set included responses from 49 participants across the Short-Better (n = 27) and Longer-Better (n = 22) conditions.

Results

Maximization

The right panel of Figure 3 plots the proportion of participants responding during the maximizing response window by condition. To test whether those in the Short-Better condition made more maximizing responses than those in the Long-Better condition, we performed a logistic regression predicting whether action was taken during the maximizing response window in the option providing the highest payout (e.g., the Short Option in the Short-Better condition) by trial, condition, and their interaction. In addition, we included their discount group (entered linearly),[1] the mean number of samples participants in the decisions-from-samples tasks ($M_{Samples}$ = 69.93; $CI_{95\%}$ [54.13, 85.73]), and their interactions with condition as predictors. Replicating findings from the previous studies, we found that the likelihood of making a maximizing response increased with experience, odds ratio = 1.09 ($CI_{95\%}$ [1.082, 1.099]), z = 22.23, p < .001. Condition was not significant, p = .89. In contrast to the previous study, however, the interaction of condition with trial indicated that learning was diminished in the Longer-Better condition, odds ratio = .98 ($CI_{95\%}$ [.973, .993]), z = −3.33, p = .001. No other significant effects or interactions were found, ps > .25.

Strategy

In line with Study 2, we found no significant difference between when the first maximizing response was made for those in the Short-Better condition ($M_{TrialNumber}$ = 29.24; $CI_{95\%}$ [17.66, 40.81]) and the Long-Better condition ($M_{TrialNumber}$ = 34.07; $CI_{95\%}$ [19.59, 48.55]). We performed a Poisson regression to examine if discounting or the average amount of sampling had any influence on when discovery of the maximizing response window occurred. The regression revealed no main effects or interactions with condition, ps > .27. Although to a lesser extent than in the previous studies, many participants (27%) failed to find the maximal reward: The likelihood of never finding the maximal reward did not differ significantly between conditions and was not significantly influenced by individual differences in discounting or sampling, ps > .40. After participants found the maximal reward, the rate of maximization was substantially higher than in previous studies, ranging from 51% to 100% across participants (M = 87%; $CI_{95\%}$ [.86, .88]). The rate of maintaining maximization was not significantly influenced by condition, the level of discounting, sampling, or their interactions, ps > .23. As in the previous study, responses that deviated from the maximizing response window after its discovery consisted primarily of shorter delays (M = 62%; $CI_{95\%}$ [.57, .66]).

Figure 7 displays the average error across conditions and the selected option. In line with the previous studies, we found that participants on average responded earlier than the maximizing time window (M = −226.52; $CI_{95\%}$ [−264.965,

[1]No relation between participants' discount rates and their mean number of drawn samples was found, $r(48)$ = −.06, p = .67.

