Quantifying the Effects of a Constricted Temporal Window in Reinforcer Pathology

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ABSTRACT

Reinforcer pathology theory describes a common pattern of decision-making underlying multiple health behaviors. These negative health behaviors feature persistent engagement with brief, intense, and reliable reinforcement offered by many health-degrading activities (smoking, overeating), over the temporally extended, low-intensity, and variable reinforcement offered by many health-promoting activities (abstinence, exercise). This pattern extends, according to reinforcer pathology theory, from an abbreviated temporal window over which the reinforcing value of behaviors is integrated. A constricted temporal window would thus support selection of brief, intense reinforcement, eroding health. This temporal window may be indexed by delay discounting, the degree to which reinforcers lose value as a function of delay to their receipt. Here, four studies interrogate components of this theory. Taken together, these studies support: (1) that temporal window constriction is a candidate trans-disease process demonstrated in multiple negative health behaviors; (2) that negative income shock manipulations engender temporal window constriction; and (3) that experimentally constricting the temporal window increases valuation of brief, intense reinforcers and decreases valuation of temporally extended reinforcers, consistent with reinforcer pathology theory.

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GENERAL AUDIENCE ABSTRACT

Health behaviors, positive and negative, can support or reduce risk for multiple chronic diseases, such as substance use disorder and obesity. These diseases are marked by overconsuming commodities that offer predictable short-term benefits, and neglecting other behaviors with variable long-term benefits (e.g., fast food is enjoyable in the moment; exercise may have delayed benefits, but moment-to-moment may not be as reinforcing as fast food). An individual's valuation of these fast food or exercise may depend on how far out into the future these benefits are considered, their temporal window. The first study shows that the temporal window is constricted among high-risk substance users than people who do not have substance problems, especially when considering higher-value choices. The second study shows that the temporal window can change depending on the environment. Specifically, engaging with stories of job loss can constrict the temporal window. The third study shows that engaging with job loss can specifically constrict the temporal window and increase the value of fast food among obese individuals. The final study shows that a similar hardship scenario, natural disasters, can constrict the temporal window, increase demand for alcohol and cigarettes, and decrease the valuation of more temporally extended reinforcers (e.g., employment, savings, and seatbelt wearing) among smoking drinkers. Together, these studies support a model, reinforcer pathology; wherein the temporal window, which can differ both between individuals and environments, drives valuation of reinforcers that impact health.

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INTRODUCTION

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"Theories are only verified hypotheses, verified by more or less numerous facts. Those verified by the most facts are the best, but even then they are never final, never to be absolutely believed."

- Claude Bernard, An Introduction to the Study of Experimental Medicine, 1865

Up to 40% of deaths from leading causes in the United States are preventable (Yoon, Bastian, Anderson, Collins, & Jaffe, 2014), but much of disease prevention requires behavior change (Mokdad, Marks, Stroup, & Gerberding, 2004). Some public health education efforts, such as those aimed at cigarette smoking, have engendered meaningful health behavior change (Levy, Chaloupka, & Gitchell, 2004), but many individuals are aware of the risks of these health behaviors and still resist change. One way to model the health behaviors in question (e.g., substance use, excessive calorie consumption, non-adherence to medications) is to describe them as a choice between immediate comforts and long-term wellness. However, even if the long-term benefits of a choice are seemingly greater in magnitude than the immediate, long-term outcomes have less control over behavior (Ainslie, 1975; Mazur, 1987; Rachlin, Raineri, & Cross, 1991). This phenomenon of delay discounting, wherein outcomes are discounted as a function of delay, has been observed across individuals and reinforcer types (Odum, 2011).

The specific *rate* at which delayed outcomes are discounted can vary across individuals (Bickel, Odum, & Madden, 1999) and environments (Haushofer, Schunk, & Fehr, 2013). Specifically, steeper delay discounting has been observed to co-occur with negative health behaviors such as smoking (Bickel et al., 1999), problem drinking (Petry, 2001), illicit drug use

(Kirby & Petry, 2004), indoor tanning (Feldman, Dempsey, Grummer, Chen, & Fleischer, 2001), and obesity (a proxy for excessive calorie consumption and sedentary activity; Jarmolowicz et al., 2014). This led to the proposal of delay discounting as a trans-disease process underlying multiple negative health behaviors (Bickel & Mueller, 2009). Steep discounting of delayed outcomes may be a risk factor for negative health behaviors *generally*, but it does not alone predict engagement in *specific* negative health behaviors (Carroll, Anker, Mach, Newman, & Perry, 2010).

Initial Statement of Reinforcer Pathology: Co-occurrence of Risk Factors

One theory of health behaviors, reinforcer pathology (Bickel, Jarmolowicz, Mueller, & Gatchalian, 2011; Carr, Daniel, Lin, & Epstein, 2011), has framed specific negative health behaviors as emerging from *both* steep discounting of delayed outcomes *and* persistently high valuation of particular reinforcers. For example, high valuation of unhealthy foods combined with steep delay discounting would then predict particular susceptibility to obesity (Epstein, Dearing, Temple, & Cavanaugh, 2008). These two risk factors may be quantified by behavioral economic tasks: discounting of delayed outcomes by tasks determining points of indifference between smaller, sooner and larger, later reinforcers (Mazur, 1987), and valuation by tasks determining the degree to which consumption changes with increases in price (Hursh, 1984). Each risk factor itself may be multiply controlled, with specific endogenous and exogenous factors impacting discounting, reinforcer valuation, or both. However, as initially described, reinforcer pathology did not state a specific mechanism by which each risk factor may impact the other.

Reinforcer Pathology Revisited: The Temporal Window Hypothesis

Central to recent revisions of reinforcer pathology (Bickel et al., 2017) is the observation (similar to early models of behavioral choices by delay discounting) that the particular reinforcers excessively valued in negative health behavior follow a common temporal pattern. That is, they offer brief, intense, reliable reinforcement directly following consumption/engagement, and offer diffuse, uncertain consequences after a delay. Individuals will tend to select reinforcers with the highest subjective value, but as delay discounting increases, the effective temporal window over which reinforcer value is integrated constricts. In contrast, many *positive* health behaviors offer temporally extended, low-intensity, and variable reinforcement. The benefits of exercise, for example, are only realized when integrating over a substantially longer time frame (i.e., weeks, months, or years) than that required to realize the benefits of fast food consumption (i.e., seconds). In a constricted temporal window, brief reinforcement will be preferred over temporally extended reinforcement; when the window is expanded, these valuations reverse (see Figure 1.1).

In this model of reinforcer valuation, delay discounting is an index of the temporal window and steep rates of delay discounting underlie high valuation of unhealthy reinforcers. Thus, reinforcer pathology observes not only the co-occurrence of two risk factors, but identifies one risk factor as promoting another. Indeed, steep delay discounting rates have been cross-sectionally associated with selection of brief, intense reinforcement across multiple domains (e.g., Mishra & Lalumière, 2017). However, this also identifies an experimental framework by which the temporal window view of reinforcer pathology can be tested.

Experimental Manipulations of the Temporal Window

Constriction of the temporal window is hypothesized to both increase valuation of brief, intense reinforcement and decrease valuation of temporally extended reinforcement. One method to constrict the temporal window is through simulation of poverty, which has previously been demonstrated to increase delay discounting (Bickel, George Wilson, Chen, Koffarnus, & Franck, 2016). The first outcome (valuation of brief, intense reinforcement) can be assessed using conventional behavioral economic purchase tasks. The second outcome (valuation of temporally extended reinforcement) may be more difficult to quantify, and no standard assay has been developed.

Taken together, the following studies comprise an investigation of the role of the temporal window in health behavior and reinforcer valuation. First, conditions under which delay discounting (the index of the temporal window) does and does not differ between healthy and substance using populations are identified. Second, methods for experimental constriction of the temporal window are examined. Third, the effects of experimental constriction of the temporal window on valuation of brief, intense reinforcers are determined. Fourth, a temporally extended reinforcer measure (TERM) is developed to assess valuation of temporally extended reinforcers after experimental constriction of the temporal window. Finally, implications for the temporal window hypothesis of reinforcer pathology are discussed.

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Figure 1.1. The temporal window model of reinforcer valuation.

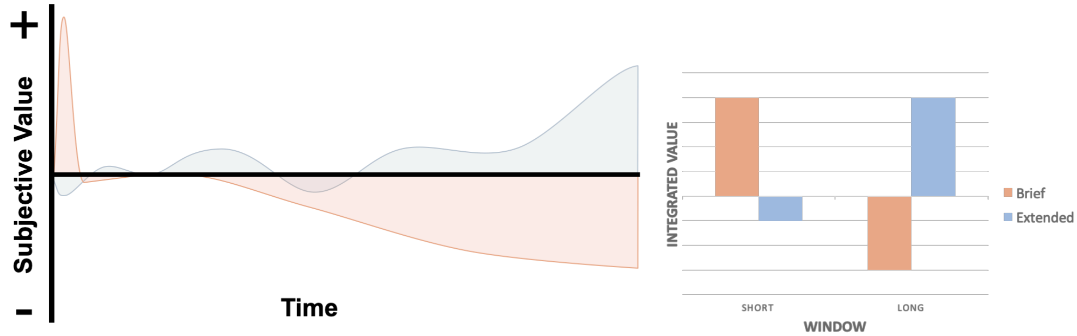

Figure 1.1 depicts the temporal window model of reinforcer valuation.

MANUSCRIPT 1

Title

A second type of magnitude effect: Discounting differences in substance use increase with magnitude

Abstract

Basic research on delay discounting, examining preference for smaller-sooner or larger-later reinforcers, has demonstrated a variety of findings of considerable generality. One of these, the magnitude effect, is the observation that individuals tend to exhibit greater preference for the immediate with smaller magnitude reinforcers. Delay discounting has also proved to be a useful marker of addiction, as demonstrated by the highly-replicated finding of greater discounting rates in substance users compared to controls. However, some research on delay discounting rates in substance users, particularly research examining discounting of small magnitude reinforcers, has not found significant differences compared to controls. Here, we hypothesize that the magnitude effect could produce ceiling effects at small magnitudes, thus obscuring differences in delay discounting between groups. We examined differences in discounting between high-risk substance users and controls over a broad range of magnitudes of monetary amounts ($0.10, $1.00, $10.00, $100.00, and $1000.00) in 116 Amazon Mechanical Turk workers. We found no significant differences in discounting rates between users and controls at the smallest reward magnitudes ($0.10 and $1.00) and further found that differences became more pronounced as magnitudes increased. These results provide an understanding of a second form of the magnitude effect: that is, differences between populations in discounting can become more evident as a function of reinforcer magnitude.

Introduction

Delay discounting is the process by which reinforcer valuation declines as a function of delay to its receipt (see Odum, 2011). This decreased valuation of temporally remote reinforcers can be observed in humans and non-human species using paradigms that present choices between smaller, sooner reinforcers and larger, later reinforcers. These preferences can be captured by hyperbolic functions of subjective value over time, where reinforcers lose subjective value more steeply over more proximal delays and less steeply over more distant delays. The discounting function can be modeled with Mazur's (1987) equation:

Equation 1. Hyperbolic Discounting Function

$$SV = \frac{A}{1 + kD}$$

Where SV is the immediate subjective value of the reward, A is the nominal, full-magnitude value, D is the delay to reward receipt, and *k* describes the discounting rate of the function.

One common observation made in studies of the discounting of delayed reinforcers is the magnitude effect, referring to an inverse relationship between rate of discounting and magnitude of reinforcer. For example, Green, Myerson, and McFadden (1997) assessed rates of delay discounting in a 24-trial monetary choice task at nominal values of \$100, \$2,000, \$25,000, and \$100,000, available at delays ranging from 3 months to 20 years. The smaller-sooner choices varied in magnitude from 1% to 99% of the delayed reward, and were always available immediately. They found that the rate of discounting estimated by the free parameter of the hyperbolic model above, *k*, decreased as the magnitude of the reward being discounted, *A*, increased. That is, at larger magnitudes of reward (\$25,000 or \$100,000), individuals made more choices for the larger, later reward. The magnitude effect has also been observed broadly in discounting procedures which determine discounting of hypothetical (Baker, Johnson, & Bickel, 2003; Grace & McLean, 2005; M. W. Johnson & Bickel, 2002) and real monetary reinforcers (M. W. Johnson & Bickel, 2002), health (Petry, 2003), and other commodities, and increases with increasing difference between the magnitudes of delayed reinforcers (Green, Myerson, Oliveira, & Chang, 2013).

Another common observation is that certain populations discount delayed reinforcers at a higher rate than control populations. Individuals who make more self-controlled choices in regards to their health and safety discount future monetary gains less steeply than those who do not (Bickel & Marsch, 2001). Increased population-level discounting rates have been found to be evident in substance use disorders and may function as a behavioral marker of substance abuse across the life course of the disorder in alcohol (MacKillop et al., 2010; J. M. Mitchell, Fields, D'Esposito, & Boettiger, 2005; Petry, 2001; Vuchinich & Simpson, 1999), nicotine (Bickel, Odum, & Madden, 1999; M. W. Johnson, Bickel, & Baker, 2007), stimulant (Heil, Johnson, Higgins, & Bickel, 2006; Hoffman et al., 2006; Mejía-Cruz, Green, Myerson, Morales-Chainé, & Nieto, 2016), and opiate use disorders (K. N. Kirby, Petry, & Bickel, 1999), as well as in use of multiple substances (see MacKillop et al., 2011 for meta-analysis; Petry, 2002). Other populations which discount delayed rewards to a relatively greater degree than controls include the overweight and obese (see Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Bickel et al., 2014; Epstein, Salvy, Carr, Dearing, & Bickel, 2010), and individuals who do not engage in health maintenance behaviors (e.g., dental visits, prostate exams, mammograms, exercise, and cholesterol testing) (Bradford, 2010). The observation of excessive discounting among a variety of disorders has led to the suggestion that delay discounting is a trans-disease process (Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012); that is, that delay discounting is a process which undergirds the etiology or phenotype of multiple disorders, making findings from one disorder relevant to others.

Many studies comparing population discounting rates have examined the discounting of magnitudes between $100 and $1,000. These tasks frequently find significant differences between controls and populations of interest in both substance use disorder (Bickel et al., 1999; Heil et al., 2006; Hoffman et al., 2006) and obesity (Bongers et al., 2015). However, the nominal full-magnitude value to be discounted varies widely across studies (i.e., $0.30 to $50,000 in (MacKillop et al., 2011)). Some of these studies at small magnitudes of reinforcers ($10) have observed small effect sizes and nonsignificant differences in mean discounting rates between certain substance users and controls (P. S. Johnson, Herrmann, & Johnson, 2015; Kris N. Kirby & Petry, 2004; Reynolds, Karraker, Horn, & Richards, 2003). This lack of effect size could be the result of no differences between populations that would observed at all magnitudes. Alternatively, this difference may result from the greater discounting associated with lower magnitudes obscuring population differences that would be evident at higher magnitudes. To the extent this is true, we call the magnitude-dependent ability to distinguish populations the second magnitude effect: that is, the differences in delay discounting between different populations can be detected at higher magnitudes.

From the perspective of the second magnitude effect, we hypothesize that at very small magnitudes, a ceiling effect on discounting rates may eliminate group differences between populations. If the second magnitude effect is observed, then it would suggest the application of the basic observation of a magnitude effect in discounting of delayed reinforcers is instrumental to translational efforts to understand differences in clinically relevant populations. In the present study, we used Amazon's Mechanical Turk (MTurk) system, a crowdsourcing platform, to observe whether differences in discounting rates are magnitude-dependent between substance using and control populations. We examined discounting of five different magnitudes of delayed money, ranging from $0.10 to $1,000 in substance users (dual cigarette smokers and alcohol drinkers) and controls. Based on prior research (Moody, Franck, Hatz, & Bickel, 2016), this population was likely to show significant differences in discount rate in at least one of the magnitudes examined.

Methods

Subjects

Participants (*N* = 129) were recruited from MTurk, which allows individuals to complete brief tasks as Human Intelligence Tasks (or HITs) and allows sampling from a large national population. High-risk substance users (*n* = 60) were required to score at least a 10 on the Alcohol Use Disorders Identification Test (AUDIT (Piccinelli, 1998)) and a 4 on the Fagerström Test for Cigarette Dependence (FTCD, (Fagerstrom, 2012)). In contrast, control participants (n=69) were required to score no more than a 7 and 3 on these scales, respectively. All participants were 18 years of age or older. Notably, we did not restrict this HIT to individuals with high HIT acceptance rates (indicating that the worker's HITs have been accepted by requesters as following instructions a majority of the time e.g., (P. S. Johnson et al., 2015)), as we were interested in recruiting from as broad a range of MTurk users as possible.

