The Power of Personal Control in Financial Decisions Under Risk

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Abstract

This study provides evidence from three different sources, a randomized controlled incentivized experiment, a natural field experiment and a large-scale longitudinal survey, that people make riskier financial decisions after experiencing helplessness. I propose a new model based on choice theory to incorporate biological mechanisms that explain the power of personal control in decisions under risk. The model does not require a probably weighting function and has the advantage of being cardinal, continuous and bounded, making it highly adaptable and generally applicable. An incentivized experiment involving 273 subjects shows that inducing helplessness using a validated induction causes significantly higher risky investment compared to the control group. Results from the experiment are robust controlling for baseline risk preferences, wealth effects, bounded rationality and gender. Three independent sources of evidence verify that a loss of personal control is a powerful determinant of financial decisions under risk.

Keywords: experience effects, financial efficacy, risk taking, personal finance, behavioral finance

JEL classification: G40; G41; D81

I. Introduction

When you have personal control over your circumstances, you don't need luck. You can be confident that your actions will deliver your desires. Losing personal control leads to greater risk taking. When we lose our personal control because of changes to our environment, we lose our self-efficacy and rely more on external factors out of our control such as luck, chance or randomness. We may even begin to overestimate our influence over chance outcomes in an attempt to maintain our sense of control, as with a phenomenon known as the illusion of control (Langer 1975). This paper sets out a general theory explaining how the experience of losing control over your circumstances induces risk taking. The proposed theory is established through an analysis of real gambling expenditure and tested using a controlled incentivized decision experiment.

Individual risk preferences appear to be moderately stable over time, but their stability is low over the life cycle (Ayton et al 2020; Banks et al 2020). There is a growing literature demonstrating that life experiences, in particular adverse experiences and environments, affect risk preferences (Kieren et al 2023; Black et al. 2017; Schildberg-Hörisch 2018; Ayton et al 2020; Hetschko and Preuss 2020, Bellucci et al. 2020; Cassar et al 2017; Beine et al 2020; Gneezy et. al 2020; Bassi et al 2013; Malmendier and Nagel 2011; Malmendier et. al 2011). Yet there is no consensus as to how such experiences might influence an individual's risk taking. Some studies find greater risk taking after an adverse experience (Bernile et al 2017; Mironova, et. al., 2019; Kibris and Uler, 2021; Eckel et al 2009; Hanaoka et al 2018). Whereas other studies show the opposite, greater risk aversion: Hetschko and Preuss (2020), Bellucci et al. (2020), Cassar et al (2017) and Beine et al (2020), Malmendier and Nagel (2011). Imas (2016) explains similarly contradictory findings of the influence of prior losses on risk attitudes by distinguishing between realized verses paper (not yet realized) financial losses. The theory proposed in this paper can explain the influence of a wider range of life experiences not necessarily involving explicit financial losses. The model presented in this paper can be generalized to allow for both greater risk taking and greater risk aversion after an adverse event. The change depending on whether the experience results in more, or less, personal control over one's environment.

Given these inconsistencies, it is important to understand what element of an adverse life experience leads to changes in risky financial decision making. Public health orders during COVID-19 that locked down some Local Government Areas (LGAs) in the Australian state of New South Wales, and not others, present a natural field experiment in which to observe the effect of a loss of personal control on post-lockdown risky financial decision making through gambling expenditure. Using publicly available government statistics, significantly higher gaming machine expenditure is observed in the 3 to 9 months after public order lockdowns ended in locked down Local Government Areas (LGA) whose residents lost their personal freedom compared to non-locked down areas in Australia. To control for a LGA's pre-lockdown expenditure, a difference-in-difference analysis is applied. These results indicate that experiencing a lockdown induces a significantly greater trajectory for gambling compared to pre-lockdown trends.

We see further evidence of greater risk taking after a loss of control from an analysis of gambling expenditure of approximately 3,700 respondents in the HILDA longitudinal survey. Individuals who experienced a substantial loss of personal control, as measured by a reported change in locus-of-control in the preceding four years, reported a significantly higher monthly dollar spend in gambling expenditure compared to respondents with no substantial loss of personal control. The results are robust to controlling for income, gender, and happiness.

To identify causation, the model is tested in a controlled incentivized decision experiment using a well-established Learned Helplessness model (Abramson et al. 1978). A standard learned helplessness induction used by psychologists involves giving subjects an unsolvable anagram task (Hiroto and Seligman, 1975; Klein et al 1976). In the experiment presented in this study, helplessness is induced by giving subjects an extremely difficult (yet solvable) timed anagram task. The level of risky investment is then observed using Gneezy and Potter's (1997) incentivised investment game. A control group is given a similar timed anagram task, except that the answers are easier to solve. Subjects in both Control and Treatment conditions are given the same baseline and risky investment prospects in which they can invest. Results show that a helplessness induction leads to an increase in average risky investment, controlling for individual baseline risk choices and other measures including gender. To rule out bounded rationality as a possible explanation for the results, a stochastically dominated gamble is offered to compare dominated choices between the treatments. There are no significant differences between treatment groups indicating that bounded rationality cannot explain the increase in risky investment.

The paper makes three profound contributions: 1) Personal control is demonstrated to be a powerful determinant of financial decisions under risk; 2) This paper is the first to propose a unified theory that explains how different life experiences can influence decisions under risk; and 3) A new, portable, and generally applicable cardinal choice model is put forward that can predict changes in individual's risk preferences without the need for a probability weighting function.

To understand how personal control influences decisions under risk, personal control is deliberately manipulated in a controlled experimental setting to observe its effect on risky investment. The well-established learned helplessness (LH) induction (Hiroto and Seligman 1975) is applied to generate the experience of helplessness. Background on the learned helplessness model and the biological mechanism that encodes risk in animal models follows to introduce the key concepts underpinning the basic framework in Section II.