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

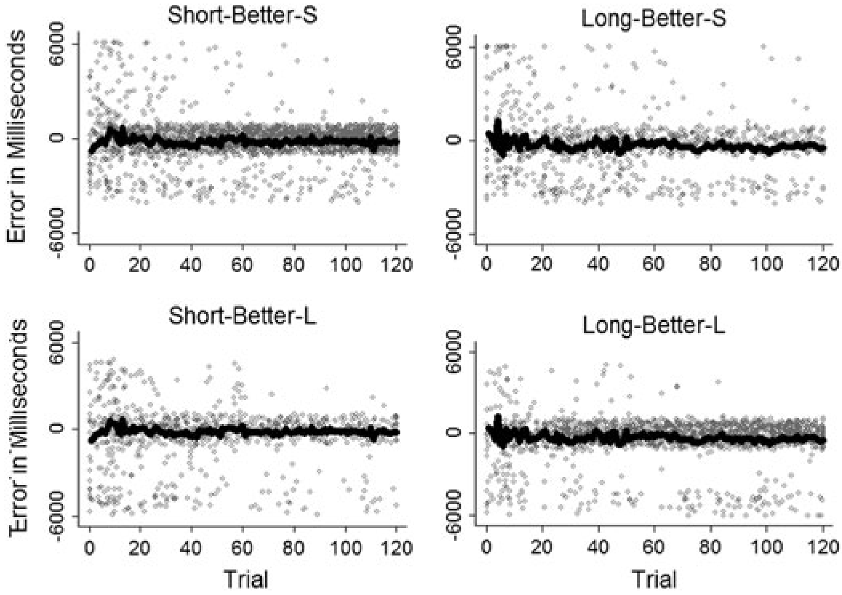

Figure 7. Error rates and response times in Study 3. The black lines represent the average error rate, while the grey points represent the individual response times, plotted over trials separately by condition (Short-Better or Long-Better) and the delay option selected: Short (S) or Long (L). Points above zero on the *y*-axis indicate overshooting; points below, undershooting

−188.071]). We regressed error onto trial, condition, option selected, and their interaction. We also regressed error onto individuals' discount rate, their average number of samples drawn, and their interactions with condition and option selected. Counter to the previous studies, undershooting increased with experience, suggesting that participants started by responding later and then decreased their wait with experience,[2] $b = -2.83$ ($CI_{95\%}$ [−4.378, −1.289]), $z = -3.60$, $p < .001$. Consistent with prior findings, the effect of selected option was significant, with undershooting increasing when the Long Option was selected, $b = -1122.23$ ($CI_{95\%}$ [−1289.638, −954.82]), $z = -13.14$, $p < .001$. The interaction between condition, trial, and option selected was significant, indicating that the increased undershooting in the Long-Better condition when the Long Option was selected decreased with experience, $b = 7.03$ ($CI_{95\%}$ [2.435, 11.615]), $z = 3$, $p = .003$. In line with our predictions, the significant two-way interaction between condition and discount rate indicated that undershooting increased for those in the Long-Better condition who discounted more, $b = -201.49$ ($CI_{95\%}$ [−342.746, −60.229]), $z = -2.80$ $p = .005$. Interestingly, greater undershooting was found for those who sampled more on average when the Long Option was selected, $b = -5.04$ ($CI_{95\%}$ [−7.618, −2.461]), $z = -3.83$, $p < .001$, an effect which was less pronounced in the Long-Better condition, $b = 9.877$ ($CI_{95\%}$ [5.759, 13.994]), $z = 4.70$, $p < .001$. All other effects and interactions failed to reach significance, $ps > .05$.

Preference

The right panel of Figure 5 plots the average rate of picking the better option (irrespective of when action was taken) by condition. We performed a logistic regression predicting selection of the better option by trial, condition, and their interaction, as well as discount rate, the average number of samples, and their interactions with condition. The regression replicated the findings from Study 2: the likelihood of selecting the better option increasing with experience, odds ratio = 1.03 ($CI_{95\%}$ [1.03, 1.04]), $z = 14.40$, $p < .001$. No other effects or interactions reached significance, $ps > .13$. Participants again showed a general preference for the Short Option (56%; $CI_{95\%}$ [.54, .57]). Although discounting was not predictive of which action was taken, $p = .55$, those who drew larger samples were more likely to pick the Short Option, odds ratio = .99 ($CI_{95\%}$ [.97, .99]), $z = -2.14$, $p = .03$.

Discussion

In Study 3, participants maximized more and undershot less than in the previous studies. This finding suggests that fixing experimental time reduced participant's reliance on time-saving decision strategies. Specifically, this manipulation ensured that participants could not save time and likely pushed them to invest more time and effort in the tasks rather than sitting in the laboratory with nothing to do. This interpretation is supported by the fact that the average number of samples drawn in our decisions-from-samples task was about five times greater than commonly reported (e.g., Ashby & Rakow, 2014; Hertwig et al., 2004; Rakow et al., 2008) and by the finding that participants entered initial wait times that were significantly greater than in the previous studies (Footnote 2). Study 3 therefore suggests that while decision makers are likely to employ strategies aligned with time-saving preferences, the influence of those