Compensation for this HIT included a $4 base payment for the completion of the survey, with an additional $1 bonus if the responses passed data quality checks related to delay discounting. These quality checks had two response options: some amount of money now vs. no money now, presented for each magnitude of reward examined (see below). To pass the data quality check, the participant had to choose the nonzero monetary amount. Each participant who passed all checks received the $1 bonus for their effort. We only included in our final data set participants who passed all quality checks for all magnitudes of reward. For this reason, we excluded data for 13 participants (9 in high-risk dual substance users and 4 in the control condition). Our final dataset thus included 116 subjects.

Procedure

We used the five-trial, adjusting-delay discounting task (Koffarnus & Bickel, 2014) to estimate delay discounting rates for each participant at five reward magnitudes: $0.10, $1.00, $10.00, $100.00, and $1,000.00, presented in random order. This task was used because it provides accurate estimates of delay discounting, is sensitive to the effects of experimental variables (including magnitude) in a manner similar to that of traditional discounting tasks, and can be completed rapidly (less than one minute per magnitude), thus making it ideal to assess discount rates across a broad range of magnitudes (Bickel, Wilson, Chen, Koffarnus, & Franck, 2016; Koffarnus & Bickel, 2014). At each magnitude, participants completed five trials in which they chose between a larger, delayed option (i.e., the magnitudes listed above) and a smaller, immediate option that was always equal to half of the delayed option. On the first trial, the delay to the larger reward was 3 weeks, with the delay adjusting over the next 4 trials depending on participants' previous choices (see Koffarnus & Bickel, 2014). The final adjusted delay served as an estimate of ED50, or the effective delay at which reinforcers lose half of their value. To allow for comparison between our results and prior literature on delay discounting which has used the discount rate parameter, k, from Mazur's (1987) hyperbolic model, we then calculated each participant's k value as a simple mathematical inverse of the ED50 (Koffarnus & Bickel, 2014;

Yoon & Higgins, 2008). These k values were then natural log-normalized to compensate for nonnormal distribution and allow for analysis with parametric statistical tests.

To compare groups and observe main effects for both group and magnitude of reward, we performed ordinary two-way ANOVAs on the log-normalized discounting rates between high-risk dual substance users and controls. To quantify the effect size of the difference between groups at each magnitude, we calculated Cohen's *d*, which is the difference in two means over their pooled standard deviation (using the RMS of the standard deviations of the groups of users and controls). To examine correspondence between discounting rates obtained at each magnitude, we generated correlation coefficients (Pearson's r) between discounting rates from each task. All data were analyzed and graphed in GraphPad Prism 6.03, and G*Power 3.1.

Results

Our sample was classified into either substance-using or control groups based on the AUDIT and FTCD cutoffs above. Demographics for these groups are described in Table 2.1. We found no significant differences between our control and high-risk substance-using group in sex, race, ethnicity, or income using chi-square analyses. A simple two-tailed unpaired t-test demonstrated no differences in age.

We compared the natural log of participants' derived k values across both groups and magnitudes (see Figure 2.1). Figure 2.1 depicts natural log transformed k values for each group across all five reinforcer magnitudes. Results of two-way ANOVA revealed a main effect for both magnitude ($F(4, 570) = 33.71$; $p < 0.0001$) and group ($F(1, 570) = 41.82$; $p < 0.0001$). We did not find a significant interaction term between group and magnitude ($F(4, 570) = 0.9892$; $p = 0.4128$).

We performed post-hoc comparisons between groups and across magnitudes using multiple T-tests with Holm-Šídáks correction for multiple comparisons (Holm, 1979). We found no significant differences between controls and current substance users at the smallest magnitudes of reward, \$0.10 ($p= 0.17$) and \$1.00 ($p=0.011$), but the groups were distinguishable at the \$10 ($p=0.0019$), \$100 ($p=0.00019$), and \$1000 ($p=0.00023$) conditions. We note that without corrections for multiple comparisons, the difference between substance users and controls was significant at the \$1.00 level, but not at the \$0.10 level. The effect size (Cohen's *d*) of the difference in mean increased with increasing magnitude. Table 2 displays the means, standard deviations, and effect sizes between groups at all magnitudes.

Table 4.2 displays Pearson's correlation coefficients between delay discounting rates across magnitudes for each group. Within both groups, all discounting rates were significantly correlated ($p<0.01$), with r values varying from .327 to .750. In general, correlation coefficients were stronger in the control group. In controls, correlation coefficients between discounting rates at the highest magnitude positively covaried with magnitude; that is, discounting at \$1000 was most closely correlated with discounting at \$100, followed by \$10, \$1.00, and \$0.10, in that order. In the dual user group, discounting at the \$1000 condition was also most closely correlated with the \$100 condition. However, discounting rates at lower magnitudes (\$10.00 and below) were not correlated with discounting at \$1000 in a magnitude-dependent fashion.

Discussion

We investigated whether dual substance users of alcohol and tobacco may be differentiable from controls over \$0.10, \$1.00, \$10.00, \$100.00, and \$1,000 delay discounting tasks. Although the direction of the differences in means between substance using and non-substance using groups was consistent with established literature that shows substance users discount more than controls, the degree of this difference varied systematically with magnitudes and was not statistically significant at or below $1. Both controls and current high-risk substance users discounted these values heavily, and there were no significant differences between substance users and controls at a $0.10 and $1 magnitudes. At the $10.00 magnitude, a difference emerged between the groups, which became more significant at higher magnitudes up to the $100 condition. We additionally found that the effect size indicating difference in mean discounting rates between our two groups increased with the magnitude of reward being discounted. We suggest that this finding is a second form of the magnitude effect; that is, the magnitude effect operates when comparing populations and therefore the study of low-magnitude reinforcers can diminish the ability to detect difference in delay discounting between populations.

Research in delay discounting has been used to try to identify differences in groups with poor health outcomes (i.e., substance users), and has been highly productive; however, some research has not found differences between groups, possibly due to the magnitude of reward in the delay discounting task used. We hypothesized that this could be due to interplay between the magnitude effect, where individuals make more immediate choices at lower magnitudes, and the group effect found when comparing controls and substance users. Our results provide a context within which to interpret other research that has found small or negligible differences in discounting between smokers and controls at smaller magnitudes, such as $10 (P. S. Johnson et al., 2015; Reynolds et al., 2003) or alcohol users and controls at $25-$85 magnitudes (Kris N. Kirby & Petry, 2004). It may also be useful when considering other negative results in comparing discounting rates of pathological gamblers to controls in discounting of $25-$85, (Madden, Petry, & Johnson, 2009) or overweight/obese participants to controls in discounting of $10 (S. A. Fields, Sabet, & Reynolds, 2013; Hendrickson & Rasmussen, 2013).

These previous studies may have also observed nonsignificant results due to an interaction between this second form of the magnitude and relatively small sample sizes. We have performed power analyses to estimate the numbers of participants required to observe significant differences between groups of high-risk dual users (a subclinical substance using population) and controls. These analyses, based on the effect sizes presented in Table 2, indicate that to distinguish between groups at a magnitude of $0.10 would require 1412 participants; to distinguish between groups at a magnitude of $1.00, 252; at $10.00, 128; at $100, 100; and finally, at $1000, 74 individuals. The majority of studies failing to report significant differences in discounting between substance users and controls did not include these sample sizes (e.g., (Kris N. Kirby & Petry, 2004; Reynolds et al., 2003). These power analyses demonstrate that delay discounting at larger magnitudes leads to a potentially greater ability to distinguish between groups at smaller sample sizes, indicating that delay discounting of $1,000 is the most sensitive measure presented here. However, distinguishing between populations is multiply determined, and we acknowledge other research *has* found discounting tasks at smaller magnitudes to be sensitive to some group differences (S. Fields, Leraas, Collins, & Reynolds, 2009; e.g., S. H. Mitchell, 1999). Future work that seeks to detect differences in delay discounting rates between populations will need to take into account not only the degree of substance use (with subclinical inclusion criteria leading to smaller effect sizes; (M. W. Johnson et al., 2007; MacKillop et al., 2011; Ohmura, Takahashi, & Kitamura, 2005), but also the magnitude of reinforcer used in the delay discounting task (with smaller magnitudes leading to smaller differences).

We acknowledge several limitations in the present study. We opted for classification of high-risk substance use behavior rather than substance dependence criteria. Our substance-using sample thus represents individuals who both drink and smoke in high-risk ranges. Future research may be better able to resolve the relationship between extent of substance use in other groups of substance users and sensitivity of discounting tasks to group differences at various magnitudes. Furthermore, due to the structure of Amazon's MTurk system, only individuals who completed the HIT (i.e., individuals who proceeded through all questionnaires and all five discounting tasks) could be compensated for their work and included in the final data set, which may have selected for more conscientious workers. Additionally, due to the sensitivity of the minute discounting task to each individual response, we did not analyze any data from participants who missed any data quality checks throughout the entirety of the HIT. This exclusion may have further encouraged selection towards individuals with relatively higher conscientiousness. We attempted to compensate for this effect by recruiting from the general Amazon MTurk population, rather than selecting for only the most dedicated workers based on high HIT acceptance rates, as has been done in other discounting work on MTurk (P. S. Johnson et al., 2015). Finally, we acknowledge the restriction of our findings to one particular delay discounting procedure, the adjusting-delay task, and recognize the need for replication with other procedures.

This line of research extends in multiple future directions. Whether the same magnitude dependent differences in discounting rates (i.e., the second form of the magnitude effect) can be observed with other populations remains to be empirically tested. To the extent that these magnitude-dependent differences exist, it would confirm the importance of this second form of magnitude effect as a determinant of detecting population differences. Further, although discounting rates from hypothetical delay discounting procedures correlate with procedures which present real or potentially real reinforcers (Wilson, Franck, Koffarnus, & Bickel, 2016), it is not clear whether these other measures may show similar magnitude-dependent differences in population-level discounting rates.

This study is an example of using basic science concerning the magnitude effect in delay discounting and translating it to address a clinical application; that is, detecting differences across populations with delay discounting. Here, we have found that differences in decision-making between controls and current substance users are most pronounced at the greatest magnitudes of reward--that is, when the stakes are highest, the substance using population demonstrated the most immediate decisions, relatively. This finding can help to inform the further application of delay discounting tasks to identify treatment outcomes and to classify substance use disorders.

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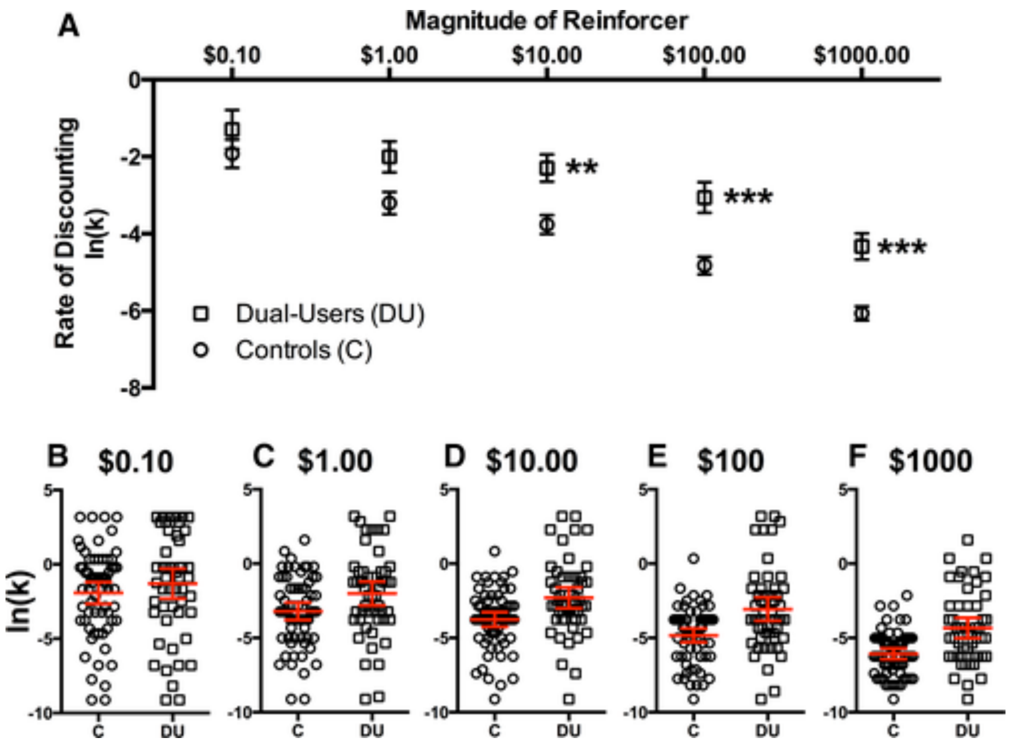
Figure 2.1. Differences in discounting between groups and over magnitudes



Displayed in panel A are group comparisons of discounting rates (as natural-log-normalized k values) between controls with low AUDIT (<8) & FTCD (<4) scores and dual-substance users with high AUDIT (>10) and FTCD (>4) scores, over all five magnitudes of reinforcer examined. Error bars indicate standard error of the mean. Asterisks denote levels of significance of group difference between mean discounting rates. Panels B-F display group data including mean and and 95% confidence intervals as well as individual data points representing individual participant's natural-log-normalized discounting rates across the $0.10, $1.00, $10.00, $100.00, and $1000.00 conditions, in that order.

Table 2.1
Participant Demographics

Characteristic	Control (*n*=65)	Dual Substance (*n*=51)
AUDIT Score (Mean, SD)	3.338, 2.340	17.647, 7.962
FTCD Score (Mean, SD)	0.861, 1.261	5.803, 1.575
Age (Mean, SD)	34.461, 12.537	32.960, 7.402
Employment Status		
Working full time	43	42
Working part time	12	3
Not working	2	3
Other	8	3
Gender		
Male	31	33
Female	34	18
Race		
Caucasian	54	47
Black	4	3
American Indian	2	2
Asian	7	2
Ethnicity		
Hispanic	4	5
Non Hispanic	61	46
Education		
Finished high school or received GED	7	11
Some College	25	15
Bachelor's degree	27	23
Advanced degree (e.g., Masters or Doctorate)	6	2
Household Income		
$1-$30,000	13	14
$30,001-$60,000	34	21
$60,001 or more	18	16
Marital Status		
Single	21	24
Married	27	19
Other	17	8

Table 2.2

Group statistics and Cohen's d *at each magnitude*

	Dual users		Controls		Cohen's *d*
Magnitude	Mean k	SD	Mean k	SD	
$0.10	-1.29	3.58	-1.92	2.94	0.192
$1.00	-2.01	2.87	-3.21	2.35	0.457
$10.00	-2.30	2.52	-3.76	1.99	0.643
$100.00	-3.06	2.83	-4.83	1.87	0.735
$1000.00	-4.33	2.44	-6.07	1.49	0.860

Table 2.3

Correlations between delay discounting rates across magnitudes

	Controls				
	$0.10	$1.00	$10.00	$100.00	$1000.00
$0.10	-				
$1.00	0.605	-			
$10.00	0.659	0.713	-		
$100.00	0.557	0.566	0.750	-	
$1000.00	0.327	0.430	0.633	0.670	-
	Dual Users				
	$0.10	$1.00	$10.00	$100.00	$1000.00
$0.10	-				
$1.00	0.690	-			
$10.00	0.582	0.602	-		
$100.00	0.490	0.590	0.600	-	
$1000.00	0.534	0.467	0.497	0.735	-

MANUSCRIPT 2

Title

Narrative theory: II. Self-generated and experimenter-provided negative income shock narratives increase delay discounting

Abstract

Reading experimenter-provided narratives of negative income shock has been previously demonstrated to increase impulsivity, as measured by discounting of delayed rewards. We hypothesized that writing these narratives would potentiate their effects of negative income shock on decision-making more than simply reading them. In the current study, 193 cigarette-smoking individuals from Amazon Mechanical Turk were assigned to either read an experimenter-provided narrative or self-generate a narrative describing either the negative income shock of job loss or a neutral condition of job transfer. Individuals then completed a task of delay discounting and measures of affective response to narratives, as well as rating various narrative qualities such as personal relevance and vividness. Consistent with past research, narratives of negative income shock increased delay discounting compared to control narratives. No significant differences existed in delay discounting after self-generating compared to reading experimenter-provided narratives. Positive affect was lower and negative affect was higher in response to narratives of job loss, but affect measures did not differ based on whether narratives were experimenter-provided or self-generated. All narratives were rated as equally realistic, but self-generated narratives (whether negative or neutral) were rated as more vivid and relevant than experimenter-provided narratives. These results indicate that the content of negative income shock narratives, regardless of source, consistently drives short-term choices.