Literature on self-efficacy and financial decision making

Self-efficacy influences how individuals perceive their ability to manage financial tasks, which can significantly impact their financial decisions and outcomes. Individuals with high self-efficacy are subsequently more likely to avoid financial distress because they more actively manage their finances (Kuhnen and Melzer 2018; Kristoffersen et al 2024). Because individuals with greater self-efficacy perceive they have greater influence on their outcomes, they perceive greater benefits of acting relative to the costs. They therefore take a more active role in their finances compared to individuals with lower self-efficacy.

Locus of control measures a personality trait in which an individual's belief system disposes them to either higher self-efficacy (internal locus of control) or lower self-efficacy (external locus of control). An internal locus of control has been associated with greater investment (Salamanca et al 2020; Pinger et al 2018) educational attainment (Coleman and DeLeire 2003), health behaviors (Conell-Price and Jamison 2015) and savings (Cobb-Clark et al 2016).

Salamanca's et al (2020) results suggest a robust relationship between internal locus of control and greater stock market investment that cannot be explained by expected return, risk, overconfidence, time preferences or financial literacy.

Previous work has examined how personality relates to investment behavior. An extensive literature shows the impact of the trait-based personality measure, locus of control, on personal finance and labor market outcomes (Bowles et al 2001; McGee & McGee 2016; Caliendo et al 2015; Tokunaga 1993). Yet little is known of how our experience of losing control impacts our risky financial decision making.

The insight of this work is that changes in an individual's state of perceived control is an important factor in risky decision making. This paper contributes to the existing literature on locus of control by establishing a relationship between a *loss* of personal control and risky investment. Insights from this work are particularly promising for policy makers. Because personality traits are relatively stable, there is more scope to target policy interventions that mitigate a loss of personal control. For example, social security programs that maintains an individual's agency and self-determination can lead to better financial outcomes for recipients.

In the following section we observe increases in risk taking after a loss of personal control on risk taking by examining real gambling expenditure data.

I. Greater gambling observed post- COVID-19 lockdown

The COVID-19 lockdowns present an opportunity to observe the effect of a loss of personal control on risky financial decision making in the natural world. On 23 June 2021, public health orders were imposed on residents in a subset of metropolitan Local Government Areas (LGAs) in the Australian state of New South Wales (NSW).

The Lockdowns lasted for 3 months ending on 11 October. During this time, residents in locked down areas had their freedoms restricted. Stay-at-home orders were in place in locked down areas. Only one person per household, per day, could leave the home for shopping, and visitors to households was limited to 5 guests including children. Outdoor public gatherings were limited to two people (excluding members of the same household) and singing indoors or at places of worship was not allowed. On August 23, more intense restrictions were imposed on a subset of LGA's already in lockdown. These 'LGAs of concern' had an additional curfew imposed from 9pm to 5am and were highly monitored by state police. Heavy fines and possible imprisonment were enforced on individuals in locked down areas who breached the public health orders.

The impact of the lock downs on risky financial decision making is tracked using gaming machine expenditure data, aggregated by LGA, reported by the NSW Government Liquor and Gaming agency. The data is publicly available and reported every 6 months between the periods of 1 December and 31 May.

Gaming machine expenditure data from a total of 91 LGAs is examined. Of these, 27 are in the lockdown group and 11 'LGAs of concern' are in the ultra lockdown group . To protect individual anonymity, the agency does not report LGAs with four or fewer venues. Data for these areas is amalgamated with neighbouring LGAs. Seven LGAs are excluded from analysis (five in the non-lock down group and two in the locked down group) because comparable data is not available due to too few gaming venues.

Government data reports the net profit from gaming machines in the LGA instead of the total money bet. Net profit is the amount of bets not returned to gamblers through winnings. To calculate the approximate value of the total money bet, net profit is multiplied by a factor of ten. A factor of ten is used because the average return of all gaming machines in NSW is 90% (NSW Liquor and Gaming). In NSW gaming machines must return at least 85% of turnover over the playing out of their full course of combinations as regulated by law.

Pre-lockdown Gaming machine expenditure (1 December 2020 to 21 May 2021) and post-lockdown gaming expenditure (1 December 2021 to 31 May 2022) is analysed using a difference-in-difference approach. The approach removes biases in post-lockdown period comparisons between the treatment and control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends due to other causes of the outcome. To rule out a broad increase in household spending across all consumption categories as an explanation of greater gaming machine consumption in post-locked down suburbs, state household spending is also examined. Monthly household consumption data suggests that spending is normalized again two months after the lockdown lifted. Suggesting that higher gaming expenditure cannot be attributed to a pent-up demand for consumption.

Results of the natural experiment

Greater increases in gaming machine expenditure is observed in the 3 to 9 months after public order lockdowns ended in locked down LGAs compared to non-locked LGAs (Figure 1). Average gaming expenditure across all LGAs increased from $222.9 M AUD in the period (1 December 2020 to 21 May 2021) before the lockdown, to $236.1 M AUD in the period after the lockdown ended (1 December 2021 to 31 May 2022). Figure 1 compares the percentage increase in gaming expenditure over the two periods by lockdown group. In the non-locked down group, the average percentage increase in dollars bet is 4.8%. In contrast, residents from lockdown LGAs increased their expenditure by 8% and ultra locked down residents in 'LGAs of concern' increased their expenditure by almost 10 percent.