[2]We examined when participants took action in the first trial in the current study ($M = 3550.16$ ms; $CI_{95\%}$ [2508.46, 4591.77]) and found that the initial wait time was greater than in Studies 1 ($M = 2057.59$; $CI_{95\%}$ [1648.62, 2466.55]) and 2 ($M = 2{,}299.94$; $CI_{95\%}$ [1768.53, 2831.34]). In fact, while only 9% and 21% of subjects waited 4500 ms or longer (half the response time window) in Studies 1 and 2, respectively, 41% did in Study 3. This pattern of results suggests that when there is no chance of saving time in a task, individuals start their search much later than when acting sooner could influence task length.

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

preferences can be diminished by changing the decision environment's incentive structure.

In terms of the relationships between discounting, exploration, and behavior, the results are mixed. While we found no evidence of a relationship between exploration and temporal discounting, we found that increased sampling was related to behavior in the current tasks. Those who sampled more showed greater preferences for the Short Option and when they selected the Long Option undershooting increased. Given these weak relations, we are hesitant to draw strong conclusions regarding the relationships between impatience across domains. Nevertheless, the current results suggest that there might be some relationships worthy of examination in future investigations (e.g., a repeated temporal discounting task with and without experience).

CROSS STUDY COMPARISON

While the studies presented here indicate a preference for saving time, there appear to be differences in how the studies were designed which had a direct effect on maximization. It therefore seems useful to directly compare the rates of maximization in each to explore these differences directly. To make these comparisons we combined all data sets and constructed a variable indexing the average rate of maximization for each subject. A one-way ANOVA revealed that the studies did vary significantly, $F(2, 236) = 16.72$, $p < .0001$. A post hoc Tukey test showed that the rate of maximization in Study 1 was significantly lower than in Study 2 and Study 3, $ps < .01$; the rates of maximization did not differ between Studies 2 and 3, $p = .35$. Thus, it appears that a reliance on temporal perception is the biggest factor impeding maximization in temporal choice.

GENERAL DISCUSSION

In three studies, we combined research about learning from experience, temporal perception, and the subjective value of time and money by investigating temporally dependent actions in novel decisions-from-experience tasks. We designed a novel research paradigm of experiential-based choice in which different response/delay times were associated with different rewards. We found that participants were able to learn the best time to take action, which demonstrates increased maximization with experience. We also found evidence supportive of our hypothesis that individuals favor time-saving strategies such as taking action quickly at first, and then slowly increasing delays. Furthermore, undershooting (i.e., taking action before the maximal outcome would be obtained) remained the norm even in later choices and there was a preference for options providing rewards after shorter delays. Nevertheless, while precision increased with experience in predictable ways, differences in the response-outcome mappings had direct effects on behavior. These findings have theoretical implications across a variety of domains.

Learning from experience

The current studies relate to theory regarding experiential learning (Rakow & Newell, 2010). As is often the case in decisions-from-experience (Ashby & Rakow, 2016) and studies of temporal perception (Wright et al., 1997), participants were able to improve their performance with experience. This similarity with previous findings is interesting given that the current studies departed from the paradigm of recent decisions-from-experience tasks where rewards are independent of when an action is taken. Thus, the current findings establish that relationships between points in time and (monetary) values can be learned with experience in the same manner as choices between different gambles with probabilistically determined payoffs.