Introduction

Substance use disorder has been described as a chronically relapsing brain disorder (Volkow, Koob, & McLellan, 2016) in which individuals impulsively and compulsively use substances (Everitt et al., 2008). Impulsivity is a critical factor in the development of substance use disorders, as individuals who abuse substances are driven towards their immediate rewards even at significant delayed costs (Bickel & Marsch, 2001). Accordingly, individuals who abuse substances demonstrate preference for smaller, sooner over larger, later rewards, as assessed by delay discounting procedures (Amlung, Vedelago, Acker, Balodis, & MacKillop, 2016; Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012). Prior research has also demonstrated the manipulability of delay discounting, indicating that preference for immediate or delayed reward receipt may be, in part, controlled by the decision-making context. For example, narratives have provided a particularly rich opportunity for manipulations of delay discounting (Bickel et al., 2017), possibly due to the ability of narratives to engage both domain-relevant and dispersed neural regions (Huth, de Heer, Griffiths, Theunissen, & Gallant, 2016).

The effects of narratives have varied across manipulations, with different narrative features engendering different effects on decision-making. Specifically, reading an experimenter-provided narrative describing economic hardship in the form of negative income shock has been shown to significantly increase delay discounting (Bickel, Wilson, Chen, Koffarnus, & Franck, 2016). In a related manipulation, episodic future thinking, participants who self-generate narratives describing positive future events, results in decreases in delay discounting (Daniel, Said, Stanton, & Epstein, 2015; Daniel, Stanton, & Epstein, 2013a, 2013b; Peters & Büchel, 2010). Notably, manipulations that alter delay discounting may also alter demand for (Snider, LaConte, & Bickel, 2016), and consumption of (Stein et al., 2016) substances of abuse. Importantly, these interventions have opposite effects on delay discounting and differ in, among other dimensions, both narrative *source* (experimenter-provided versus self-generated) and narrative *content* (negative versus positive events).

In the present study, we have examined the impact of these narrative dimensions, source and content, on decision-making. Specifically, we compared the effect of experimenter-provided and self-generated narratives about either negative income shock or an economically neutral job transfer on delay discounting. Self-generated narratives were hypothesized to be more relevant and vivid to participants than the experimenter-provided ones. Additionally, personalized, self-generated narratives about negative income shock were hypothesized to produce steeper discount rates than experimenter-provided narratives of negative income shock, due to their greater relevance and vividness; and both source-types were hypothesized to produce steeper discount rates than control narratives.

Methods

Participants

This study was presented as a Human Intelligence Task (HIT) on Amazon's Mechanical Turk (Mturk) crowdsourcing platform. Participants completed a brief screener to ensure that they smoked >10 cigarettes a day. A total of 191 participants completed the HIT. Participants were randomly assigned to one of four narrative manipulations: reading an experimenter-provided narrative describing job loss and ensuing negative income shock (n=43), reading a narrative describing an economically neutral scenario (n=38), writing a self-generated narrative describing job loss and negative income shock (n=39), or writing a narrative describing an economically neutral scenario (n=36). Participants were assessed for demographic variables, including degree of cigarette dependence using the Fagerström Test of Cigarette Dependence (Fagerstrom, 2012). Data were excluded for participants who provided discounting data that violated the criteria described by Johnson and Bickel (2008; n=30), or who failed to follow instructions (n=4), as by failing to synthesize the presented information into their narrative. Demographic data for the final included sample (n=157) are presented in Table 3.1.

Narrative manipulation

Participants were randomized into a 2-by-2 study design, in which both narrative source (experimenter or self) and narrative content (negative income shock or neutral) varied. The experimenter-provided narratives were as described in Bickel (2016).

In the experimenter-provided condition participants were instructed to read the scenario and imagine themselves in the situation.

Experimenter-provided negative income shock condition:

> *"You have just been fired from your job. You will now have to move in with a relative who lives in a part of the country you dislike, and you will have to spend all of your savings to move there. You do not qualify for unemployment, so you will not be making any income until you find another job."*

Experimenter-provided neutral condition:

> *"At your job, you have just been transferred to a different department in a location across town. It is a similar distance from where you live so you will not have to move. You will be making 2% more than you previously were."*

In the self-generated narrative condition, participants were instructed to generate their own narratives, synthesizing information matched to the experimenter-provided narratives into personal stories, and answering additional questions to ensure the inclusion of personal details. First, participants read instructions regarding the narratives to be generated.

Self-generated negative income shock condition:

> *"In this task you will be asked to describe and elaborate on an event that could happen to you today. Imagine that, today, you are losing your job. You know you will have to move, and spend all your savings to do so."*

Self-generated neutral condition:

> *"In this task you will be asked to describe and elaborate on an event that could happen to you today. Imagine that, today, you are being transferred to a different department across town at your job. You know you will not have to move, and will be making 2% more than you previously were."*

Participants were then asked to answer follow-up questions to enhance the imagery of the experience. "As you think about what you would be doing immediately after [losing your job]/[being transferred], answer the following questions. In this situation: Who are you with? What are you doing? Where are you? What are you feeling?" Finally, participants synthesized this information into personalized narratives describing their scenario, incorporating the answers to these follow-up imagery questions.

Narrative Evaluation

Participants completed the Positive and Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988) to assess mood as well as visual analogue scale responses for key qualities of the narratives. Participants each answered questions about the narrative they read or generated with a slider bar (0-100): “How frightening is this story?”, “How realistic is this story?”, “How vivid is this story?”, “How relevant is this story to your life?”, and “How depressing is this story?”.

Delay Discounting

To assess preference for immediate versus delayed rewards, participants completed a 7-delay, 5-trial adjusting amount task of delay discounting (Du, Green, & Myerson, 2002). Participants chose between $X now and $1000 at each of seven delays (1 day, 1 week, 1 month, 6 months, 1 year, 5 years, or 25 years in the future), with X increasing or decreasing with each trial depending on participants prior responses within each delay. This task thus titrates to an indifference point at each delay, which can then be fit to Mazur’s hyperbolic model of delay discounting (Mazur, 1987):

$$V = \frac{A}{1 + kD}$$

The adjusting amount discount task, particularly at magnitudes of $1000, allows for assessment of a broad range of delay discount rates, reducing the likelihood that manipulations to increase delay discounting would reach a ceiling of the task (Mellis, Woodford, Stein, & Bickel, 2017). Data were excluded from participants based on violation of established rules regarding orderly delay discounting data (Johnson & Bickel, 2008). Participants were instructed to make choices as if their choices were real (that is, as if they would actually receive the monetary reward at the delay they chose), and as if the narratives with which they had just engaged had happened to them.

Data Analysis

Delay discounting data were analyzed by fitting the above hyperbolic discounting model to each individual's indifference points using the nlmrt (John, 2013) function in R version 3.3.3 (R Core Team, 2017). The natural-log-normalized, fitted *k* parameter was compared between groups by convention (Odum, 2011). Narrative content was evaluated using the Flesch-Kincaid measure of readability (Flesch, 1948) with the readability package in R (Bailin & Grafstein, 2016). Normality for all outcome measures was assessed by visual inspection of normal quartile-quartile plots, and using absolute skew and kurtosis cutoffs of >2 and > 7, respectively (Kim, 2013). Positive affect, natural log transformed discount rates, and VAS ratings of narrative vividness and relevance all met this standard for normality, and were analyzed by two-way fixed-effects ANOVA. Due to non-normal distribution of negative affect and visual analogue scale ratings of narrative qualities of fear, realisticness, and depression, these data were analyzed by two independent Mann-Whitney U tests of the effect of each factor (narrative source and narrative content).This method does not permit interpretation of interaction terms, but does allow for non-normality. Figures were generated with GraphPad Prism 7 (GraphPad, 2016).

Results

Demographics and narrative content

Participant demographics are presented in Table 3.1. No significant differences in demographics were present between groups. Due to a trending but nonsignificant difference between groups in education, parametric analyses described below were repeated including education as a covariate, but observed no change in results.

The experimenter-provided narratives were 60 and 43 words in length in the negative income shock and neutral conditions, respectively. Self-generated narratives varied in length, with an average length of M=83 (SD=50) and M=84 (SD=41) words in the negative and neutral conditions, respectively. The experimenter-provided narratives had a Flesch-Kincaid reading level of 7.74 in the negative income shock and 7.66 in the neutral conditions. The self-generated narratives had reading levels of 5.65 (SD=4.89) and 7.83 (SD=2.26) in the negative income shock and neutral conditions, respectively. A t-test with Welch's correction applied for unequal variances showed statistically significant differences in reading level between the two content groups within the self-generated condition ($p=0.025$).

Narrative response

Figure 3.1 depicts differences in responses to narrative manipulations. Overall, a significant main effect of scenario content ($F(1,153) = 35.67$, $p<0.0001$) was observed on delay discounting (see Figure 3.1, panel A), with individuals who experienced narratives of job loss and negative income shock reporting greater preference for smaller, sooner rewards than individuals who experienced neutral narratives of a job transfer. No significant main effect of narrative source ($F(1,53)=0.33$, $p=0.56$) was observed. Whether in the experimenter-provided narrative group or the self-generated group, post-hoc contrasts revealed a significant increase in natural log normalized rates of delay discounting when presented with the negative income shock compared to the neutral narrative ($p<0.0001$ and $p=0.009$, respectively).

No differences were observed between experimenter-provided and self-generated narratives on positive nor negative affect, although narrative content had a significant effect on both measures (with negative income shock decreasing positive affect: $F(1,153)=16.00$, $p<0.0001$; and increasing negative affect: $W=1617$, $p<0.0001$, compared to neutral job transfer). Visual Analogue Scale ratings of narrative qualities demonstrated differences between both narrative content and source on distinct measures (see Figure 3.1, panel B). Consistent with our hypothesis, we observed that VAS ratings of narrative vividness ($F(1,152)=8.04$, $p=0.0052$) and narrative relevance ($F(1,152)=11.54$, $p=0.0008$) were significantly higher in the self-generated than in the experimenter-provided conditions, with no significant main effects of narrative content on either vividness or relevance. A significant main effect of narrative content was obtained on VAS ratings of how frightening narratives were ($W=438.5$, $p<0.0001$), and how depressing ($W= 215$, $p < 0.0001$). All scenarios were rated as similarly realistic, across both narrative content and source.

Discussion

These results suggest that, regardless of whether stories are generated by the participant or by an experimenter, negative income shock narratives increase delay discounting. Similarly, these narratives increase negative and decrease positive affect. Although self-generated stories were longer and rated as marginally more vivid and relevant than stories written by others, these differences do not seem to co-occur with greater impact of these narratives on decision-making. Specifically, regardless of level of vividness or perceived reality of a given scenario, the information provided by scenarios of job loss and ensuing negative income shock drove individuals to prefer smaller, sooner over larger, later rewards. Given that adverse financial events are also associated with relapse to smoking among former smokers, and continued smoking among current smokers (McKee, Maciejewski, Falba, & Mazure, 2003), these data support the impact of negative income shock information as also increasing other smoking-related risk factors (that is, delay discounting).

These results also extend the literature distinguishing between the effects of self-generated and experimenter-provided manipulations. For example, the standard delivery of implementation intentions involves asking individuals to generate their own descriptions of how to best adhere to their own intentions to avoid substance use. However, self-generated and experimenter-provided implementation intentions both comparably reduce clinically relevant outcome measures such as alcohol consumption (Armitage, 2009). For example, participants were asked to either indicate which of a set of experimenter-provided implementation intentions they would use to moderate drinking, or to generate their own. Consistent with our findings, individuals who merely indicated their choice with a check box, rather than writing out the implementation intention fully, demonstrated similar reductions in alcohol consumption.

In another study, Neroni et al. (2016) compared the content, detail, and qualities of self-generated *narratives* with information elicited from experimenter-provided or self-generated *cues*. This group observed that participants generated narratives of future events richer in event-specific details in response to experimenter-provided cues than in response to self-generated cues, but that the narratives created in response to self-generated cues were more personally relevant. These results may support the notion that differences in relevance of narratives may be derived not from the act of synthesizing information into a narrative, but from the generation of said information. However, in the present study, in order to standardize the information described across both groups, we dictated narrative content. Consequently, we cannot know if narratives of economic hardship may have had similar effects on delay discounting if they were spontaneously self-generated rather than simply relying on participants to synthesize information they had already been given. An alternative design, in which participants generate any story of hardship and only those which describe negative income shock are analyzed may provide an interesting future direction of this research question to assess differences in purely generated versus synthesized information on decision-making.

Furthermore, the content of the negative income shock condition may have itself impacted level of elaboration within the self-generated narrative group. Although word length was greater and ratings of vividness and reality were higher in the self-generated condition, individuals in the self-generated negative income shock group wrote narratives of significantly lower reading level than those in the self-generated neutral condition. Past research has indicated that resource scarcity may negatively impact cognition (Mani, Mullainathan, Shafir, & Zhao, 2013), and also that negative affect is associated with reduced control of attention and task-related motivation (Brose, Schmiedek, Lövdén, & Lindenberger, 2012). These effects may interfere with ability to more deeply elaborate on information as might be expected from the act of synthesizing said information into a narrative. Finally, these narratives may have differed in the information they did synthesize due to the differences in instructions between the experimenter-provided and self-generated groups. Specifically, the experimenter-provided condition explicitly stated that income would be depleted and that future sources of income would be uncertain after the negative income shock event. In contrast, self-generated narratives did not necessarily elaborate on the ongoing nature of income depletion. Future research might address this by comparing the effects of engagement with experimenter-provided or self-generated positive scenarios, the content of which would not be hypothesized to interfere with cognition and motivation.

These results provide some support for future research relying on narratives to manipulate delay discounting. Specifically, if two narratives provide similar narrative content and information, they may have similar effects on preference for immediate and delayed rewards regardless of the narrative source. Indeed, the act of *generating* episodes may not be as important as the act of simply attending to and *engaging* with these scenarios. In light of past research demonstrating that generating narrative episodes can alter preference and craving for substances of abuse (Snider et al., 2016; Stein et al., 2016), future research may determine whether shared effects on delay discounting between experimenter-provided and self-generated narratives are also observable in these potentially clinically-relevant measures. Additionally, future research may pursue applying pre-generated scenarios with content similar to those that have been demonstrated to increase rather than decrease preference for delayed rewards to the same effect, streamlining and standardizing the processes by which the future is valued.

