Income shock increases delay discounting independently of emotion

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Abstract

How to distribute resource consumption over time is a critical optimization problem. If an agent were to consume all available resources, they would be left with insufficient resources in the future. Inversely, if an agent were to save all their resources for later, they might not live long enough to consume them. The first error is common due to “temporal discounting” - the tendency to value immediate rewards over equivalent future rewards. A major research goal is to identify the factors that influence the temporal discounting rate, so that policy makers could develop interventions to correct for imbalance. It has been shown that a negative change in life circumstances, such as loss of income, is associated with an increase in temporal discounting. Interestingly, negative affect is also associated with increased temporal discounting. Here, we test whether both negative income shock and negative affect lead to greater temporal discounting, and whether they do so independently. We tested 1,145 individuals as the market was crashing in late March 2020 and unemployment rising due to the COVID-19 crisis and then retested 200 individuals as the market was recovering in June 2020. We found that income shock was strongly related to an increase in delay discounting using cross-sectional and longitudinal data. Importantly, this relationship was independent of the negative impact on affect. These findings suggest that the link between income change and delay discounting is a direct result of liquidity constraints, not of changes in affect. This independence may be adaptive, as affect is a noisy reflection of environmental constraints, which may introduce noise to the decision problem leading to suboptimal choice.

Keywords: Delay Discounting, Temporal Discounting, Emotion, Affect, Income shock

Achieving desirable long-term outcomes, such as a comfortable retirement, often requires making immediate investments, such as saving more and spending less. Whether an individual will choose to make such an investment partially depends on how much they value delayed outcomes relative to immediate outcomes (Samuelson, 1937). Most people discount future rewards relative to immediate rewards (Frederick et al., 2002; Green & Myerson, 2004). There are substantial individual differences however in the rate at which people do so (Casey et al., 2011; Mischel et al., 1989). This rate, known as the *temporal discounting rate*, has been shown to be associated with education, health and income. In particular, low education, poor health and low income is associated with higher temporal discounting rate (de Wit et al., 2007; Dohmen et al., 2018; Mischel et al., 2011; Reimers et al., 2009; Schlam et al., 2013).

It is possible that when such demographic characteristics change, an individual's temporal discounting rate may also alter. There is some data in support of this hypothesis in relation to sudden decrease in income (known as an income shock). In particular, one study showed that when payment is taken away from subjects in a laboratory game their temporal discounting rate increases (Haushofer et al., 2013). Two other studies have shown a similar association in a natural setting where farmers in a developing country experienced income shock due to changes in rainfall (Di Falco et al., 2019; Tanaka et al., 2010). It is unknown, however, whether this association between naturally occurring income shock and temporal discounting will generalize more broadly to a diverse population beyond farmers in the developing world.

In addition to demographic characteristics, the temporal discounting rate has also been shown to be sensitive to changes in the emotional state of the individual. In particular, induction of negative affect in laboratory settings lead to an increase in temporal discounting rate (Lempert & Phelps, 2016; Lerner et al., 2013; Moore et al., 1976; Schwarz & Pollack, 1977; Seeman & Schwarz, 1974). This may be because negative affect is associated with an inability to vividly imagine the future (which is associated with low delay discounting; Lebreton et al., 2013), as observed in people with depression (Morina et al., 2011). Yet, to the best of our knowledge the influence of emotion due to 'real-life' naturally occurring events (rather than laboratory induced emotion) on delay discounting has never been investigated.

The possible relationship between affect and discounting rate triggered the hypothesis that the association between demographic characteristics (e.g., low income, low education, poor health) and temporal discounting is the direct result of negative affect (Haushofer & Fehr, 2014). That is, difficult life circumstances generate negative mood, which in turn may lead to high temporal discounting. Alternatively, the impact of demographics on temporal discounting may be independent of mood. That is, difficult life circumstances may lead to high temporal discounting for a number of reasons, such as low cash flow, regardless of mood. Investigating the possible relationship between these three factors (namely, income shock, negative affect, and delay discounting rate) is important, because if negative affect increases delay discounting rate, one could potentially decrease individuals' temporal discounting rate using an affective manipulation, even if income remains low. If delay discounting is independent of mood, then decreasing temporal discounting in individuals experiencing difficult life circumstances will likely require a direct change to those circumstances.