More importantly, the current research suggests that the ability to learn was greatly constricted by the confines of temporal perception, which indicates the importance of understanding the limitations of cognitive systems when examining human behavior in experiential learning (Ashby & Rakow, 2016; Rakow, Newell, & Zougkou, 2010). Specifically, when decisions were reliant on temporal estimation, there was an incentive for minimizing wait. Participants started their searches by taking action quickly, then gradually increased the delay on subsequent decisions (trials). For many participants, this strategy prevented them from ever finding the maximum reward. While one might have predicted this stair-climbing pattern, it is also possible that participants would have first waited until the end of the possible response window and then worked their way backward to find the largest possible reward. Such a strategy might be predicted given that longer waits are often associated with bigger rewards (e.g., more hours at work lead to higher pay and longer experiment generally pay more than shorter ones). We note that this was essentially the pattern found for early decisions in Study 3, where wait times were made explicit and there was no benefit of employing time-saving decision strategies. It appears that our participants employed different decision strategies when decisions were reliant on temporal estimation and/or constrained by the decision environment. The fact that our participants responded earlier rather than later suggests that they wanted to conserve time and that this bias was greatest when decisions were reliant on temporal perception. Thus, the current findings provide novel insight into decision making in temporally dependent environments: a preference for saving time might be the norm, but its impact can be reduced by shifting the decision environment.

Temporal perception

We found similarities between the current investigation and previous findings examining the cognitive underpinnings of temporal perception (Grondin, 2010; Matthews & Meck, 2014). First, in line with findings that practice in duration estimation increases precision (Wright et al., 1997), maximization increased and undershooting decreased with experience. However, counter to the scalar variability effect frequently observed in Peak-Interval timing tasks (Ekman, 1959; Gibbon, 1977), participants' mean responses in the

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

current studies undershot the maximizing time window. Notably, when time delays were explicitly stated (not reliant on temporal estimation) and the experimental time was fixed, the mean response was much closer to the maximizing response window (i.e., undershooting was reduced). These results indicate that a large portion of the effects observed in Study 1 were likely the result of constraints in temporal perception and their interaction with decision strategy. It seems that when estimate precision is motivated by small increases in earnings and is reliant on temporal estimation, participants favor shorter rather than longer delays.

One explanation for the increased undershooting when temporal estimation was required is that participants grew frustrated with not being able to consistently maximize. This frustration may have led to participants erring on the side of reacting too soon lest they potentially waste time (overshoot) and receive a similar or smaller outcome by waiting too long. Another potential contributor is that participants generally discounted the value of rewards over delays, even the short ones employed in these studies. However, this possibility seems less likely considering that participants maintained high maximization rates after finding the maximizing response time. In sum, while there appears to be some consistency in behavior when temporal perception is involved, the goals of the task, environmental constraints, and how rewards are delivered in time likely play a sizeable role.

Time and money

Most participants started off by responding quickly, particularly when decisions were reliant on temporal estimation and the duration of the experiment was not fixed. Participants also preferred the shorter-delay option in two out of the three studies. These findings suggest that participants sought to minimize their wait, even at the cost of earning less, similar to behavior seen in studies of temporal discounting over longer delays (Loewenstein & Prelec, 1992; Loewenstein & Thaler, 1989). This phenomenon could indicate that participants in the current studies regarded waiting time as lost time and that lost time had some value at least in part consonant with the value of the monetary rewards provided. In addition, we did observe some relation between individuals discounting in descriptive choice over longer periods of time and their behavior in the current tasks. Specifically, discounting was related to increased deviations from maximization and increased undershooting when the selected option required a longer delay.

Nevertheless, preferences for the shorter-delay option were not particularly large and relations to temporal discounting were weak. Furthermore, participants who discovered the maximizing response time tended to continue to make maximizing responses rather than consistently opting for shorter waits and smaller rewards, behaviors which would be predicted by impatience and research on temporal discounting. This might suggest that with experience, impatience gives way to maximization. It is also possible that the short waits we employed were insufficient to trigger impatience and a strong discounting of future rewards. As such, one line of future research will be to explore the role experience plays on temporal discounting and the influence of the delays involved.

ACKNOWLEDGEMENTS

This research was supported by a National Science Foundation Award (1154012) to Cleotilde Gonzalez. The authors thank Fei Lu, Emmanouil Konstantinidis, Lukasz Walasek, and Rebecca Wright, and Nalyn Sriwattanakomen, for their insightful comments.