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Figure 3.1. Effects of Narratives

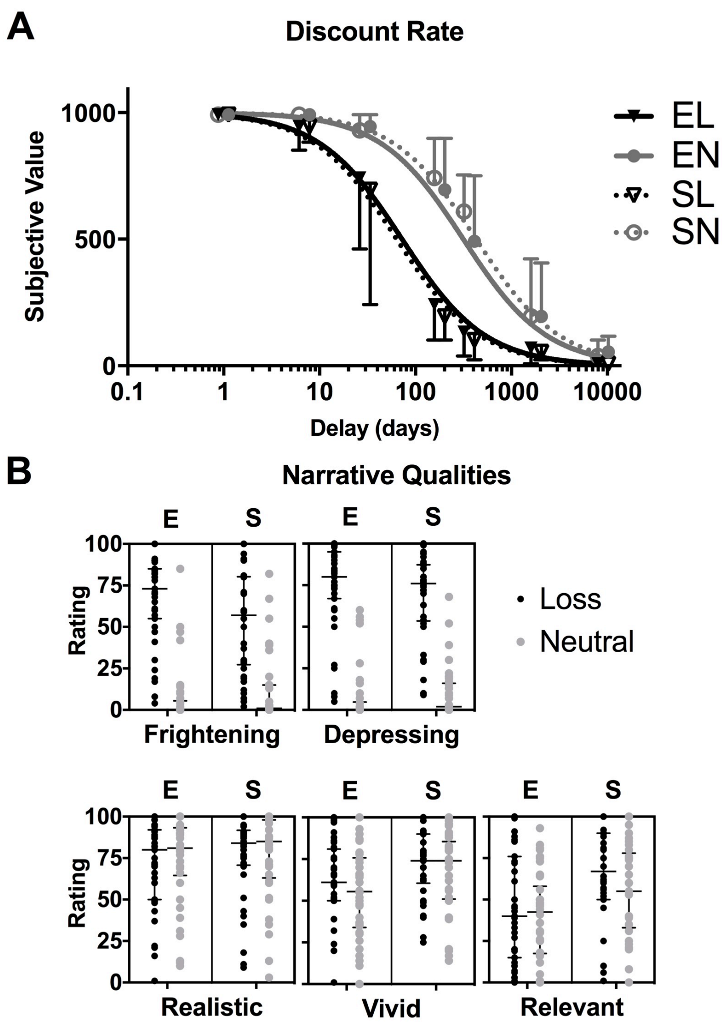

Figure 3.1 depicts responses to narrative manipulations. Panel A shows the discount rate across four groups: experimenter-provided job loss and negative income shock (EL), experimenter-provided neutral (EN), self-generated job loss and ensuing negative income shock (SL), and self-generated neutral (SN). The X axis depicts delay to reward receipt in days, and the Y depicts subjective value of receipt of a $1000 reward at each delay. Points reflect jittered median points of indifference between immediate and delayed reward receipt within groups, and error bars indicate interquartile range. Panel B shows individual subject ratings of narrative qualities. In all

graphs, the left panel ("E") indicates experimenter-provided narratives, and the right panel ("S") indicates self-generated narratives. Participants rating of each narrative quality on a visual analogue scale (0-100) is indicated on the Y axis. Bars indicate median ratings within groups, and error bars indicate interquartile range. *$p<0.05$

Table 3.1. Demographics

	Experimenter-Provided		Self-Generated	
	Negative	Neutral	Negative	Neutral
n	43	38	39	37
Age (years ± SD)	33.65 ± 8.68	33.24 ± 9.56	34.23 ± 9.71	36.43 ± 12.01
Gender				
n male (%)	18 (41.9)	21 (55.3)	19 (48.7)	15 (40.5)
Education				
n < high school (%)	0 (0.0)	1 (2.6)	0 (0.0)	0 (0.0)
n high school (%)	11 (25.6)	4 (10.5)	2 (5.1)	1 (2.7)
n some college (%)	17 (39.5)	11 (28.9)	11 (28.2)	12 (32.4)
n 2-year degree (%)	1 (2.3)	7 (18.4)	4 (10.3)	7 (18.9)
n 4-year degree (%)	11 (25.6)	12 (31.6)	16 (41.0)	13 (35.1)
n advanced degree (%)	3 (7.0)	3 (7.9)	6 (15.4)	4 (10.8)
Income				
n <$10k (%)	4 (9.3)	10 (26.3)	7 (17.9)	7 (18.9)
n $10-29k (%)	12 (27.9)	10 (26.3)	14 (35.9)	8 (21.6)
n $30-49k (%)	18 (41.9)	7 (18.4)	9 (23.1)	11 (29.7)
n $50-70k (%)	6 (14.0)	9 (23.7)	6 (15.4)	4 (10.8)
n $70-89k (%)	1 (2.3)	2 (5.3)	3 (7.7)	4 (10.8)
n $90k+ (%)	0 (0.0)	0 (0.0)	0 (0.0)	2 (5.4)
n Refuse to answer (%)	2 (4.7)	0 (0.0)	0 (0.0)	1(2.7)
Race				
n White (%)	34 (79.1)	30 (78.9)	29 (74.4)	29 (78.4)
n Black (%)	6 (14.0)	0 (0.0)	2 (5.1)	3 (8.1)
n Asian (%)	1 (2.3)	5 (13.2)	5 (12.8)	4 (10.8)
n Other (%)	2 (4.7)	3 (7.9)	3 (7.7)	1 (2.7)
Ethnicity				
n hispanic (%)	6 (14.0)	1 (2.6)	3 (7.7)	4 (10.8)
Smoking Measures				
FTCD ± SD	16.44 ± 7.01	15.24 ± 5.11	15.36 ± 6.13	13.73 ± 4.25
Cigarettes per day ± SD	5.51 ± 1.82	5.21 ± 1.63	5.36 ± 1.81	5.16 ± 1.88

FTCD: Fagerstrom Test of Cigarette Dependence

MANUSCRIPT 3

Title

Less is more: Negative income shock increases immediate preference in cross commodity discounting and food demand.

Abstract

Negative income shock, or the rapid reduction in financial stability, has previously been shown to increase impulsive choice for money and demand for fast food. The interplay of these conditions for obesity is called reinforcer pathology. The present work examines the impact of negative income shock on monetary and fast food discounting using a cross-commodity delay discounting task and on purchasing of fast food and an alternative commodity. An obese sample (n=120) was recruited from Amazon Mechanical Turk and assigned to read one of two narratives: negative income shock (n=60) or control (n=60). Participants then completed both within- and cross-commodity discounting tasks of money and food, and purchase tasks for fast food and bottled water. The negative income shock group demonstrated greater impulsive choice across discounting tasks, as well as higher intensity of demand for fast food but not for a non-caloric control commodity (bottled water). These results suggest that negative income shock increases preference for immediate reinforcement regardless of commodity type (money or fast food), but has specific effects increasing demand for particular commodities (fast food but not an alternative). In a reinforcer pathology framework, negative income shock increasing discounting of the future while increasing demand for fast food specifically represents a high-risk state for negative health behavior in obesity.

Introduction

Obesity is epidemic and is especially challenging, in the United States, among those of low socioeconomic status (SES) (Wang & Beydoun, 2007). Economic hardships, such as job loss and ensuing negative income shock, or the rapid reduction in financial stability, may promote increases in body weight (Morris, Cook, & Shaper, 1992), especially among those who are already overweight or obese (Deb, Gallo, Ayyagari, Fletcher, & Sindelar, 2011). Although low SES, and negative income shock, are also associated with multiple environmental factors (e.g., decreased access to and familiarity with healthier food options) that increase the risk of obesity (see Ford & Dzewaltowski, 2008), they may also aggravate obesity by promoting maladaptive patterns of decision-making (see Bickel, Moody, Quisenberry, Ramey, & Sheffer, 2014 for review).

Specifically, obesity may extend from a state of reinforcer pathology (Bickel, Jarmolowicz, Mueller, & Gatchalian, 2011; Carr, Daniel, Lin, & Epstein, 2011), which may be exacerbated in conditions related to resource scarcity (Sze, Stein, Bickel, Paluch, & Epstein, 2017a). Reinforcer pathology emerges from the confluence of two related factors: first, excessive preference for immediate reinforcement (typically measured with monetary delay discounting) and second, excessive preference for particular, unhealthy reinforcers (typically measured with purchase tasks). Each of these methods of assessment are defined below. Reinforcer pathology as a model of decision-making has been applied to multiple risks and health conditions, including obesity (Carr et al., 2011), problematic ultraviolet indoor tanning (Reed, 2015), and drug use disorders (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014). However, the particular relationship between the two component processes of reinforcer pathology has not yet been defined. That is, these two processes may behave additively (where conditions promoting excessive preference for the immediate also independently promote preference for particular unhealthy reinforcers) or interactively (where excessive preference for immediate reinforcers consequently increases preference for particular unhealthy commodities).

The first component of reinforcer pathology is excessive preference for immediate reinforcement, a component of impulsivity. The behavioral economic assessment of this preference, delay discounting, determines individual preference between smaller, sooner and larger, later quantities of a reinforcer, typically money (e.g., $10 today or $100 tomorrow, a form of "within-commodity discounting") (Odum, 2011). Steeper discounting of monetary reinforcers has been observed, compared to control populations, in obesity, substance use disorders, and problem gambling (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Amlung, Vedelago, Acker, Balodis, & MacKillop, 2016; MacKillop et al., 2011). Furthermore, delay discounting rates for monetary reinforcers are relatively higher after both real (Haushofer, Schunk, & Fehr, 2013) and hypothetical (Bickel, George Wilson, Chen, Koffarnus, & Franck, 2016) negative income shocks, including in an obese sample (Sze et al., 2017a). Delay discounting rates when choosing between other commodities have also been compared between groups--and indeed, the effect size when comparing differences in discounting between the obese and normal-weight controls are larger for food discounting than for money discounting (Amlung, Petker, et al., 2016; Barlow, Reeves, McKee, Galea, & Stuckler, 2016; Hendrickson, Rasmussen, & Lawyer, 2015). Overall, discounting of non-monetary reinforcers corresponds to some degree with discounting of money, though with food and other consumable reinforcers being more steeply discounted than money across populations (Bickel, Landes, et al., 2011; Odum, Baumann, & Rimington, 2006; Odum & Rainaud, 2003).

The second component of reinforcer pathology is high demand for particular, unhealthy reinforcers, such as high-energy density but low-nutrient-quality foods. This can be assessed through purchase tasks, in which individuals make decisions about how much of a specific commodity to consume at different prices. Purchase tasks measure two factors related to food reinforcement (Epstein, Stein, Paluch, MacKillop, & Bickel, 2018): intensity (level of demand when a commodity is free) and elasticity (defense of purchasing across increasing price). Indeed, obese individuals demonstrate higher valuation of high energy density food than healthy weight controls in purchase tasks, which combines with excessive preference for immediate reinforcement to place these individuals at the greatest risk for health consequences (Epstein et al., 2014; Epstein, Salvy, Carr, Dearing, & Bickel, 2010). Within this framework, negative income shock has also been demonstrated to increase intensity of demand for fast food, in an obese sample (Sze et al., 2017a). The specificity and selectivity of this effect is unknown, however. No research to date has determined whether this increase in intensity of demand (purchasing when a commodity is free) is truly limited to reinforcer pathology-associated commodities, or whether it extends to other commodities that are not specifically associated with negative health behaviors.

Previous investigations of reinforcer pathology have relied on separate investigations of each component process (preference for immediate reinforcement, as with delay discounting, and preference for particular reinforcers, as with purchasing). However, one task, cross-commodity discounting, allows for simultaneous assessment of both components of reinforcer pathology. Cross-commodity discounting tasks vary not only the magnitude and delay of reinforcers, but also the reinforcers themselves. For example, participants may choose between $10 now and $100 worth of food later. These tasks offer several advantages: first, they more accurately reflect the real-world decisions between alternative choices; second, in conjunction with more conventional (within-commodity) discounting, they allow for simultaneous assessment of preference for immediate reinforcement and a particular reinforcer. Cross-commodity discounting has been assessed in cocaine users (Bickel, Landes, et al., 2011), and alcohol users (Moody, Tegge, & Bickel, 2017) and, in conjunction with within-commodity discounting, can assess *relative* discounting of, and utility, for each commodity (Bickel, Landes, et al., 2011). In this case, assessing discounting both across commodities (food now, money later; money now, food later) and within commodities (food now and later; money now and later) allows for the finest resolution of relative preference of the distinct effects of each of these factors, indicating how preference may shift towards or away from specific kinds of reward, independent of how that reward may be discounted. To our knowledge, no research to date has determined the effects of negative income shock, as a manipulation of monetary discounting, on delay discounting of all combinations of immediate and delayed monetary and food commodities (i.e., both cross-commodity and within-commodity discounting).

The present study examines how socioeconomic stress, in the form of negative income shock, may contribute to negative health outcomes through a reinforcer pathology framework. Specifically, the effects of negative income shock on both monetary and food reinforcement in an obese sample have not been fully explored. Delay discounting of all combinations of immediate and delayed money and fast food were examined, in addition to purchasing of both fast food and a control commodity not associated with reinforcer pathology. Two hypotheses extended from the reinforcer pathology framework: (1) that within-commodity delay discounting of both money and food would be steeper in the negative income shock group; and (2) that negative income shock would selectively increase demand for fast food, but not for an alternative commodity, in the purchase task. We also assessed, for the first time, cross-commodity discounting of money and food to determine how relative discounting and utility for each of these commodities may change in negative income shock.

Material and Methods

Participation in the study was voluntary. Participants read a consent statement before enrollment, and consent was implied by submission of the study questionnaire. This study was approved by the Institutional Review Board (IRB) at Virginia Polytechnic Institute and State University.

Participants

120 participants completed the present study as a Human Intelligence Task (HIT) on Amazon Mechanical Turk. As the purpose of the study was to explore possible differences in cross-commodity discounting tasks between groups, no a priori power analyses were performed. Participants were compensated \$1.50 for completing the study and an additional \$2.00 for passing attention check questions. To be eligible for the HIT, participants were required to (1) be located in the United States; (2) have a HIT approval rate greater than 90%; (3) reported a height and weight which calculated a BMI in the obese range (>30). Those who were deemed eligible to participate in the study, completed baseline assessments of demographics, the Personal Health Questionnaire-9 (PHQ-9), in addition to other discounting, demand, and health and consumption related assessments.

Fast Food Consumption

Participants were asked to select their most preferred item from a list of 14 popular, branded fast food options (e.g., McDonald's cheeseburger, Chick-Fil-A chicken nuggets; see (Sze et al., 2017a) for the full list) then rated how much they liked the food they chose from 1 to

5, and categorized it as either healthy or unhealthy. Their selected food item was incorporated in the subsequent discounting and purchasing tasks.

Narrative Manipulation

Participants were randomly assigned to read and assume that they were experiencing either an economically negative (n=60) or neutral (n=60) scenario. The economically negative scenario described sudden job loss and transition to poverty, and the economically neutral scenario described a switch to a different department at work and receiving a small cost-of-living income adjustment, intended to control for both presentation of a hypothetical job-related scenario and for imagining of sudden job-related change (Bickel, George Wilson, et al., 2016; Mellis, Snider, & Bickel, 2018; Sze, Stein, Bickel, Paluch, & Epstein, 2017b).

Assessments

Delay Discounting. Participants completed four counterbalanced iterations of the five-trial adjusting-delay discounting task (see Koffarnus & Bickel, 2014), featuring all four pairwise combinations of immediate and delayed money and food: (1) money now-money later; (2) money now-food later; (3) food now-money later; and (4) food now-food later; i.e., both within- and cross-commodity discounting. In these tasks, food was presented as a food gift card to control for the magnitude of the commodity being discounted (Mellis, Woodford, Stein, & Bickel, 2017) without converting to units of food, which may be differently discounted based on the units presented (e.g., a single serving of one sandwich compared to a single serving of 8 chicken pieces) (Brady DeHart, 2017) Participants were instructed in each delay discounting task to choose as if their answers were real and as if the scenario they had just read was happening to them right now. When the discounting task involved a food gift card as a choice, participants were instructed that the food gift card could only be used for the food they had selected; that the gift card does not expire; that the gift card cannot be sold or given away; and that the gift card cannot be used for food that is shared or bought for others.

In each task, participants repeatedly choose between a fixed immediate amount (either $50 or a $50 food gift card) and a larger, delayed amount (either $100 or a $100 food gift card), while the delay to the larger amount adjusted trial-by-trial to estimate the delay (from 1 hour to 25 years) at which a participant was indifferent between the immediate and delayed options. For example, if at the first trial a participant selected $50 now over $100 in three weeks, the second trial would then present a choice between $50 now and $100 in one day. This point is the effective delay 50% value, or ED50, representing the delay to reinforcer receipt at which a reinforcer has lost half of its value (or the delay of indifference of $50). The discount rate parameter, k from Mazur's (1987) hyperbolic discount equation, can be estimated by the inverse of ED50 expressed in days (Koffarnus & Bickel, 2014; Yoon & Higgins, 2008) .

To assess participant valuation of the food gift cards, participants were asked to indicate the maximum amount of money they would pay for a $100 food gift card after being presented with the narrative but before starting the discounting tasks.

To determine if participants thoughtfully attended to each choice, participants were asked whether they preferred to receive $0 now or $100 now, and $0 now or $100 after a delay. Participants that selected "$0 now" failed the attention check.

Purchase Tasks. Participants completed two purchase tasks, one of individual servings of the participant's preferred fast food and one of individual bottles of water. Similar to the process used by Sze et al. (2017), participants were asked to indicate the number of individual servings they would like to purchase and use over a week without sharing, stockpiling, or giving away the commodity; without other access to that specific commodity but with other access to substitutes; and with the same income or savings as in the scenario they had just read.

Participants were then asked how many servings of their preferred fast food or bottles of water they would prefer to purchase when the commodity was free (a "price" of $0.00) and at 12 non-zero prices per serving: $0.03, $0.06, $0.12, $0.25, $0.50, $1.00, $2.00, $4.00, $8.00, $16.00, $32.00, and $64.00. Bottled water was chosen as a control commodity due to its similarity to fast food in two dimensions: (1) it is a consumable product that meets a biological need (drinking, eating), but also (2) daily consumption is not required, nor even usual, to meet that need.

Additional Assessments. Participants then completed the state Food Craving Questionnaire (Moreno, Rodríguez, Fernandez, Tamez, & Cepeda-Benito, 2008) and the restraint portion of the Three-Factor Eating Questionnaire (Bond, McDowell, & Wilkinson, 2001). Finally, participants were asked to report their estimated health impact of receiving the $100 gift card for their preferred food, as "positive", "negative", or "neither."