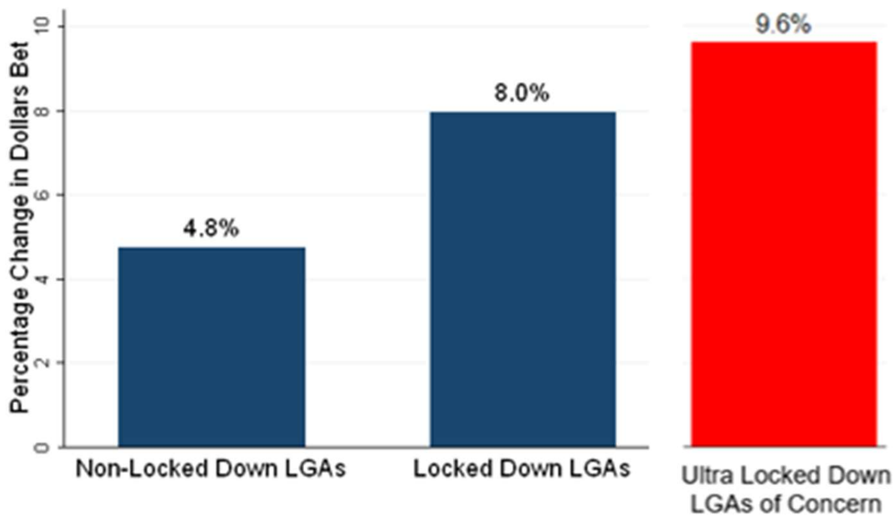

Figure 1: Higher percentage increase in gaming machine expenditure in locked down and ultra locked down LGAs compared to non-locked down LGAs.

To control for both pre-lockdown expenditure and differences between the locked down and non-locked down groups, a DID analysis is performed by estimating a panel regression model. The results of the two-period log-linear random effects panel model is reported in Table 1. The interaction term between time and lockdown group, *Time*Lockdown,* captures the DID marginal effect of the lockdown on post-lockdown percentage change in gaming machine expenditure. The DID term is significant at (p<0.001) indicating that gaming expenditure increased disproportionately after the lockdowns were lifted in locked down LGAs compared to LGAs that did not lockdown.

Table 1`: Difference-in-difference panel analysis

Dependent Variable: Log Gaming Machine Expenditure ($M)	**(1)**
Constant	17.980*** (0.021)
Time	0.029 (0.021)
Lockdown	1.445*** (0.214)
Time*Lockdown	0.064*** (0.026)
Number of Machines	0.000*** (.000)
R-Sq	0.395
Observations (groups)	182(91)

Notes: ***, **, * show statistical significance at 1, 5 and 10 per cent levels respectively. Random effects panel estimation.

To rule out the explanation that after a few months of lockdown in their homes people are bored and want to make up for the lost time afterwards we examine household spending, by state, across all consumption categories in post-locked down suburbs (Figure 2). A comparison of state household spending between states with greater lockdown restrictions is investigated because no household spending data is available at the Local Government Area level. Data from the Australian Bureau of Statistics shows a strong percentage increase in post-lockdown spending for NSW in November 2021, the month after lockdowns were lifted. However, subsequent months (December and January) show a return to moderate increases with little differences between states such as QLD and WA who implemented less stringent restrictions. A similar pattern is observed for the state of VIC, who like NSW, also implemented stringent restrictions.

Because gaming machine expenditure is examined starting approximately two months after the lockdowns were lifted (ie from December 2021 to May 2022), the normalization of monthly household consumption by December suggests that the significantly higher gaming expenditure in post-locked down LGAs cannot be attributed to a broader pent-up demand for consumption.

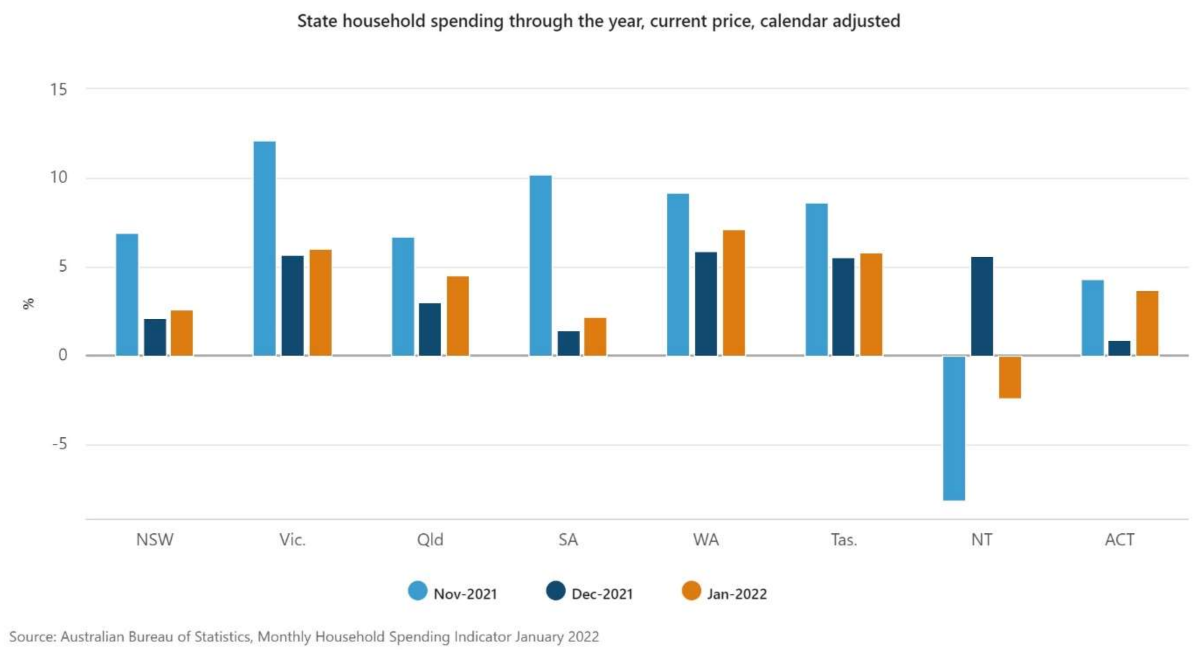

Figure 2: Percentage change in monthly household spending through the year by Australian state. Calculated using bank transactions and National Accounts data. Source: Australian Bureau of Statistics.