REFERENCES

Ashby, N. J., & Rakow, T. (2014). Forgetting the past: Individual differences in recency in subjective valuations from experience. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *40*(4), 1153–1162. 10.1037/a0036352.

Ashby, N. J., & Rakow, T. (2016). Eyes on the prize? Evidence of diminishing attention to experienced and foregone outcomes in repeated experiential choice. *Journal of Behavioral Decision Making*, *29*(2-3), 183–193.

Balci, F., Freestone, D., & Gallistel, C. R. (2009). Risk assessment in man and mouse. *Proceedings of the National Academy of Sciences*, *106*(7), 2459–2463.

Barron, G., & Erev, I. (2003). Small feedback based decisions and their limited correspondence to description based decisions. *Journal of Behavioral Decision Making*, *16*(3), 215–233. 10.1002/bdm.443.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*, *75*(299), 493–517.

Block, R. A. (Ed) (2014). *Cognitive models of psychological time*. New York, NY: Psychology Press.

Block, R. A., & Gruber, R. P. (2014). Time perception, attention, and memory: A selective review. *Acta Psychologica*, *149*, 129–133.

Block, R. A., Zakay, D., & Hancock, P. A. (1999). Developmental changes in human duration judgments: A meta-analytic review. *Developmental Review*, *19*(1), 183–211.

Busemeyer, J. R., & Myung, I. J. (1987). Resource allocation decision making in an uncertain environment. *Acta Psychologica*, *66*(1), 1–19.

Chang, C., Chang, S., Chang, J., & Chien, Y. (2013). Which is the better option? Quicker or cheaper? *Psychology and Marketing*, *30*, 90–101.

Chapman, G. B., & Elstein, A. S. (1995). Valuing the future temporal discounting of health and money. *Medical Decision Making*, *15*(4), 373–386.

DeVoe, S. E., & House, J. (2012). Time, money, and happiness: How does putting a price on time affect our ability to smell the roses? *Journal of Experimental Social Psychology*, *48*, 466–474.

Ekman, G. (1959). Weber's law and related functions. *The Journal of Psychology*, *47*(2), 343–352.

Erev, I., Ert, E., Roth, A. E., Haruvy, E., Herzog, S. M., Hau, R., et al. (2010). A choice prediction competition: Choices from experience and from description. *Journal of Behavioral Decision Making*, *23*(1), 15–47.

Munichor, N., Erev, I., & Lotem, A. (2006). Risk attitude in small timesaving decisions. *Journal of Experimental Psychology. Applied*, *12*(3), 129.

Fishburn, P. C., & Rubinstein, A. (1982). Time preference. *International Economic Review*, *23*(3), 677–694.

Forster, S. E., & Brown, J. W. (2011). Medial prefrontal cortex predicts and evaluates the timing of action outcomes. *NeuroImage*, *55*(1), 253–265.

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, *40*(2), 351–401.

Gibbon, J. (1977). Scalar expectancy theory and Weber's law in animal timing. *Psychological Review*, *84*(3), 279–325.

Graham, R. J. (1981). The role of perception of time in consumer research. *Journal of Consumer Research*, *7*(4), 335–342.

Green, L., Fristoe, N., & Myerson, J. (1994). Temporal discounting and preference reversals in choice between delayed outcomes. *Psychonomic Bulletin & Review*, *1*(3), 383–389.

Grondin, S. (2010). Timing and time perception: a review of recent behavioral and neuroscience findings and theoretical directions. *Attention, Perception, & Psychophysics*, *72*(3), 561–582.

Gross, B. L. (1987). Time scarcity: Interdisciplinary perspectives and implications for consumer behavior. *Research in Consumer Behavior*, *2*, 1–54.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*(8), 534–539.

Hertwig, R., & Erev, I. (2009). The description-experience gap in risky choice. *Trends in Cognitive Sciences*, *13*(12), 517–523. 10.1016/j.tics.2009.09.004.

Jessup, R. K., Bishara, A. J., & Busemeyer, J. R. (2008). Feedback produces divergence from prospect theory in descriptive choice. *Psychological Science*, *19*(10), 1015–1022.