Data Analysis

All participants passed attention check questions, and were included in the analyses. Demographics, baseline assessments, and other food assessments were compared using Mann-Whitney U tests for continuous and chi-square tests for categorical data using R.

Delay discounting data from all participants (no delay discounting datasets were excluded, based on responses to attention check questions) were analyzed by natural-log transforming the estimated *k* parameters from each of the four discounting tasks (prior to transformation, Shapiro-Wilk's $W = 0.72$, $p = 0.02$ for the negative income shock group and $W = 0.69$, $p = 0.01$ for the neutral group; after transformation, $W = 0.85$, $p = 0.22$ for the negative income shock group and $W = 0.81$, $p = 0.12$ for the neutral group). Discount rates were then compared in a single model using a generalized estimating equation (GEE) in R using the gee package (Carey, Lumley, & Ripley, 2012). Observations of discount rates on each task were matched within subjects and compared between groups. Data were analyzed using gaussian distributions and an unstructured correlation between clusters, indicating that discount rates may be correlated within individuals but not specifying the nature of this correlation. Four planned pairwise comparisons were then performed between groups using t-tests with the Holm-Sidak correction for multiple comparisons.

Purchase data was first assessed for non-systematic purchasing, using standard diagnostic criteria (Stein, Koffarnus, Snider, Quisenberry, & Bickel, 2015). Within the food purchase task, one dataset from the negative income shock narrative group was excluded for both "bounce" (i.e., the quantity purchased was variable and inconsistent across prices--0 purchases at \$0.00 and 800 purchases at \$8.00). No datasets were excluded from the bottled water purchase analyses. Datasets in which participants did not purchase the commodity at all were included in the present analyses. Data from the remaining systematic purchase task responses were initially analyzed by fitting the exponentiated demand equation (Koffarnus, Franck, Stein, & Bickel, 2015) to purchases across all prices:

$$Q = Q_0 \times 10^{k(e^{-\alpha Q_0 C}-1)}$$

Where Q is purchasing of a given commodity at price C, Q_0 is the intensity of demand, α is demand elasticity, and k is the span of the function in $\log_{10}$ units. The k parameter was estimated to be shared between all data sets as the log of average purchasing at the highest price subtracted from the log of the average purchasing at the lowest non-zero price (\$0.03). Purchasing data collected at the \$0.00 "price" were analyzed independently as an additional measure of demand intensity and compared to Q_0 with a nonparametric correlation (for food purchasing: Shapiro-Wilk's $W = 0.25$, $p < 0.0001$ for the negative income shock group; $W = 0.19$, $p <0.0001$ for the neutral group; for bottled water purchasing, $W = 0.67$, $p < 0.0001$ for the negative income shock and $W = 0.82$, $p < 0.0001$ for the neutral group). Finally, both Q_0 and α were compared using two sum-of-squares F tests. All purchase analyses were performed in GraphPad Prism 7.

Results

Participants

No differences between groups at baseline in demographic variables, health status, nor frequency of fast food or bottled water purchasing existed. Participant characteristics are depicted in Table 4.1.

Delay Discounting

Using a single GEE, significant effects of both group and task were observed, with the negative income shock narrative group showing overall greater discounting of the future than the neutral narrative group ($\beta = 1.37$, robust $z = 5.29$, $p < 0.05$), with no group by task interaction. Compared to the money-money task, participants across both groups were more impulsive in the money now-food later ($\beta = 3.55$, robust $z = 10.32$, $p < 0.05$) and food now-food later ($\beta = 0.55$, robust $z = 2.11$, $p < 0.05$) tasks. Participants were less impulsive in the food now-money later task ($\beta = -0.47$, robust $z = -1.978$, $p < 0.05$). Pairwise comparisons between groups were then performed with four unpaired t-tests. In the money-money task ($t(118) = 4.26$, $p = 0.0001$), food-money task ($t(118) = 3.99$, $p = 0.0003$), and food-food task ($t(118 = 3.83$, $p = 0.0004$) individuals in the negative income shock group discounted more steeply than individuals in the neutral group; in the money-food task ($t(118) = 1.89$, $p = 0.061$), this test did not indicate significant differences.

To examine concordance between discount rates across tasks, nonparametric correlations were examined between task types in the full sample as well as both narrative groups. In the full sample, discount rate between all task types was significantly correlated ($p < 0.01$) with the exception of discounting between the money now-food later and food now-money later task, which were not significantly correlated ($p > 0.05$). These associations were similar within both the negative and neutral groups.

Purchasing

Purchase data (see Figure 4.2) as analyzed were well described by Equation 1. R squared for group curves (reflective of inter-subject variability in purchasing) were 0.296 for the negative and 0.342 for the neutral groups in food purchasing, respectively; and 0.375 for the negative and 0.554 for the neutral groups in bottled water purchasing. R squared for the average points of purchasing for the food purchase task were 0.994 and 0.964 for the negative and neutral groups, respectively; and for the water purchase task were 0.991 and 0.998 for negative and neutral groups. Across both purchase tasks, elasticity of demand was not significantly different between the negative and neutral narrative groups ($p > 0.05$). Furthermore, intensity of demand in purchasing of bottled water did not differ between the negative and neutral narrative groups ($F (1, 1268) = 1.101, p > 0.05$). However, intensity of demand for purchasing of food was higher in the negative income shock group than in the neutral group ($F (1, 1376) = 48.12, p < 0.001$); see Figure 4.2, top panels.

To verify concordance between purchasing at \$0.00 and fitted intensity of demand values, \$0.00 purchasing at fitted Q_0 were nonparametrically correlated. Correlations were performed separately within each commodity and within each group. In all cases, fitted and actual intensity of demand measures were closely correlated ($\rho > 0.87, p < 0.0001$ in all cases).

Furthermore, when directly comparing between groups (see Figure 4.2, bottom panels), a Mann-Whitney test indicated that the purchasing of fast food at $0.00 was marginally but not significantly lower for the neutral (Mdn = 8) than for the negative income shock (Mdn = 14) narrative group, U=1433, p=0.0518.

Additional Assessments

Scores on the restraint portion of the TFEQ were not different between groups (Negative mdn = 6.00 and IQR = [3.00, 10.00], Neutral mdn = 7, [4.75, 11.25]; $\chi^2 = 2.83$, $p > 0.05$). Furthermore, FCQ scores were the same across groups (Negative mdn = 49.50, [40.75, 58.00], Neutral mdn = 7, [4.75, 11.25]; $\chi^2 = 1.0$, $p > 0.05$). Participants between groups also did not differ in their estimation of the health impact of receiving the gift card (Negative 66.7% "negative", 20.0% "neither", Neutral 75% "negative", 21.7% "neither"; $\chi^2 = 3.93$, $p > 0.05$). However, the two groups did differ in their estimation of the maximum amount they would pay for the $100 gift card for their preferred food product, with reported valuation of this card being lower in the negative income shock narrative group (Negative mdn = $50.00 [20.00, 69.25], Neutral mdn = $67.50 [50.00, 90.00]; $\chi^2 = 12.6$, $p < 0.001$).

Discussion

The present study investigated the effect of socioeconomic stress, in the form of a simulated negative income shock manipulation, on both monetary and food reinforcement in an obese sample. Analysis showed that obese individuals demonstrate increased preference for immediate reinforcement and increased valuation for fast food after a negative income shock manipulation compared to a neutral condition. This study replicates and extends past work observing greater intensity of demand for unhealthy food in an obese sample after simulated negative income shocks (Sze et al., 2017a), and demonstrate the effect of commodity type in delay discounting after such manipulation, compared to a control manipulation. Furthermore, these results are consistent with work showing the effects of real negative income shocks on delay discounting rates (Haushofer et al., 2013); and the effects of simulated negative income shocks in other populations (Bickel, Wilson, Chen, Koffarnus, & Franck, 2016; Mellis et al., 2018). Below, we discuss: (1) the results supporting our hypothesis, that within-commodity delay discounting of both food and money would increase in the negative income shock group and the interpretation of those cross-commodity discounting results; (2) the results supporting our hypothesis that demand for fast food, but not bottled water, would increase in the negative income shock group; (3) potential limitations; and (4) implications of the present work on the utility of reinforcer pathology for clarifying the link between socioeconomic stressors and obesity.

In the within-commodity discounting tasks, we replicated past findings of steeper monetary discounting in negative income shock conditions, both simulated (Bickel, Wilson, et al., 2016) and real (Haushofer et al., 2013). These results also extend to within-commodity discounting of fast food and both cross-commodity discounting conditions of food and money. Furthermore, we replicated past findings that discounting of consumable commodities is steeper than discounting of money (Friedel, DeHart, Madden, & Odum, 2014) and that rates of discounting across tasks correlate, but cross-commodity discounting rates are less strongly correlated than within-commodity discounting rates (Bickel, Landes, et al., 2011). These replications support the use of a gift card redeemable for fast food as a food commodity in these discounting tasks. Overall, individuals in the negative income shock group demonstrated preference for the immediately-received commodity regardless of type; notably, preference was not driven specifically towards the monetary or food commodity.

Bickel and colleagues (Bickel, Landes, et al., 2011) propose a distinction between the discount function and the utility function between commodities, which may be uniquely interrogated by cross-commodity discounting. Both of these functions describe the perceived value of a commodity, with the discount function describing decay in value over time, and the utility function describing diminishing marginal returns of additional units of a commodity, and may be differentially impacted by decision-making contexts such as negative income shock. The utility function is typically concave, showing that additional benefits from acquiring more of a reinforcer decreases as the magnitude grows larger. The relative rate of discounting between all combinations of within- and cross-commodity discounting can reveal whether the rate of discounting varies between commodities, as well as whether the utility of the two commodities differs. In our study, in both groups, relative discount rates across tasks were consistent with Bickel et al.'s model showing, a steeper discounting function and a less concave utility function for food compared to money. Our results mirror those results from a prior study demonstrating less concave cocaine utility and steeper cocaine discounting, compared to money, among cocaine addicts. Furthermore, they suggest that the discount and utility functions for money and food were not differentially impacted by the negative income shock scenario. Food was not more highly valued, nor was it more steeply discounted compared to money. Instead, both reinforcers were discounted more steeply. This supports the notion that negative income shock may promote decision-making that leads to poor health by increasing *discounting*, but it does not specifically increase the utility of fast food and make the utility function of food less concave.

The purchase task revealed a selective effect of the impact of negative income shock on purchasing of a consumable commodity. We extended past research on the impact of negative income shock narratives on valuation of unhealthy food in three ways: by assessing a purchase task for food and a non-food commodity; by assessing craving for food; and by assessing the maximum amount individuals would pay for a gift card for fast food. We did not observe differences between groups in their craving for fast food, and the maximum amount individuals would pay for the fast food gift card was, predictably, lower after income depletion. However, the purchase task analyses replicated past research (Sze et al., 2017a), showing that intensity of demand for fast food was higher in the negative income shock group than the neutral group. Extending these results by including a purchase task for bottled water (a consumable commodity with similar elasticity of demand) revealed that this effect did not extend to a non-food commodity. Although these results may be due to the presence of a nearly-free alternative to bottled water (tap water), they support the reinforcer pathology framework and are consistent with other research (Stein, Mellis, & Bickel, n.d.) showing specificity of negative income shock effects on intensity of demand for commodities with negative long-term consequences.

Several limitations to the present work exist. The fact that neither group valued the gift card for food at its full-face value challenges interpretations of discount rates across tasks. Typically, consumable commodities are discounted more steeply than money (Friedel et al., 2014). However, given that small magnitude reinforcers are also discounted more steeply than large magnitude reinforcers (Odum, 2011), comment on relative discount rates between the money-money and food-food tasks is not possible. We also note that neither group valued the gift card used as a representation of the food commodity in cross-commodity and food delay discounting tasks at its face value, and the negative income shock group demonstrated significantly lower valuation of the gift card than the neutral group. Indeed, consistent with the observation of a magnitude effect on delay discounting (that lower magnitude reinforcers are discounted more steeply), discount rates were slightly higher in the food-food condition;

however, it is unclear whether participants viewed this commodity more as "food" or more as a fungible, monetary commodity. Moreover, the negative income shock group even demonstrated greater delay discounting than the neutral group in the food now - money later condition. This may represent a ceiling effect in measurement--that the present task did not allow for detection of even more impulsive rates of delay discounting. Indeed, interpretation of a choice between $50 now or a $100 food gift card later may not be appropriate as a representation of delay discounting if the true "worth" of the gift card is also $50. Furthermore, as noted above, commenting on specificity of the negative income shock effect *towards* fast food requires further research with a wider array of other consumable commodities beyond bottled water.

Finally, overall, the present study was implemented using an online survey collection platform and thus relied on self-reported responses to hypothetical scenarios, in addition to using hypothetical discounting tasks (Hendrickson et al., 2015; Robertson & Rasmussen, 2018). For example, in the present study, we used a hypothetical scenario simulating negative income shock comparing to a job transfer with a small cost of living adjustment (controlling for employment-related change but also possibly impacting discounting and purchasing behavior). Future research may extend this work to study real negative income shocks, real or potentially-real discounting and purchasing tasks, and include additional biometric data collection, including verification of height and weight measures.

The findings of increased preference for immediate reinforcement and higher demand for fast food among the scarcity group are consistent with past research demonstrating the impact of socioeconomic status and poverty on obesity. Experimental inductions that lead to viewing the self as poor increased calorie consumption (Bratanova, Loughnan, Klein, Claassen, & Wood, 2016). At an epidemiologic level, lower socioeconomic status families have been observed to consume more high energy density and low nutrient density foods (Appelhans et al., 2012), for a variety of reasons (Darmon & Drewnowski, 2008). Indeed, improving health-related decision-making alone among individuals of low SES would not close the SES-related mortality gap (Lantz et al., 1998); instead, understanding the impact of poverty may aid in improving health behavior (Drewnowski, 2012).

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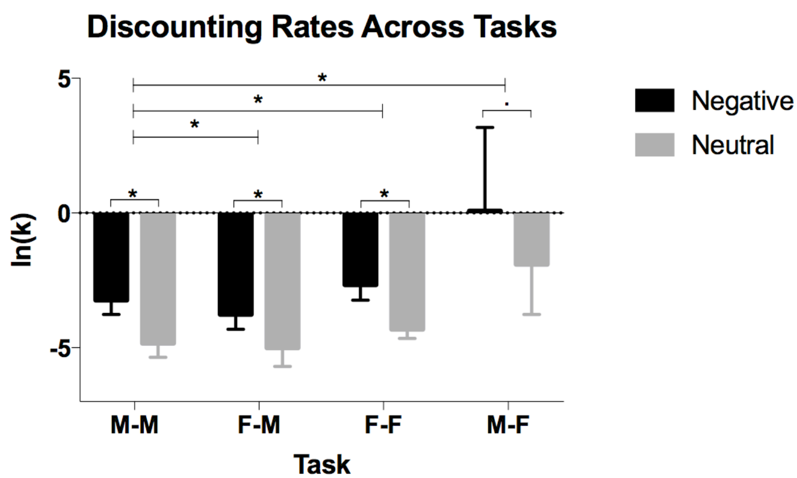
Figure 4.1: Delay discounting rates.



CAPTION: Figure 4.1 depicts natural-log-normalized discount rates in all four delay discounting tasks: money now-money later (M-M), money now-food later (M-F), food now-food later (F-F), and food now-money later (F-M). The X axis indicates task type, and the Y axis indicates ln(*k*), with higher values indicating greater or more impulsive discount rates. Bars are located at medians and error bars indicate 95% confidence intervals. * indicates significant differences at the $p < 0.05$ level; . indicates no significant difference ($p > 0.05$).