II. Greater gambling after a loss of control in HILDA survey

HILDA is an annual social and economic survey of Australians that began in 2000. Monthly Gambling Expenditure is measured in 2015 and 2018. Respondents' personal control (Locus of Control) is measured every 4 years in 2007, 2011, 2015, 2019. A personal control score [7-33] is constructed from a 7-item locus-of-control (LOC) measure and the difference in scores between the time periods, 2015 and 2011 are examined for analysis. The personal control scores are used to determine the marginal effect of a loss of control on reported gambling expenditure. Panel regression analysis suggests that a substantial reduction in internal locus of control (LOC) precedes risky financial decision making. That is, respondents in the HILDA survey who report a substantial reduction in their internal locus-of-control, gamble significantly greater amounts on average.

Results of HILDA survey

Table 5 reports the marginal effect of personal control on respondents' monthly gambling expenditure (AUD), controlling for other contributing factors. Individuals whose repeated LOC measures indicate a substantial loss of personal control, scoring more than a 3-point difference as scored by the *Loss-of-control dummy* variable (Table 5 model (3)), gambled \$27 more a month on average. The magnitude of the increased spending is greater than all other estimated regressors, including gender, where females spent an average of \$21.51 a month less than males.

Locus-of-control by itself is not predictive of risky financial decision making. Table 5, model (1) reports the non-significant marginal estimate of *Locus-of-control* on monthly gambling expenditure from the HILDA survey. The *Difference-locus-of-control* which captures the difference in the respondent's 2015 score and 2011 score is similarly non-significant in Table model (2). The important predictor for risky financial decision making appears to be a *loss* of personal control, not the level of one's personal control. The *Difference-locus-of-control* is not predictive because the difference captures some people gaining internal control and some losing internal control, where the effect of the opposing influences obscures the pure effect of losing personal control on gambling expenditure.

The results from Table 2 imply that losing personal control is more predictive of risky financial decision making than one's absolute level of personal control. Results on the influence of LOC from previous studies are mixed. Gong and Zhu (2019) similarly find that LOC is not predictive of gambling participation, though they do find that LOC is predictive of problem gambling. Von der Heiden and Egloff (2021) find that a high external LOC was predictive of problem gambling while Clarke (2004) did not find any significant differences between the LOC of problem and non-problem gamblers. In contrast to previous studies, the results reported here highlight the importance of examining changes in LOC over time rather than examining static measures of LOC. The size of the R-squares reported in Table 2 are slightly higher than those typically reported (usually $R^2 = 0.01$) by previous studies estimating gambling predictors using HILDA data (Von der Heiden and Egloff 2021; Churchill and Farrell 2020).

Another interesting aspect of these results is the persistent effects of helplessness over long time horizons. There is a period of 4 years between the first and second observation of LOC, suggesting that persistent disempowerment can result in persistent risk taking.

Table 2: Estimated marginal impact of personal control, and its loss, on respondent's monthly gambling expenditure in 2015.

Dependent Variable: Monthly Gambling Expenditure ($)	**(1)**	**(2)**	**(3)**
Constant	-53.952 (49.493)	-53.160 (46.952)	-56.650 (46.944)

Female	- 20.858*** (5.874)	-21.601*** (6.337)	-21.516*** (6.333)
Ln income (total annual gross)	2.577 (3.091)	2.613 (3.303)	2.891 (3.303)
Age	0.686*** (0.224)	0.749*** (0.245)	0.710*** (0.245)
Impulsiveness	5.520*** (1.728)	5.638*** (1.868)	5.416*** (1.869)
Happy	-0.521 (2.490)	0.000 (2.713)	-0.249 (2.713)
Drink alcohol	1.407 (1.208)	1.614 (1.293)	1.627 (1.292)
Alcohol expenditure	0.440*** (0.073)	0.412*** (0.081)	0.412*** (0.081)
Cigarette expenditure pa	0.002 (0.001)	0.003* (0.002)	0.003* (0.002)
Education	4.821*** (1.123)	5.046*** (1.208)	4.992*** (1.208)
Locus-of-control	0. 245 (0.851)	-	-
Difference-locus-of-control	-	-0.867 (0.722)	-2.398** (0.961)
Loss-of-control dummy	-	-	27.307*** (11.330)
R-Sq	0.023	0.024	0.025
Observations (subjects)	4,404	3,776	3,776

Notes: ***, **, * show statistical significance at 1, 5 and 10 per cent levels respectively. OLS cross-section estimation. Variance Inflation Factor (VIF) <2 for all models (no multicollinearity). Full description of variables in supplementary information.

In order to explain this natural world behaviour, I present a model based on choice theory and neuroscience which I then test using a randomized incentivized controlled experiment.

III. A model of personal control for decisions under risk

Building on the neuroscience foundation of economic decision making proposed by Malmendier (2021) and others, neuroscience provides an explanation of how experiences shape economic preference through a dynamic learning context. Experiments using animal models have established that the dopamine system responds to reward anticipation and outcome evaluation in decisions under risk (Preuschoff et al 2006; and Platt and Huettel 2008; Liu et al 2011). Dopamine is a type of neurotransmitter that is released by the brain in anticipation of a reward. Uncertain rewards provoke more dopamine activation than certain rewards (Fiorillo et al. 2003). Hence pursuing uncertain rewards are one avenue for obtaining more dopamine.