Kirby, K. N., & Maraković, N. N. (1995). Modeling myopic decisions: Evidence for hyperbolic delay-discounting within subjects and amounts. *Organizational Behavior and Human Decision Processes*, *64*(1), 22–30.

Lempert, K. M., & Phelps, E. A. (2016). The malleability of intertemporal choice. *Trends in Cognitive Sciences*, *20*(1), 64–74.

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *The Quarterly Journal of Economics*, *107*(2), 573–597.

Loewenstein, G., & Thaler, R. H. (1989). Anomalies: Intertemporal choice. *Journal of Economic Perspectives*, *3*(4), 181–193. 10.1257/jep.3.4.181.

Matthews, W. J., & Meck, W. H. (2014). Time perception: The bad news and the good. *Wiley Interdisciplinary Reviews: Cognitive Science*, *5*(4), 429–446.

Meck, W. H. (1996). Neuropharmacology of timing and time perception. *Cognitive Brain Research*, *3*(3), 227–242.

Mehlhorn, K., Ben-Asher, N., Dutt, V., & Gonzalez, C. (2014). Observed variability and values matter: Towards a better understanding of information search and decision from experience. *Journal of Behavioral Decision Making*, *27*(4), 328–339. 10.1002/bdm.1809.

Okada, E. M., & Hoch, S. J. (2004). Spending time versus spending money. *Journal of Consumer Research*, *31*, 313–323.

Rakow, T., Demes, K. A., & Newell, B. R. (2008). Biased samples not mode of presentation: Re-examining the apparent underweighting of rare events in experience-based choice. *Organizational Behavior and Human Decision Processes*, *106*(2), 168–179.

Rakow, T., & Newell, B. R. (2010). Degrees of uncertainty: An overview and framework for future research on experience-based choice. *Journal of Behavioral Decision Making*, *23*(1), 1–14.

Rakow, T., Newell, B. R., & Zougkou, K. (2010). The role of working memory in information acquisition and decision making: Lessons from the binary prediction task. *The Quarterly Journal of Experimental Psychology*, *63*(7), 1335–1360.

Rakitin, B. C., Gibbon, J., Penney, T. B., Malapani, C., Hinton, S. C., & Meck, W. H. (1998). Scalar expectancy theory and peak-interval timing in humans. *Journal of Experimental Psychology. Animal Behavior Processes*, *24*(1), 15–33.

Rogers, W. H. (1993). sg17: Regression standard errors in clustered samples. *Stata Technical Bulletin*, *13*, 19–23.

Saini, R., & Monga, A. (2008). How I decide depends on what I spend: Use of heuristics is greater for time than for money. *Journal of Consumer Research*, *34*, 914–922.

Schmidt, R. A. (1975). A schema theory of discrete motor skill learning. *Psychological Review*, *82*(4), 225–260.

Skinner, B. F. (1938). *The behavior of organisms: An experimental analysis*. New York, NY: Appleton-Century.

Soman, D. (2001). The mental accounting of sunk time costs: Why time is not like money. *Journal of Behavioral Decision Making*, *14*, 169–185.

Weber, E. U., Johnson, E. J., Milch, K. F., Chang, H., Brodscholl, J. C., & Goldstein, D. G. (2007). Asymmetric discounting in intertemporal choice a query-theory account. *Psychological Science*, *18*(6), 516–523.

Wright, B. A., Buonomano, D. V., Mahncke, H. W., & Merzenich, M. M. (1997). Learning and generalization of auditory temporal–interval discrimination in humans. *The Journal of Neuroscience*, *17*(10), 3956–3963.

Zauberman, G., & Lynch, J. (2005). Resource slack and propensity to discount delayed investments of time versus money. *Journal of Experimental Psychology. General*, *134*, 23–37.

Copyright © 2017 John Wiley & Sons, Ltd.

DOI: 10.1002/bdm