Figure 4.2: Purchasing of Food and Bottled Water

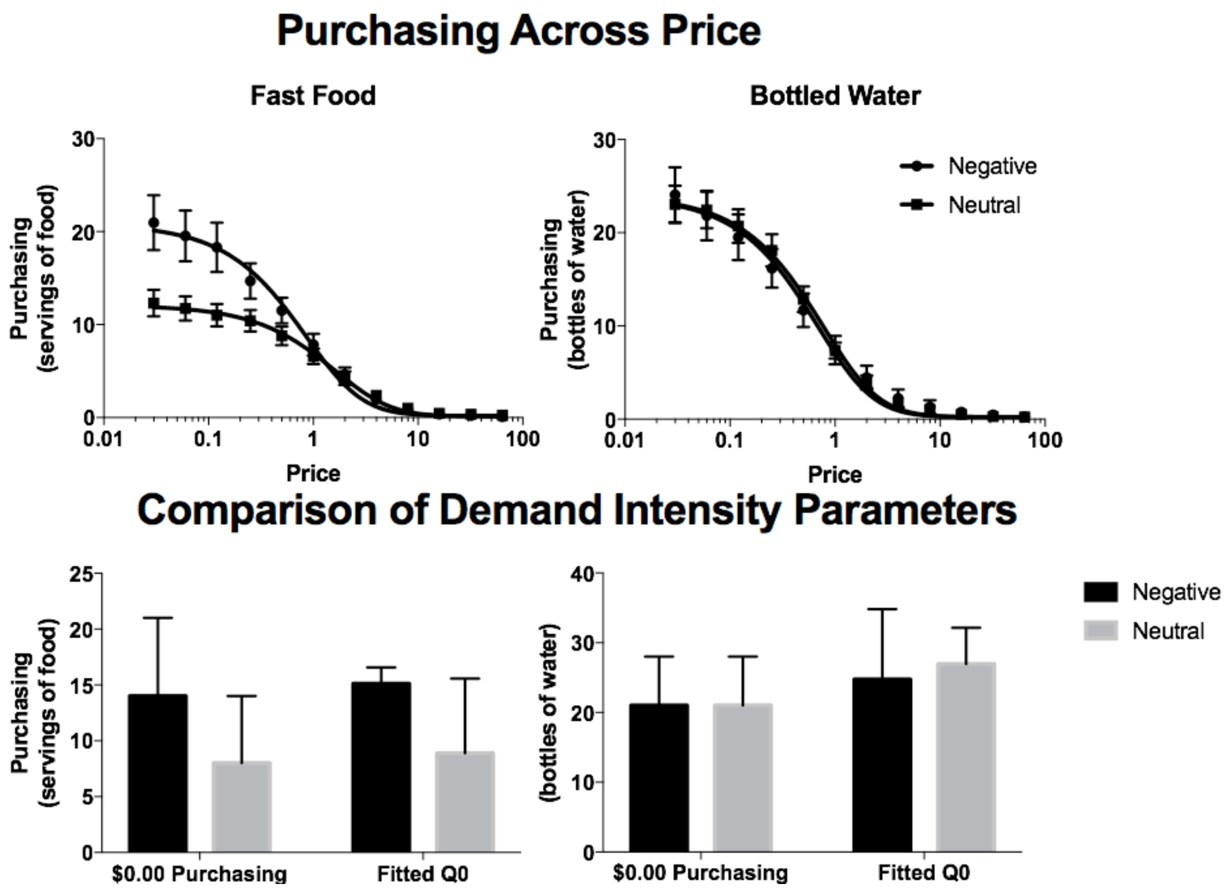


Figure 4.2 depicts purchasing of both fast food (left side) and bottled water (right side) between negative income shock and neutral narrative groups. In the top two panels, the X axis indicates price and the Y indicates quantity purchased. Points indicate mean purchasing at each price within groups, and bars indicate SEM. In the bottom two panels, the X axis indicates measure of demand intensity and the Y axis indicates the quantity purchased. Bars are located at medians and errors indicated are 95% confidence intervals.

Table 4.1. Participant characteristics at baseline

	Negative	Neutral
n	60	60
Age (mdn [IQR])	34.00 [28.00, 37.00]	34.00 [30.00, 42.00]
BMI (mdn [IQR])	35.44 [32.30, 39.93]	32.92 [31.01, 38.57]
PHQ9 (mdn [IQR])	7.00 [3.00, 11.25]	8.00 [4.75, 14.00]
Race = White count (%)	50 (83.3)	47 (78.3)
Ethnicity = Hispanic/Latino count (%)	6 (10.0)	9 (15.0)
Gender = Female count (%)	28 (46.7)	27 (45.0)
Highest Degree count (%)		
Less than HS	0 (0.0)	1 (1.7)
High School diploma/GED	29 (49.2)	19 (31.7)
Associate degree	7 (11.9)	13 (21.7)
Bachelor's degree	19 (32.2)	24 (40.0)
Graduate or similaar	4 (6.8)	3 (5.0)
Personal Income count (%)		
Less than $9,999	14 (23.3)	13 (21.7)
$10,000 through $29,999	17 (28.3)	19 (31.7)
$30,000 through $49,999	15 (25.0)	11 (18.3)
$50,000 through $69,999	9 (15.0)	12 (20.0)
$70,000 through $89,999	3 (5.0)	2 (3.3)
$90,000 through $109,999	1 (1.7)	1 (1.7)
$110,000 and more	1 (1.7)	2 (3.3)
Fast Food Purchasing count (%)		
Never	2 (3.3)	1 (1.7)
Less than monthly	16 (26.7)	18 (30.0)
Monthly	9 (15.0)	15 (25.0)
Weekly	29 (48.3)	24 (40.0)
Daily or almost daily	4 (6.7)	2 (3.3)
Bottled Water Purchasing count (%)		
Never	14 (23.3)	18 (30.0)
Less than monthly	13 (21.7)	9 (15.0)
Monthly	15 (25.0)	6 (10.0)
Weekly	13 (21.7)	22 (36.7)
Daily or almost daily	5 (8.3)	5 (8.3)
Rating Fast Food as Unhealthy count (%)	55 (91.7)	56 (93.3)
Food liking (mdn [IQR])	5.00 [4.75, 5.00]	5.00 [4.00, 5.00]

Table 4.2. Correlation of discount rates across tasks

Full Sample (n=120)				
	M-M	M-F	F-F	F-M
M-M	-			
M-F	0.251**	-		
F-F	0.727***	0.329***	-	
F-M	0.792***	0.025	0.712***	-

CAPTION: Table 2 indicates Spearman's ρ between discount rates across tasks. * indicates $p < 0.05$ ** indicates $p < 0.01$ *** indicates $p < 0.001$

MANUSCRIPT 4

Title

Testing Reinforcer Pathology with a Temporally Extended Reinforcer Measure

Abstract

Negative health behaviors such as substance use can emerge from repeated choices to consume reinforcers offering brief, intense benefits over those offering more protracted benefits. Reinforcer pathology theory states that steep delay discounting, or excessive preference for smaller, sooner over larger, later rewards, indexes the temporal window over which reinforcement is integrated. This leads to the hypothesis that constricted temporal windows would support greater valuation of brief, intense reinforcers and lesser valuation of temporally extended reinforcers. However, no method exists to quantify valuation of temporally extended reinforcement. The Temporally Extended Reinforcer Measure (TERM) was developed based on preliminary data collection in an online sample of both substance users and non-users, indicating relationships between valuation of temporally extended reinforcers, delay discounting, and substance use. The 32 items of the TERM were then presented to individuals after an experimental constriction of the temporal window or a control condition. Constriction of the temporal window engendered increased valuation of both alcohol and cigarettes (brief, intense reinforcers) in conventional purchasing tasks, and decreased valuation of temporally extended reinforcement as measured by the TERM. Thus, the temporal window hypothesis of reinforcer pathology and suggests that delay discounting may drive (and not merely correspond with) reinforcer valuation.

Introduction

Average life expectancy has declined in the United States for three consecutive years (Dyer 2018). Critically, as treatment of disease of genetic or infectious origin progresses, diseases resulting from lifestyle factors remain prevalent (N. B. Johnson et al. 2014). These lifestyle factors include dysfunctional health behaviors linked to declining life expectancy, including overweight/obesity (Preston, Vierboom, and Stokes 2018), opiate use (Dowell et al. 2017), and other substance use disorders (Imtiaz, Probst, and Rehm 2018). Each of these behaviors extends from a similar selection of brief, intense reinforcement despite long-term costs, including consumption of high-calorie density foods and substances of abuse.

These decisions, such as choices between the immediate gratification of a drink and the delayed health benefits of abstinence, can be modeled by behavioral economic methods. Preference for immediate reinforcement is assessed through delay discounting, indicating a preference between smaller, sooner and larger, later values. Steep delay discounting rates indicate that the value of a reinforcer declines rapidly as a function of time, and are common across multiple disease states (MacKillop et al. 2011; Amlung, Petker, et al. 2016; Amlung, Vedelago, et al. 2016; Bickel and Mueller 2009). Furthermore, excessive preference for specific unhealthy reinforcers (high demand, as of cigarettes, fast food, or alcohol) increases the risk for a particular dysfunctional health behavior (Kiselica, Webber, and Bornovalova 2016). These components have been recently united under a theoretical model of disease-related decision-making termed reinforcer pathology (Bickel et al. 2014). Under this model, individuals with steep delay discounting rates and high subjective value of unhealthy reinforcers are at the greatest risk for disease burden.

This model has been applied to findings from addiction (Bickel et al. 2017), obesity (A. Carr et al., n.d.), ultraviolet indoor tanning (Reed 2015), and others. For example, delay discounting rate and degree of food reinforcement predict normalized BMI in discordant sibling pairs (Feda et al. 2015). Furthermore, a recent meta-analysis by Stojek and MacKillop (2017) observed that obese individuals with higher delay discount rates tended to also express higher demand for food, consistent with the temporal window model of reinforcer valuation. Indeed, delay discounting itself may indicate the length of an individual's temporal window, with steep discount rates indicating a constricted temporal perspective and increasing preference for brief, intense reinforcement.

If the temporal window, indexed by delay discounting rate, predicts subjective valuation of brief, intense reinforcers, it may also predict subjective valuation of *other* reinforcers with distinct temporal patterns of value. In *this* model, delay discounting and demand may both reflect an individual's temporal window of reinforcer valuation, the time period over which the relative costs and benefits of particular reinforcers are assessed. A short temporal window (indicated by steep discounting rates) will drive both preferences for immediate reinforcement in general and preference for particular reinforcers, based on the periods over which they deliver their greatest reinforcing value. Many reinforcers associated with negative health outcomes (e.g., alcohol, cigarettes, and fast food) deliver brief, intense, and reliable reinforcement, with their greatest benefits, received nearly-immediately and costs accruing over time. In contrast, many healthy and prosocial reinforcers (e.g., exercise, employment) deliver some up-front costs with long-term, low-intensity benefits. These *temporally extended reinforcers* will be more highly valued when they are integrated over an expanded temporal window. In contrast, *brief, intense reinforcers* will be less valued when integrated over an expanded temporal window because they represent a lower portion of the total reinforcing value available, or even have negative value due to the accrual of deleterious health effects. Constriction of the temporal window may then reverse these valuations, supporting dysfunctional health behavior.

Typical behavioral economic methods, such as a purchasing task, can be used to measure the valuation of reinforcers offering brief, intense rewards; and to measure valuation of reinforcers received after a delay (as with common delay discounting tasks). Multiple self-report measures have been developed to indicate similar constructs, such as time perspective (Zimbardo 1990) or ability to delay gratification (Hoerger, Quirk, and Weed 2011), but these measures do not directly assess the subjective value of reinforcers offering temporally extended benefits. Additionally, multiple conventional psychometric measurements have been constructed to assess anhedonia (Snaith et al. 1995), or valuation of all potentially-enjoyable reinforcers. To date, however, only one effort has been made to quantify valuation of only long-term, low-intensity reinforcers (Mellis and Bickel 2017). These preliminary results demonstrated that a manipulation that increases delay discounting also decreases self-reported, 7-point Likert valuation of a set of ten temporally extended reinforcers.

The Temporally Extended Reinforcer Measure (the TERM) was developed to assess the subjective value of temporally extended reinforcers and test the hypotheses of reinforcer pathology. This measure took the form Likert scale ratings of the value of various temporally extended reinforcers across multiple domains. Initially, participants with varying degrees of reinforcer pathology completed a preliminary TERM, and this data was used for initial structural analyses, to select the final TERM items, and to demonstrate initial convergent validity. The TERM was then experimentally tested by presentation to participants after either a manipulation constricting the temporal window (a narrative of hurricane-associated loss) or a control manipulation.

Materials and Methods

Participants

Development and validation of a temporally extended reinforcer measure (TERM) proceeded with the collection of data from an online sample. Participants were recruited from Amazon Mechanical Turk, and the data collection instrument was completed as a Human Intelligence Task, or HIT. The instrument was advertised as taking under one hour to complete, and participants were compensated a $3 base and $3 bonus, contingent upon passing attention check questions. Inclusion criteria required that participants have a HIT approval rating greater than 90%, indicating that more than 90% of their previous HITs had been accepted by past posters. Exclusion criteria were that participants must not be currently or previously employed by Virginia Tech. A reCAPTCHA v2 system was also used to ensure human responses. Recruitment oversampled from substance-using groups, requiring that 200 participants also endorse regular heavy drinking (consuming at least 6 drinks in a drinking episode at least once a week) and/or smoking (consuming at least 10 cigarettes per day every day for the past month). Responses were received from 391 participants. Of these, 370 were complete responses and were used in later analyses. Attention check failures were relatively common (21% of responses failed at least one attention check or 81 responses). Complete responses without any attention check failures (n=294) were used in subsequent instrument development analysis.

For experimental manipulations of the TERM, participants were again recruited from Amazon Mechanical Turk. Participants (N=100) were compensated $1.50 base and $2 bonus for an assessment requiring approximately 30 minutes. Inclusion criteria were identical to the instrument development HIT, with the addition that participants reported both high-risk smoking (>10 cigarettes/day) and high-risk drinking (consumption of at least 6 drinks per day, at least weekly).

Scale development of the TERM

Each TERM item took the form of a Likert rating of how enjoyable or valuable participants found a particular behavior. Prior to item writing, a test blueprint and internal model were developed to promote validity. Items were written to cover a broad range of possible temporally extended reinforcers in four categories informed by previous work identifying correlates of delay discounting (Reimers et al. 2009) and delay of gratification (Ward et al. 2013): health, self-improvement, financial, and social behaviors. An excess of items was written (79 items) and subjected to review by two subject matter experts prior to data collection. To control for prosociality of these behaviors, a subset of five items were also included to represent temporally extended antisocial behavior (e.g., "planning a trick" or "plotting revenge"). Items indicated as best corresponding to the construct of "temporally extended reinforcers" were then used in data collection (a total of 52 items), and presented to participants in randomized order, and two attention check questions were used for each set of Likert responses ("choose one for this question" and "choose three for this question").

Analyses proceeded on complete responses without any attention check failures (n=294). A factor analysis was performed to achieve both data reduction (shortening the scale by selecting the candidate items best capturing meaningful variance) and to identify possibly meaningful factors within the TERM, indicating dimensionality within the construct.

First, the inter-item correlation matrix was visually examined (Supplementary Figure 1). This visual analysis indicated that items added to represent antisocial but temporally extended reinforcers (e.g., “planning a trick”) were anti-correlated with the remaining items. These items were dropped from remaining factor analyses. Sample size adequacy for factoring the remaining 47 items was then assessed using the KMO index, a measure of the proportion of variance that may be common across items, finding the KMO MSA to be 0.95, or “marvelous” (Weiner 2012). Bartlett’s test of sphericity supported factoring adequacy, indicated a X^2 value of 7073.8 (df=1081, $p < 0.0001$), supporting factoring adequacy. Three factors were chosen after parallel analysis and visual examination of the scree plot. Cronbach’s alpha, an indicator of overall item-total consistency (also called reliability) was extremely high (0.96), suggesting redundancy between items and further supporting item selection.

An exploratory factor analysis using oblique rotation was performed using the *fa* function in the *psych* package (Revelle 2017). Although orthogonal factors are often preferred when seeking uncorrelated subscales of items, the TERM includes possible subscales that would be hypothesized to be intercorrelated if each factor also represented the same underlying construct (namely, temporally extended reinforcer valuation). An oblique solution was found, accounting for 42% of the variance observed in the total item set (adequate for initial scale development). The RMSA was 0.04 (df corrected 0.04), and the Tucker-Lewis index of factoring reliability was 0.894. The RMSEA index was 0.048, with 10% confidence intervals 0.04-0.049. The three subscales were found to be highly intercorrelated: F1-F3, 0.78, F1-F2, 0.60, and F2-F3, 0.69.

Items to be retained were identified by defining a cut point of 0.4 for factor loadings. This cut point is at the upper range of the 0.3-0.4 recommendation for factor loading cut points to reduce measure length while still capturing variance. Items that loaded on to a single factor with loading greater than 0.4 were retained, regardless of cross-loadings. This retained 32 items. Factor 1 contained items largely describing activities involving health and self-improvement and was dubbed the “self-improvement” factor. Factor 2 contained largely financial items, and was dubbed the “financial” factor. Factor 3, containing largely social items, was dubbed the “social” factor. Factor loadings are depicted in Table 5.4.