Dopamine is associated with feelings of pleasure. The dopamine system can be thought to encode the subjective valuation of uncertain prospects via the intensity of dopaminergic activation. Dopaminergic activation occurs when dopamine is released and binds to dopamine receptors located on the surface of neurons. After a period of neuronal activation, dopamine is reabsorbed, and receptors become unbound.

Outcome evaluation is encoded by the dopamine system through what is known as a prediction error. If the reward is less (more) pleasurable than expected, the brain reduces (increases) the release of dopamine to code the prediction error. If the received reward is what was expected, then there is no prediction error. This feedback is what is thought to guide learning and forms the basis of reinforcement learning theory (Glimcher 2011).

Learned helplessness is associated with lower levels of dopamine activation (Kram et al 2002; Abler et al 2005). Dopaminergic activation appears to play an important role in motivation and goal attainment (Shohamy 2011).

Rats induced with LH demonstrate significantly greater risk taking in the rat gambling model compared to a control group (Nobrega et al 2016). However, no study has tested the effect of LH on human risk financial risk taking.

We begin with a model that uses insights from neurobiology by capturing the effect of prediction errors on the valuation of risky prospects. Assume that an individual *i*'s valuation of an uncertain prospect, D_{ixt}, is equivalent to their dopaminergic activation prior to the reward x which represents their evaluation of the net expected reward from the prospect. An individual's valuation of a prospect, at time t, is given by:

$$\text{Valuation}_{ixt} = D_{ixt}=mx_{it} + ne_{ixt-1} \quad (1)$$

Where $x_t \geq 0$ represents the dopamine activation from the anticipated intrinsic consumption utility from the reward at time t and $e_{t-1} = x_{t-1} - x_{t-2}$ represents the dopaminergic prediction error of the previous period. The prediction error provides feedback to the decision maker by lowering dopamine activation if the prediction error is negative, that is, the reward is less than expected in the previous period, or increasing dopamine activation if the reward is more than expected in the previous period. If no prior experience/feedback of the prospect is available, then the valuation function is simply $D_{ixt} = mx_t$.

We now extend the model so that D_{ixt} represents a downward sloping demand function ($p = a - bq$). When the quantity of existing dopamine activation is scarce, the price one is willing to pay for more activation is high, resulting in greater dopamine activation. When existing dopamine activation is in abundance, an uncertain reward becomes less attractive because of the diminishing value of dopamine activation. We now expand the scope of the model to capture the existing quantity of dopamine from sources exogenous to the reference gamble. Orthodox economic valuation models are closed models in regard to the reference gamble, whereas this heterodox model explicitly models the influence of exogenous changes in dopamine on prospect valuation.

Let us take the case of a negative prediction error, $e_{kt-1} = k_{t-1} - k_{t-2}$, generated from an unavoidable loss of personal control k. As with above, the decision maker experiences dopaminergic activation in anticipation of consumption utility of x_t. which is adjusted by the prediction error of x, e_{xt-1}, accordingly. However, there is now a second prediction error, generated by the unavoidable loss of personal control, e_{kt-1}, that reduces existing dopamine such that the individual becomes dopamine seeking:

$$\text{Valuation} = mx_t + ne_{xt-1} - re_{kt-1} \qquad (2)$$

In line with a downward sloping demand curve, the negative sign on the last term in Eqn. (2) reverses the direction of the effect so that lower dopamine, induced by a loss of personal control, *increases* the demand for the uncertain prospect with reward x. The result is a greater demand for uncertain rewards. Because uncertain rewards induce more dopamine release than certain rewards. In contrast, an abundance of dopamine generated by a positive prediction from a gain in control, reduces the demand for the uncertain prospect.

The model can be generalized to incorporate the effect of aggregate prediction errors from multiple domains. A generalized model can be then used to predict the effect of a variety of life experiences on an individual's risk preferences.

$$\text{Valuation} = mx_t + ne_{xt-1} - \sum re_{yt-1} \qquad (3)$$

Where $\sum re_{yt-1}$ is the sum of prediction errors exogenous to the uncertain prospect.

To further develop the model, Glimcher and Tymula's (2023) descriptive choice model is adapted and simplified to incorporate two important biological properties into the valuation function. The first biological property is finite activation bounded by an individual's biological limit for activation. The second property is continuity because biological systems rarely ever employ discontinuous (kinked) functions. A disposition parameter α>0 is also applied to x_t to allow for stable differences in individual dispositions towards risk. To reflect the biological processes generating an individual's subjective valuation, Equation 3 is expanded and normalized so that:

$$\text{Subjective Valuation } (x) = \frac{x_t^{\alpha} + (x_{t-1} - x_{t-2}) - (k_{t-1} - k_{t-2})}{x_t^{\alpha} + x_{t-1} + k_{t-2}} \quad (4)$$

The denominator represents the total potential dopaminergic activation that could be generated from maximum prediction errors. The numerator represents the dopaminergic activation from the actual prediction errors. The subjective value function takes values between 0 and 1 consistent with the property of bounded activation. The advantage of Glimcher and Tymula's (2023) approach is that the subjective function is cardinal and does not require a probability weighting function. Because the function is divisively normalized by itself, it guarantees that the subjective value function always adjusts to the problem at hand.