Factor-based scores, rather than factor scores, were calculated by summing scores for the 32 retained items across all factors. Factor-based scores were used due to the ultimate goal of developing a scale which may be scored as a simple sum of items. This factor-based score was then examined against demographic and psychological variables to examine bias and convergent validity using nonparametric correlations.

Convergent Validity Assessments

All participants completed demographic questions, as well as questions indicating the severity of substance use problems. Severity was assessed using the Alcohol Use Disorder Identification Test (AUDIT); Fagerstrom Test for Cigarette Dependence (FTCD); and Drug Use Disorder Identification Test (DUDIT). As an additional measure of the temporal window, distinct from delay discounting, participants also completed the Consideration of Future Consequences Scale (CFCS).

The delay discounting task used was a titrating, adjusting-amount procedure presenting choices between a fixed amount ($1000) at each of 7 delays (1 day, 1 week, 1 month, 3 months, 1 year, 5 years, and 25 years into the future), and a varying ($7.80-$992.20) immediate amount (Du, Green, and Myerson 2002). From choices between these immediate and delayed options, a hyperbolic decay function was fit to individual indifference point data (Mazur 1987), and the log-normalized hyperbolic decay parameter (*k*) was used for group analyses. Data from responses violating previously published criteria for nonsystematic discounting were excluded (M. W. Johnson and Bickel 2008).

Experimental Manipulations

In the temporal window constriction manipulation, participants were randomly assigned to read either a scenario of hardship or a control scenario. The hurricane scenario described a sudden hurricane and subsequent hurricane-associated loss. The control scenario described a minor storm dinging your car, and an insurance company covering the repair.

Experimental Outcomes

After random assignment, participants completed a delay discounting assessment, two purchasing tasks, and the 32-item TERM constructed in study 1.

Delay discounting. Procedures for this adjusting-amount discounting task were identical to the ones used in the initial assessment of delay discounting except that the magnitude of the reinforcer was lower ($100 instead of $1000) and the delays used oversampled from the further future (1 week, 3 months, 1 year, 2 years, 4 years, 8 years, and 16 years). These modifications were made to assess discounting at a steeper baseline level, by both decreasing magnitude and increasing delay, which has been shown to increase the sensitivity of discounting to experimental manipulations (Athamneh et al., in preparation). Participants were instructed to complete this assessment as if their assigned scenario had just really happened to them. A hyperbolic decay function was fit to individual indifference point data obtained from this task, and the log-normalized hyperbolic decay parameter (k) was used for group analyses.

Alcohol and cigarette purchase tasks. Participants completed an alcohol purchase task (Murphy and MacKillop 2006), responding with the number of drinks they wished to purchase over 20 prices ($0.00-$20.00 per drink) during a four-hour drinking period if these drinks were the only ones available and could not be sold or shared. In the cigarette purchase task (MacKillop et al. 2008), participants reported the number of cigarettes they wished to purchase over 12 prices ($0.00-$64.00 per cigarette) if the cigarettes were the only ones available to be used within a single day and not sold or shared. Participants were instructed to respond as if their scenario had really happened to them. Data from participants who violated published criteria for non-systematic purchase data were excluded from analysis (Stein et al. 2015). Demand curves were generated by fitting the individual units purchased to an exponentiated demand equation (Koffarnus et al. 2015), with two free parameters representing demand intensity, or the quantity purchased at the lowest price (Q_0) and demand elasticity, or sensitivity of purchasing to increases in price (α).

Results

Preliminary Convergent Validity Assessments

Participants. Participant characteristics of complete cases (N=370) are in Table 1.

Differences in TERM scores by substance use. Overall, TERM scores were significantly different between substance use groups, as defined by FTCD and AUDIT scores ($F_3 = 5.89$, $p = 0.0006$). Post-hoc comparisons using estimated marginal means and Tukey's HSD adjustment indicated a significant difference between polysubstance users low-risk users ($t(366) = 3.69$, $p = 0.002$) and polysubstance users against smokers ($t(366) = 3.16$, $p = 0.009$), but no other significant group differences. TERM scores were also significantly negatively correlated with FTCD scores (Spearman's $\rho = -0.14$, $p = 0.015$), AUDIT scores (Spearman's $\rho = -0.23$, $p < 0.0001$), and DUDIT scores (calculated only among participants who reported some illegal drug use; Spearman's $\rho = -0.35$, $p < 0.0001$) after Bonferroni's correction for multiple comparisons. These analyses were repeated with the three-factor subscores of the TERM, and no meaningful differences were observed in relationships with substance use group or substance use severity. Subsequent analyses proceeded with whole TERM scores, rather than factor-based scores.

Convergent validity with other assessments. Weak nonparametric associations were found between summed scores on the 32 retained items of the TERM and natural-log-normalized delay discounting rate (Spearman's $\rho = -0.12$, $p = 0.02$), and between the TERM and scores on the Consideration of Future Consequences Scale (CFCS; Spearman's $\rho = -0.22$, $p < 0.0001$). Overall, these associations did not differ by substance use status. See Figure 2.

Experimental manipulation

Participants. The 32 selected items of the TERM were presented to participants (N=100) after random assignment to either a temporal window constriction condition ("Hurricane") or a control condition ("Neutral"). No significant differences in demographics were observed between groups; see Table 2.

Group comparisons. TERM scores were significantly lower in the Hurricane (mn = 115.3, SD = 21.9) than the Neutral (mn = 128.7, SD = 15.2) condition (unpaired T test with Welch's correction; $t83.12 = 3.37$, $p = 0.0012$). Log-normalized discounting rates were higher in the Hurricane (mn = -2.27, SD = 0.33) than the Neutral (mn = -5.41, SD = 0.33) condition (unpaired T test; $t84 = 6.92$, $p < 0.0001$). Best-fit values for alcohol intensity of demand were higher in the Hurricane (Best-fit Q0 = 19.53, 95% CI = 16.39-22.89) than the Neutral (Best-fit Q0 = 11.39, 95% CI = 10.45-12.35) condition (overall $F = 15.2$ (2, 2016), $p < 0.0001$); however, elasticity of demand did not differ. Best-fit values for cigarette intensity of demand were higher in the Hurricane (Best-fit Q0 = 19.53, 95% CI = 16.39-22.89) than the Neutral (Best-fit Q0 = 86.17, 95% CI = 68.12-106.3) condition (overall $F = 21.6$ (2, 1295), $p < 0.001$); again, elasticity of demand did not differ. See Figure 3.

Discussion

Under reinforcer pathology theory, the temporal window (indicated by delay discounting rate) undergirds valuation of both brief, intense and temporally extended reinforcers. The TERM was developed to quantify valuation of temporally extended reinforcers and test this prediction of reinforcer pathology. Preliminary analyses led to the development of a 32-item scale modestly correlated with other measures of the temporal window (delay discounting rate and the Consideration of Future Consequences Scale). Experimental manipulations constricting the temporal window also reduced valuation of these 32 items of the TERM, as well as increasing the intensity of demand for both alcohol and cigarettes among drinking smokers. Taken together, these results support the use of the TERM in future research investigating the role of the temporal window in reinforcer valuation. Validation for this use will be discussed under Messick's validity framework (Messick 1995), which identifies six types of validity evidence: content evidence, substantive evidence, structural evidence, generalizability evidence, and external evidence. Finally, the implications of the present work for reinforcer pathology theory will be discussed.

The first two of these, content and substantive validity, will be discussed together. Content validity, in the Messick framework, includes evidence of content relevance, representativeness, and technical quality in item writing (see also Lennon 1956). Substantive validity refers to the empirical evidence that the theoretical processes are actually engaged by respondents when they answer items. To address content and substantive validity of the TERM, a construct map, and internal model was developed, items were written to correspond to a broad range of temporally extended behaviors, and items were subjected to subject matter expert review before data collection.

Structural validity refers to the degree to which relationships between items conform to the theoretical view of the construct. Despite past research identifying multidimensionality within related constructs (including impulsivity, delay of gratification, and valuation), no empirical evidence supporting specific dimensions within temporally extended reinforcer valuation has been collected. This supports the use of exploratory, rather than confirmatory, factor analysis and the need for replication of the TERM factor structure in an independent sample in future research. However, given the high intercorrelation among factors and failure to replicate a three-factor structure after preliminary data collection, a unidimensional description of the TERM is likely more appropriate. Future data collection with a larger sample, and without experimental manipulation, is required to determine the structure of the TERM, although a reduced factor or even unidimensional structure is plausible. If, however, these future analyses support a unidimensional TERM, Rasch modeling (Bond and Fox 2013), rather than classical testing theory, may be used for further refinement of the TERM. This may be especially promising for reducing the length of the TERM, as the distribution of TERM scores is non-normal and no participants received the minimum score, suggesting overrepresentation of "easy" items that may be cut from the instrument.

Generalizability, or the applicability of scores across a broad range of target populations, was supported by recruiting from both control (e.g., healthy adults) and specific reference groups (e.g., substance users). Although preliminary data collection in the current study was performed in an inclusive population, the experimental manipulation of the TERM was performed only among dual-users of alcohol and cigarettes. Furthermore, although constriction of the temporal window reduced TERM scores, expansion of the temporal window may not--which may indicate differences in the functioning of the instrument or limitations on the ability to experimentally manipulate the underlying construct. Future research will be needed to define the contours of this performance.

External validity evidence refers to how the construct of temporally extended reinforcer valuation is expected to relate to other constructs and variables, similar to convergent and discriminant validity (Baumgarten and Wetzel 2017). In the present sample, TERM scores related as hypothesized with expected reinforcer pathology indicators. TERM scores were lower among individuals with higher alcohol and cigarette substance use severity. Continuous associations between TERM score and both delay discounting and the CFCS indicated higher TERM scores with a longer temporal window, further supporting the use of this instrument.

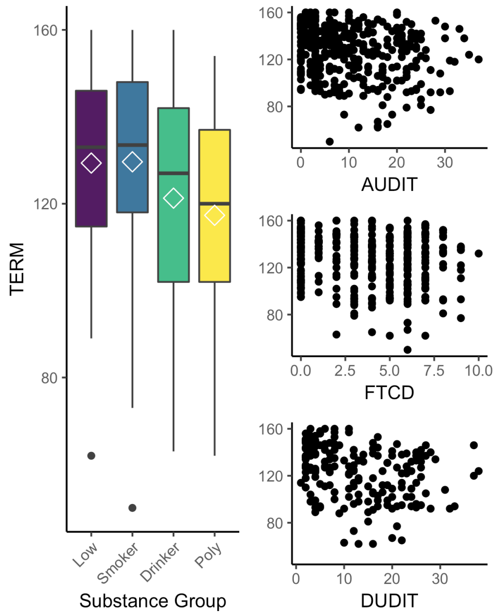
Critically, in order to test the hypotheses of reinforcer pathology, this instrument must be useful in the design of experiments manipulating the temporal window. In the present study, constriction of the temporal window was shown to reduce TERM scores. However, this constriction was performed with only one experimental manipulation (a hypothetical scenario describing a natural disaster). Multiple experimental paradigms have been shown to alter the temporal window (Rung and Madden 2018), and this pattern must be replicated with alternative manipulations to support the reinforcer pathology model of temporally extended reinforcer valuation. The TERM may be a promising tool to test these hypotheses in future research, but it comes with limitations common to multiple self-report and survey-based measures (e.g., demand characteristics (McCambridge, de Bruin, and Witton 2012)). Alternative assessment paradigms, such as time-use surveys permitting estimation of actual engagement with activities offering temporally extended reinforcement, or tasks assessing preference between games that offer immediate and lower-magnitude rewards versus games offering longer-term accumulation of rewards, may avoid some of these problems and offer alternative methods to measure temporally extended reinforcer valuation.

Overall, the present work provides a meaningful contribution to the theory of reinforcer pathology. If delay discounting indexes the temporal window and indicates the time over which the benefits of reinforcers are integrated, constriction of this temporal window would be hypothesized to predict greater valuation of brief, intense reinforcers and reduced valuation of temporally extended reinforcers. The present results follow precisely this pattern. This is the first time constriction of the temporal window has been shown specifically to reduce valuation of temporally extended reinforcers.

Table 5.1. Participant characteristics for TERM development.

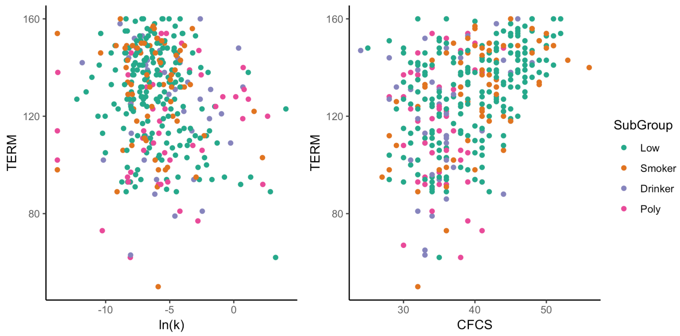
n	370
AUDIT (mean (sd))	10.04 (8.51)
FTCD (mean (sd))	3.83 (2.69)
DUDIT (mean (sd))	6.67 (9.08)
Age (mean (sd))	34.38 (9.24)
Gender = Male (%)	248 (67)
Education (%)	
Some High School (10th or 11th grade)	5 (1.4)
High School	46 (12.4)
Some College or Vocational Training	64 (17.3)
Completed a 2-year college degree	52 (14.1)
Completed a 4-year college degree	163 (44.1)
Completed Graduate Degree	40 (10.8)
Personal Income (%)	
Less than $9,999	30 (8.1)
$10,000 through $29,999	107 (28.9)
$30,000 through $49,999	108 (29.2)
$50,000 through $69,999	66 (17.8)
$70,000 through $89,999	38 (10.3)
$90,000+	19 (5.2)
Refuse to Answer	2 (0.5)
Race (%)	
White	288 (77.8)
American Indian/Alaskan Native	4 (1.1)
Asian	37 (10)
Black or African American	33 (8.9)
Multiple	7 (1.9)
Native Hawaiian/Pacific Islander	1 (0.3)
ln*k* (mean (sd))	-5.68 (3.01)

Figure 5.1. TERM scores and substance use.



The left panel depicts TERM scores over substance use group, as defined by FTCD and AUDIT scores. The right panel depicts TERM scores over AUDIT, FTCD, and DUDIT scores (from top to bottom).

Figure 5.2. Continuous associations with TERM scores.

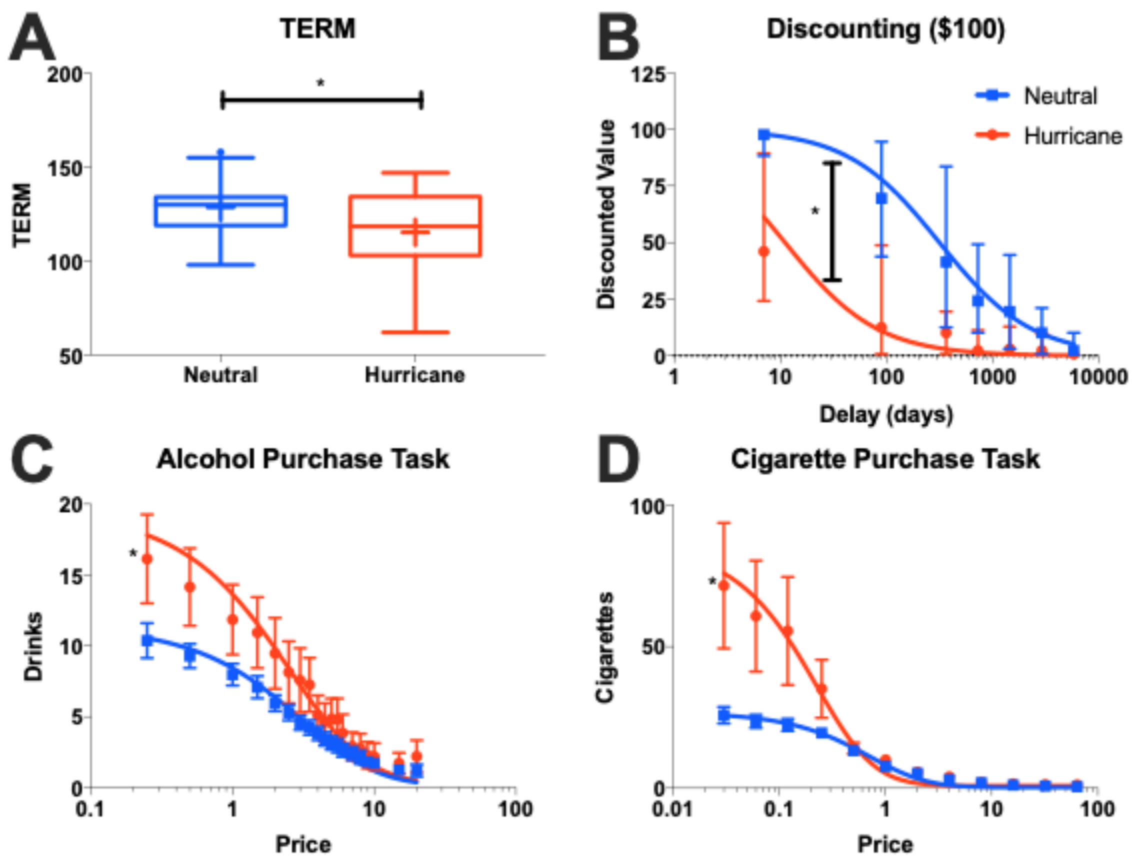


The left panel depicts individual TERM scores over log-normalized discounting rates. The right panel depicts individual TERM scores over CFCS scores. Color indicates substance-using group, where "Low" indicates only low-risk use of cigarettes (based on FTCD scores) and alcohol (based on AUDIT scores), smoker indicates high-risk use of cigarettes but low-risk use of alcohol, drinker indicates high-risk use of alcohol but low-risk use of cigarettes and poly indicates use of both alcohol and cigarettes.