IV. Experiment

Experimental design

Does a loss of personal control lead to greater risk taking? To answer this question, an incentivized controlled experiment with three conditions in a between-subject design is conducted. An experiment has the advantage of being able to establish causation by controlling all aspects of the environment. The first experimental condition is a control group. Two conditions are treated with a standard validated helplessness induction based on the theory of learned helplessness (Abramson et al. 1978; Hiroto 1974). The treatment conditions vary from the Control condition in the anagram task. The LH treatments received very hard anagrams designed to expose subjects to persistent and unavoidable failure. While the control group received the same number of anagrams with the same time limit except that the anagrams were much easier to solve. The second treatment condition, LH_2, was designed to rule-out the possible explanation that an ego-threat may be causing the effect. LH_2 is identical to LH_1, except that the ego threat is removed by de-personalising the attribution of performance in the anagram task. The Control and LH_1 conditions, emphasise the subject's cognitive ability in solving anagrams before the anagram task, while LH_2 does not refer to cognitive ability instead emphasizing the random nature of the task. Subjects were randomly assigned to one of three conditions determining which set of anagrams they would receive, easy (Control) or hard (LH). Table 3 summarizes the experimental conditions and sequence of tasks.

Table: 3 Summary of experimental conditions and sequence

Condition Sequence	**Control**	***LH_1* Treatment**	***LH_2* Treatment**
1	Investment 1 decision – Baseline risk elicitation		
2	Easy anagram induction	LH anagram induction	LH anagram induction + nullified ego threat
3	Investment 2 decision – Primary Outcome variable		
4	Investment 3 decision – Bounded rationality test		
5	Payoff information		
6	Control measures questionnaire		

Experimental procedures

At the commencement of the experiment, all subjects earn an initial $10 in the experiment by confirming their payment (PayID) details and are told that their final earnings would depend on the choices they made throughout the experiment. A baseline measure of subjects' risk preferences using Gneezy and Potter's (1997) investment game is first elicited. See Condition Sequence 1 investment choice in Table 3. In this first stage, subjects had the opportunity to invest the \$10 they earned from confirming their Payid in an investment prospect. They could invest between zero and \$10 within two decimal points. The investment prospect was a 1/2 (50%) chance of losing the amount they invested and a 1/2 (50%) chance of earning two times the amount they invested. After entering and confirming their investment choice between zero and \$10 subjects were then introduced to the next task without being given the outcome of the risky investment. We draw all the outcomes of the experiment's risky prospects at the end of the experiment to avoid the possibility of wealth and reinforcement effects (Nielsen 2019). That is, the possibility that individuals take on more risk after a gain and take on less risk after a loss. Subjects therefore, do not know their returns or losses on the amounts they invest until the payment information is given at the end of the experiment.

Subjects are then given an anagram task. Before subjects begin the task, they are told they earn a flat rate of \$20 for completing the anagram task and that they will then have an opportunity to use these earnings to invest in investment prospects. Subjects in all treatment conditions earn \$20 regardless of how they performed in the task. Subjects in all three treatment conditions are given a time limit of 15 seconds to solve each anagram. After 15 seconds, the next page appears. Subjects can proceed to the next page early if they chose to. However, they can not go back and solve previous anagrams once they clicked 'next' or 15 seconds had expired. A total of 10 anagrams are given to subjects. Subjects in the Control treatment condition have a set of 10 relatively easy anagrams to solve. While subjects in LH_1 and LH_2 are given very hard (solvable) anagrams to solve. The LH_2 treatment is the same as LH_1 except that the description of the task un-linked the performance in the task to subjects personal ability by removing the reference to cognitive ability and was only referred to as a randomized anagram task.

At the completion of the anagram task, the number of correctly answered anagrams are displayed. As a manipulation check, the participants are asked to judge their own performance on a 5-point scale (1= my performance was very bad to 5= my performance was very good). The manipulation is presumed to have worked on the subjects in the LH treatments if they do not appraise their own performance in the anagram task highly (ie 4 and above).

Subjects are then given a second investment decision task (Investment 2 decision, Table 1). Subjects are presented with another risky prospect in the form of Gneezy and Potter's (1997) investment game. Like before, they can invest between zero and $10 within two decimal points. The investment prospect is 2/3 (67%) chance of losing the amount they invested and a 1/3 (33%) chance of earning three times the amount invested.

To explore the effect of bounded rationality, we introduce a third investment task (Investment 3 decision, Table 1) that allows us to measure the proportion of stochastically dominated gambles chosen in each treatment. In the third investment task, subjects are given a choice to invest up to $10 between three investment prospects. The choice set was designed so that Prospect C stochastically dominates Prospects A and B. Prospect C also has a higher expected payoff than A and B. Therefore, one should always choose Prospect C, regardless of risk preference. Once subjects make their choice of Prospect, they have the opportunity to invest between zero to $10 in their chosen prospect.

At the conclusion of stage 3, earnings from each stage and total earnings are displayed to subjects.

A questionnaire is administered containing validated instruments for related psychological measures. Locus of control (Rotter 1966), the degree to which a person perceives an outcome as being dependent on their own actions or those of external forces, is measured using Lumpkin's (1985) brief six item locus of control scale. The scale is scored such that a larger score on the five-point agree/disagree scale indicates a more internal locus of control.

Participants were asked to rate their global self-esteem on a 5-point scale (1 = not at all true of me, to 5 = very true of me) using the validated Single Item Self Esteem Scale (Robins et al 2001). The exact wording of the SISE is "Please indicate to what extent the following statement applies to you. I have high self-esteem".

State rumination was measured by responding to a single item (Napolitano et al 2020), "In the time since you completed the anagram task, To what extent did you reflect on your performance in the anagram task?" on a 5-point Likert scale (1 = Not at all, 5 = Extremely).

Dispositional optimism is associated with economic choices (Puri and Robinson 2007). The Revised Life Orientation Test (Scheier et al 1994) measure was used to control for dispositional optimism.

A total of 273 subjects (approximately 90 subjects per treatment) participated in the online experiment. Of these subjects, 127(47%) were female and 146(53%) were male. The experiment was conducted from November 2021 to March 2022. The decisions were elicited using Limesurvey software. Limesurvey software is an online survey tool similar to Qualtrics. The participants were recruited using the online database system ORSEE (Greiner 2015). The experiment lasted approximately 30 minutes and participants earned on average $31.65 AUD.

Results of experiment

We exclude 10 subjects (6 in the LH_1 and 4 in the LH_2 treatments) because they had high self-appraisals of 4 and above and therefore did not meet the LH manipulation check criteria. The analysed sample size for the experiment is 263 subjects. Analysis of the full sample, for comparison, is contained in the Supplementary Material.

We first compare average investment across the three conditions (Table 2). Our results show higher average investment in the LH_1 condition compared to the control. We then refine our analysis by controlling for psychological and other measures in a regression model. A difference-in-difference random effects regression analysis is applied to control for baseline investment and differences between the Control and treatment groups using a panel data structure. We find that, on average, both LH treatments leads to significantly greater risky investment holding all else equal. We observe no associations between psychological disposition and risky investment of the measures we collected. Finally, a manipulation verification, and the number of stochastically dominated choices between conditions is compared to rule out bounded rationality as an alternative explanation.

Table 4: Average risky investment by condition

Condition	**Control** **Mean (s.d)**	***LH_1*** **Mean (s.d)**	***LH_2*** **Mean (s.d)**
Mean investment males	5.95 (2.08)	6.76 (2.44)	6.03 (2.48)
Mean investment females	6.11 (2.07)	5.91 (2.34)	5.62 (2.63)
Mean investment	6.02 (207)	6.38 (2.42)	5.83 (2.54)
Number of Subjects (males)	91 (48)	87 (48)	85 (44)

LH induces risky investment

Table 4 reports average risky investment by condition. Males in the Control condition invested an average of \$5.95 compared to \$6.76 in the LH_1 treatment. The difference is statistically significant using a one-sided *t*-test, (p=0.040). While there is no statistically significant difference between male average investment in the LH_2 treatment and the Control (p=0.427). Females in the Control condition invested an average of \$6.11 with no statistically significant difference between LH treatments. Both men and women in the Control condition invested an average of \$6.02 in the Control condition compared to \$6.38 in LH_1 and \$5.83 in LH_2.

To ensure that the slight proportional imbalance of men between conditions is not responsible for the aggregate results, we control for gender in a random effect panel regression. We now examine average Investment 2 allocations after the anagram task/induction. A difference-in-difference (DID) approach allows us to control for subjects' baseline Investment 1 and reduce the noise associated with variance across individuals. Using random effects estimation and DID interaction terms to control for baseline Investment 1, and other variables, we find risky investment after the anagram induction is significantly higher (p-value = 0.000), in Treatments LH_1 and LH_2 compared the Control group (Col (1), Table 3).

To further understand investment behaviour across conditions we now investigate the distribution of average amounts invested in Figure 3. We see that there is a greater density at high investments for the LH treatments compared to the Control group. Figure 1 illustrates the distribution of investment choices across all three investment tasks for each treatment group. The mode investment in the Control group is \$6. For the LH treatments, the mode shifts to \$10.

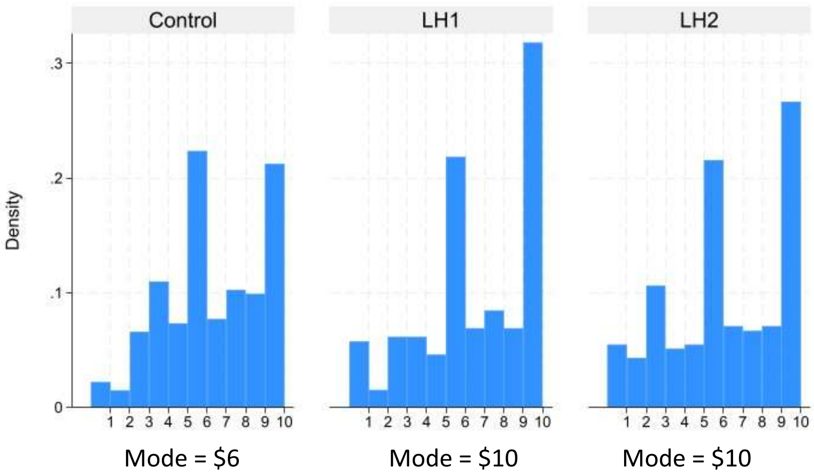

Figure 3: Histogram of investment choices (\$AUD) by treatment

Psychological measures has little association with risky investment

We regress subjects' psychological measures to their baseline investment to identify and control for any potential relationships between their dispositional attributes and risky investment (Table 5, Model (3)). This regression yielded no significant estimates suggesting that these measures were not predictive of risky investment.