Table 5.2. Participant characteristics for experimental manipulation.

	Hurricane	Mild Storm	p test
n	56	44	
AUDIT (mean (sd))	18.04 (7.73)	16.27 (8.09)	0.27
Cigs/Day (mean (sd))	24.32 (22.88)	17.64 (9.49)	0.072
Age (mean (sd))	35.27 (11.28)	35.89 (11.04)	0.784
Gender = Male (%)	36 (64.3)	29 (65.9)	1
Education (%)			0.858
High School	7 (12.5)	5 (11.4)	
Some College or Vocational Training	16 (28.6)	12 (27.3)	
Completed a 2-year college degree	3 (5.4)	5 (11.4)	
Completed a 4-year college degree	23 (41.1)	16 (36.4)	
Completed Graduate Degree	7 (12.5)	6 (13.6)	
Personal Income (%)			0.79
Less than $9,999	4 (7.1)	4 (9.1)	
$10,000 through $29,999	11 (19.6)	9 (20.5)	
$30,000 through $49,999	16 (28.6)	12 (27.3)	
$50,000 through $69,999	14 (25.0)	12 (27.3)	
$70,000 through $89,999	3 (5.4)	4 (9.1)	
$90,000 +	8 (14.3)	3 (6.9)	
Race (%)			0.745
American Indian/Alaskan Native	1 (1.8)	0 (0.0)	
Asian	3 (5.4)	1 (2.3)	
Black or African American	5 (8.9)	4 (9.1)	
Multi	2 (3.6)	3 (6.8)	
Native Hawaiian/Pacific Islander	1 (1.8)	0 (0.0)	
White	44 (78.6)	36 (81.8)	

Figure 5.3. Group differences between Hurricane and Neutral conditions.



Panel A depicts Tukey boxplots of TERM scores over the group. * indicates significant group differences in summed TERM scores, $p < 0.001$. Panel B depicts medians and interquartile ranges of the discounted value of $100 at group indifference points, as well as fit hyperbolic discounting curves, over increasing delays. * indicates significant group differences in log-normalized hyperbolic discounting rates between groups, $p < 0.001$. Panel C depicts the mean and SEM of the number of alcoholic drinks purchased over increasing (log 10) price, as well as fit exponentiated demand functions. * indicates significant group differences in intensity of alcohol demand, Q0, between groups, $p < 0.0001$. Panel D depicts the mean and SEM of the number of individual cigarettes purchased over increasing (log 10) price, as well as fit exponentiated demand functions. * indicates significant group differences in intensity of cigarette demand, Q0, between groups, $p < 0.0001$.

Table 5.3. Initially written TERM item set

No.	Item
1	Eating a healthy diet
2	Wearing a seat belt
3	Flossing
4	Going to the doctor for a check
5	Using protection during sex (condoms, birth control, etc.)
6	Exercising
7	Getting up early in the morning
8	Improving my health (having my teeth fixed, getting new glasses, changing my diet, etc.)
9	Doing physically demanding chores or work
10	Avoiding snacks and eating only at mealtime
11	Abstaining from cigarettes
12	Abstaining from alcohol
13	Abstaining from drugs
14	Avoiding fast food
15	Cooking meals at home instead of eating out
16	Getting tested for sexually transmitted diseases
17	Plan my food shopping in advance
18	Tracking my calories
19	Taking my medications as prescribed
20	Getting my cholesterol tested
21	Stretching
22	Having a consistent diet and exercise plan
23	Using sunscreen
24	Texting while driving
25	Taking turns
26	Volunteering
27	Maintaining a long
28	Maintaining a personal relationship
29	Telling the truth
30	Being considerate of other people
31	Teaching someone
32	Spending time with family
33	Spending time with children
34	Working with others as a team
35	Working on community service projects
36	Protesting social, political, or environmental conditions
37	Donating money to charity
38	Going to community events (church, meetings, etc.)
39	Counseling someone
40	Defending or protecting people; stopping fraud or abuse
41	Doing favors for people
42	Being generous with people
43	Saving money for emergencies
44	Saving money for retirement
45	Investing money
46	Paying for life insurance
47	Paying for health insurance
48	Paying my credit card off in full
49	Not taking out loans
50	Paying my bills on time
51	Spending less than I make every month
52	Living frugally

53	Making more than my minimum loan payments
54	Planning for my financial future
55	Repairing instead of replacing things
56	Working on my finances
57	Checking my credit score
58	Making a budget
59	Sticking to a budget
60	Tracking my expenses
61	Saving money not for retirement
62	Doing a job well
63	Studying for a test
64	Finishing a project or task
65	Starting a project or task
66	Going to work
67	Being employed
68	Doing hard work
69	Learning a new skill
70	Working hard to accomplish a task
71	Building something
72	Solving a problem
73	Practicing to get better at something (a sport, instrument, language, etc.)
74	Budgeting my time
75	Planning or organizing something
76	Seeing something through to the end
77	Crafting or making things
78	Learning something difficult
79	Getting revenge
80	Scamming someone
81	Planning a trick
82	Planning how to accomplish something or pull something off
83	Putting up with something to get your way later
84	*Taking drugs*
85	*Smoking cigarettes*
86	*Drinking alcohol*
86	*Eating fast food*
87	*Having sex*

Figure 5.4. Inter-item correlation matrix of the TERM

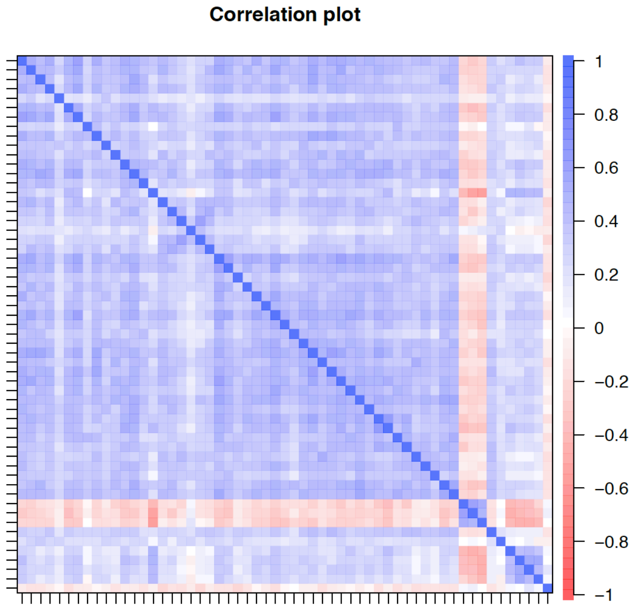


Table 5.4. Factor Loadings

Item	F1	F2	F3
Texting while driving	0.82		-0.27
Being employed	0.81		
Taking my medications as prescribed	0.72		
Exercising	0.60		
Going to work	0.59		
Getting screened for heart disease, cancer, etc.	0.57		0.20
Improving my health (having my teeth fixed, getting new glasses, changing my diet, etc.)	0.56		
Wearing a seat belt	0.54		
Paying my bills on time	0.49	0.36	
Saving money for emergencies	0.46	0.41	
Saving money for retirement	0.46		
Studying for a test	0.44		
Going to the doctor for a check-up	0.43		0.21
Making a budget	0.42	0.36	
Preparing meals at home instead of eating out		0.70	
Making more than my minimum loan payments		0.69	
Living frugally		0.69	
Repairing instead of replacing things		0.66	
Sticking to a budget	0.27	0.54	
Planning my food shopping in advance		0.51	0.22
Planning for my financial future	0.30	0.50	
Spending less than I make every month	0.32	0.49	-0.23
Not taking out loans	0.24	0.48	
Working on my finances	0.24	0.43	
Building or making something		0.42	0.42
Seeing something through to the end	0.21	0.40	
Counseling someone		-0.22	0.83
Teaching someone			0.79
Going to community events (local meetings, etc.)	-0.24		0.65
Doing favors for people			0.59
Being considerate of other people	0.30		0.53
Planning or organizing something			0.42
*Making sacrifices to maintain a long-term relationship**		*0.29*	*0.32*
*Doing physically demanding chores or work**		*0.33*	*0.29*
*Practicing to get better at something (a sport, instrument, language, etc.)**		*0.35*	*0.27*
*Working hard to accomplish a task**	*0.33*		*0.22*
*Doing a job "the right way"**	*0.22*	*0.36*	*0.21*
*Learning something difficult**		*0.38*	
*Wearing sunscreen**	*0.22*		
*Investing money**		*0.31*	
*Doing hard work**	*0.21*	*0.27*	
*Paying for insurance**	*0.37*		
*Using protection during sex (condoms, birth control, etc.)**	*0.27*		
*Flossing**	*0.22*	*0.38*	
*Getting tested for sexually transmitted diseases**	*0.28*	*0.23*	
*Eating a healthy diet**	*0.39*	*0.37*	
*Paying my credit card off in full**	*0.38*	*0.37*	

* indicates that factor loadings were less than 0.4 for each factor, and so the item was dropped

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CONCLUSIONS

Summary

The temporal window model of reinforcer pathology theory seeks to frame health behavior, both positive and negative, as emergent from the time period over which reinforcer value is integrated. In this model, "unhealthy" reinforcers, such as fast food, alcohol, and cigarettes, are identified as sharing a common temporal pattern: offering brief, intense, and reliable reinforcement, with greatest negative outcomes occurring only after a delay. Many prosocial reinforcers, by contrast, share a distinct pattern: offering temporally extended, low-intensity, and variable reinforcement, with the greatest positive outcomes accruing over time. Each study reported here makes a distinct contribution to reinforcer pathology theory.

The first study explored whether delay discounting rates differentiate substance-using and non-substance using populations in a magnitude-dependent manner, testing the hypothesis that differences between groups may be greater at higher magnitudes. This study replicated extensive past findings of substantial differences in rates of delay discounting between populations and, as hypothesized, the effect size of this difference increased with the magnitude of the discounted reinforcer. This study provides insight for future research seeking to identify possible behavioral markers for addiction and other forms of reinforcer pathology by noting that delay discounting tasks at higher magnitudes (e.g., $100 or $1000) may be more sensitive to differences between using and non-using groups. Moreover, identification of the assays most closely corresponding to actual health behavior is critical to the employment of these markers in an experimental medicine approach (Bernard 1957). Based on this and past research investigating delay discounting as a behavioral marker of the addiction process (Bickel et al. 2014).

The second study examined the possibility that delay discounting may be manipulated by experimental paradigms involving either the presentation or generation of scenarios, testing the hypothesis that participant-generated scenarios would have the greatest impact on delay discounting rates. This study replicated past findings that narratives describing job loss increased delay discounting rates, and did not confirm the hypothesis that participant-generated narratives have the greatest impact on discounting. Overall, no impact of the act of narrative generation on discounting rates was detected. Given that the use of narratives to change delay discounting rates may have experimental and even translational potential (Bickel et al. 2017), the finding that narrative content, not the source, drives differences in discounting may inform future experimental designs. These findings may also prove relevant to the impact of consuming narratives of hardship outside of experimental contexts. Based on this and other literature observing that scarcity changes delay discounting (Bickel et al. 2016), the subsequent study investigated whether these effects extended to valuation of particular, unhealthy reinforcers.

The third study tested a fundamental hypothesis of reinforcer pathology, that constriction of the temporal window increases valuation of brief, intense reinforcers. Indeed, narratives describing job loss increased delay discounting rates and intensity of demand for fast food among obese individuals, compared to control narratives. Increased intensity of demand was not observed for a control commodity, bottled water. This both supports the temporal window model and aligns with existing research that obesity is more common among individuals with low socioeconomic status. Critically, however, the third study did not examine the valuation of temporally extended reinforcers.

The fourth study extended from this body of results to specifically test the hypothesis that constriction of the temporal window simultaneously increases valuation of brief, intense reinforcers and decreases valuation of temporally extended reinforcers. In order to test this hypothesis, a Temporally Extended Reinforcer Measure (TERM) was developed. Consistent with the temporal window model, narratives describing hurricane-associated loss increased delay discounting rates, increased intensity of demand for cigarettes and alcohol, and decreased TERM scores among individuals with comorbid cigarette smoking and high-risk drinking, compared to a control narrative. This orderly pattern of results suggests that temporal window constriction, especially as evoked by stressful scenarios, supports patterns of valuation that may lead to detrimental health behavior.

Specific limitations apply to each of these studies separately and have been discussed in the context of each independent finding. However, select limitations apply to all of these studies collectively, and future research is necessary to determine the generality of these results and possible boundary conditions of the predictions of the temporal window model.

All four of these studies employed similar methodologies. These include online recruitment of participants through a single crowdsourcing platform and employment of hypothetical tasks and self-report measures (Hebert et al. 1995). Each of the experimental studies used narrative presentation paradigms that may be especially susceptible to demand characteristics (Rung and Madden 2018; Stein et al. 2017), and failures to replicate. Each of the experimental studies reported here employed narratives of hardship or scarcity to constrict the temporal window. Although past research has also indicated that expansion of the temporal window through prospection also reduces the valuation of a specific brief, intense reinforcer (Snider, LaConte, and Bickel 2016; Daniel, Stanton, and Epstein 2013; Stein et al. 2016), this effect has not been observed for valuation of temporally extended reinforcers. Evidence of this experimental symmetry would provide substantially stronger support for the temporal window model of reinforcer valuation, by: (1) addressing the confounding possibility that "hardship" has independent effects on the temporal window and valuation of reinforcers (both brief and temporally extended); and (2) supporting the translational and therapeutic relevance of temporal window expansion. The possibility also exists, however, that expansion of the temporal window alters reinforcer valuation only if individual's baseline is below some threshold or "adequate" level. Indeed, sensitivity to temporal window manipulations may be determined, in part, by participant's baseline degree of discounting, with the most impulsive individuals also showing the greatest response to manipulation (Bickel, Quisenberry, and Snider 2016; Quisenberry, Snider, and Bickel 2016; Snider, Quisenberry, and Bickel 2016). Only through future research can the contours of the temporal window model of reinforcer pathology be fully defined.

In sum, these results replicate and extend past research into: (1) population differences in delay discounting rates observed between substance users and controls; (2) manipulation of the temporal window through scarcity narratives; (3) manipulation of the valuation of brief, intense reinforcers via temporal window constriction; and (4) manipulation of the valuation of temporally extended reinforcers via constriction of the temporal window. Delay discounting is an important and emerging behavioral marker of substance use disorder and other negative health behaviors, and may be a critical target for interventions via narratives to not only alter time perspective but also valuation of hedonic commodities. Future research will elucidate the potential therapeutic potential, but the current work provides a foundation of the mechanism and variables by which it operates.

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Appendix A. IRB Permission Letter

MEMORANDUM
DATE: May 2, 2017
TO: Warren K Bickel, Lexie Mellis, Jeffrey S Stein, Kirstin Gatchalian, Elan Samuel Perry, Liqa Athamneh, Allison Tegge

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)

PROTOCOL TITLE: Episodic thinking effects on decisionmaking
IRB NUMBER: 17-460
Effective May 2, 2017, the Virginia Tech Institution Review Board (IRB) Chair, David M Moore, approved the New Application request for the above-mentioned research protocol.
This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.
Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.
All investigators (listed above) are required to comply with the researcher requirements outlined at: http://www.irb.vt.edu/pages/responsibilities.htm
(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:
Approved As: Exempt, under 45 CFR 46.110 category(ies) 2
Protocol Approval Date: May 2, 2017
Protocol Expiration Date: N/A
Continuing Review Due Date*: N/A