Table 5: Difference-in-difference random effects regression output all treatments

Dependent Variable: Investment ($)	**(1)**	**(2) Bounded Rationality**	**(3) Psych Measures**	**(4) Gender Interaction**
Constant	6.749***	6.770***	6.971***	7.007***
	(1.070)	(0.842)	(0.954)	(1.209)
Time dummy	-1.496***	-1.496***	-1.496***	-1.496***
	(0.150)	(0.150)	(0.150)	(0.151)
Treatment 1	-2.003**	-2.206***	-2.351***	-2.281***
	(0.810)	(0.803)	(0.804)	(0.766)
Treatment 2	-2.150**	-2.380***	-2.539***	-2.477***
	(0.885)	(0.898)	(0.944)	(0.911)
Time dummy* LH_1	**1.216***	**1.216***	**1.216***	**0.993***
	(0.127)	**(0.127)**	**(0.127)**	**(0.172)**
Time dummy* LH_2	**1.018***	**1.018***	**1.018***	**0.831***
	(0.185)	**(0.185)**	**(0.186)**	**(0.212)**
# Correct answers	-0.010	-0.0151	-0.0435	-0.0305
	(0.104)	(0.104)	(0.110)	(0.107)
Male	0.355	0.394	0.345	-0.148
	(0.340)	(0.320)	(0.338)	(0.379)
Dominated choice		0.894***	0.917***	1.050***
		(0.331)	(0.308)	(0.300)
Optimism measure			-0.436**	-0.400**
			(0.210)	(0.202)
Rumination measure			-0.289	-0.0860
			(0.488)	(0.177)
Self-esteem measure			0.0688	0.0727
			(0.150)	(0.155)
Locus of control measure			0.324	0.0189
			(0.286)	(0.0404)
Timedummy* LH_1 *male				0.405**
				(0.171)
Timedummy* LH_2 *male				0.360
				(0.250)
R-Sq (overall)	0.045	0.059	0.068	0.070
Observations (subjects)	789 (263)	789 (273)	789 (263)	789 (263)

Notes: ***, **, * show statistical significance at 1, 5 and 10 per cent levels respectively. *Time dummy*LH* represent the Diff-in-Diff variables. Errors clustered at the individual level. Reported estimates are relative to the base Control condition.

Bounded rationality is not significantly different between treatments

To examine the possibility that bounded rationality may be influencing investment decision due to the increased difficulty of the LH anagrams, the number of stochastically dominated choices in the Investment 3 decision is compared between conditions (Figure 4). The proportion of statistically dominated choices between the conditions is not significantly different using Pearson's Chi^2 test ($p = 0.613$).

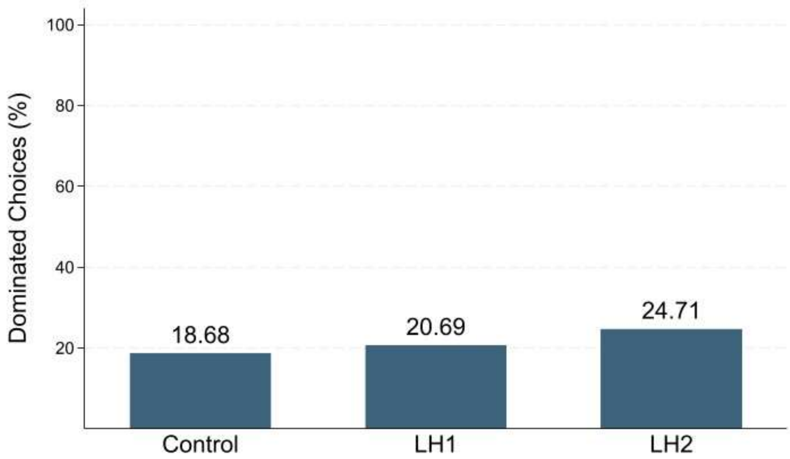

Figure 4: Proportion of dominated choices by treatment (263 subjects).

Induction confirmed by manipulation check

Two measures, (1) number of "correct anagrams" and (2) "performance self-assessment score" are used as a manipulation check. These test whether the LH inductions indeed induced in a persistent failure to succeed. This is confirmed with the average number of correct anagrams being approximately 1.3 (out of 10) for the LH_1 and LH_2 Treatments compared to 8.2 for the Control treatment. Further, subjects in the LH_1 and LH_2 treatments rated their own performance much lower on average, at around 1 out of 5, than subjects in the Control condition (3.9 out of 5).

Table 5, Model (1) reports the LH_1 and LH_2 treatments' marginal impact on investment compared to the Control condition controlling for the time trend, number of correct anagram answers and gender. The interaction terms, *Time dummy** LH_1 and *Time* dummy* LH_2 are the difference-in-difference (DID) terms. The DID terms represent the change in slope after the anagram task relative to the Control group. The coefficients on both DID terms across the models indicate an average $1 increase (out of $10) in average investment after an LH induction compared to the Control condition.

V. Conclusion

The paper puts forward a novel theory that proposes personal control as a determinant of risky decision making. The theory of personal control on risky decision making explains how a variety of life experiences can influence risk preferences. Life events can change a person's decisions under risk by its influence on personal control. Helplessness is particularly incidious in its influence on risk taking because helplessness not only increases an individual's demand for dopamine, but reduces one's personal efficacy and hence one's ability to restore dopamine through goals and actions. Restorative rewards must come from external and passive avenues such as lotteries. Many events may lead individuals to experience lower dopamine through un-met expectations. However, decision makers who experience both un-met expectations and a state of helplessness, are particularly vulnerable to excessive risk taking.

The paper constructs a subjective valuation model based on biological mechanisms. In doing so, we can now translate life experiences to cardinal changes in an individual's risk preferences without the need for a probability weighting function. The model is therefore highly adaptable and generally applicable. The theory can be used to develop new approaches for encouraging behaviour change, problem gambling, personal financial management and the protection of financially fragile cohorts.

The theory is supported by publically available data on gaming machine expenditure during COVID-19 and gambling expenditure from a large scale longitudinal survey

The randomized incentived experiment is the first to identify helplessness as a causitative factor in risk taking. Unlike previous field studies that observe the effect of life experiences on risk taking, the paper establishes causation by testing a hypothesis in a controlled environment.. Interestingly, the results from this study show that the effects of losing personal control can persist for months and even years.

Further research and replication studies are needed to confirm the reliability of this promising new theory.

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