Here, we test whether naturally occurring subjective income shock increased delay discounting rate in a large diverse sample and whether this relationship was mediated by affect. To this end, we recorded income shock, affective state and delayed discounting rates of 1,145 individuals in the United States on March 26-29 2020, when the economy was experiencing a downturn. The downturn was characterised by a financial market crash and growing

unemployment due to the COVID-19 crisis (**Figure 1**). The financial crash of 2020 began on March 9, with the largest point dive of the US market in history only to be outdone by additional point falls in the weeks that followed. As the pandemic led to a substantial loss of income for many (not only those invested in the market) it allowed us to investigate the following novel questions: Firstly, is naturally occurring negative income shock related to increased delay discounting in a large diverse Western population? Secondly, is negative affective state due to ‘real-world’ circumstances related to increased delay discounting? Thirdly, is the relationship between income shock and delay discounting dependent or independent of affect? We then tested 200 individuals again on June 6-7, 2020 as the market was recovering. This allowed us to additionally measure changes in income shock, discounting rates and affect in order to investigate how alterations to these factors due to the changing environment are related to each other in the same individuals.

Figure 1. Timing of the Experiment. We tested 1145 individuals on March 26-29, 2020 as the financial markets were plummeting (blue) and the unemployment was sharply increasing (red); we then tested 200 of those individuals again on June 6-7, 2020 as the markets were recovering and the unemployment rate started to decrease (*Bureau of Labor Statistics Data*, n.d.; *INDEXDJX: .DJI - Google Search*, n.d.).

Results

Income shock is related to greater delay discounting

One thousand, one hundred forty-five participants (546 males, age = 44 ± 16 (mean $\pm$ SD), median yearly income = \$52,500; see **supplementary figure 1A-D**) in the United States completed our online study on March 26-29, 2020. Here, we used a subjective measure of income shock which allows us to account for the fact that an objective change in income can be interpreted differently by different individuals. That is, we wanted to account for the fact that a \$1K income shock can be perceived as large or small by different individuals due, for example, to their net worth, spending habits, income expectations, etc. In other words, people may have unobservable information (Jappelli & Pistaferri, 2010; Kahneman & Tversky, 2013). Thus, participants were asked to indicate the impact of Covid-19 on their income on a 6-point Likert scale from none (1) to extremely high (6). The average reported impact was $3.11(\pm 0.05$ SE) (see **supplementary figure 2**).

To test the relationship between income shock and delay discounting, participants completed 27 choice trials (Kirby et al., 1999), each requiring them to choose between a smaller, immediate reward (e.g., \$25 today) versus a larger delayed reward (e.g., \$35 in 25 days; see methods for details). We then estimated the discounting rate for each participant by fitting a simple hyperbolic model to the intertemporal choice data. More specifically, immediate reward choices were fitted using a standard softmax function of the utility (U_i) difference between the two options, which provides the probability of choosing the immediate reward (Luce, 1958):

$$P_{\text{immediate reward}} = \frac{1}{1 + \exp\left(-\beta(U_{\text{delayed reward}} - U_{\text{immediate reward}})\right)}$$

where β is a reversed temperature parameter that adjusts the stochasticity of choices. The utility of each option assumes that reward is discounted by time in a hyperbolic fashion:

$$U_{\text{delayed reward}} = \frac{\text{delayed reward}}{1 + k \times \text{delay}}$$

where k is the temporal discounting rate (see methods for details). The model provided a good fit to participants' choices (pseudo- $R^2 = 0.69 \pm 0.0059$, mean $\pm$ SE; balanced accuracy = 0.87 ± 0.004 , mean $\pm$ SE; see **figure 2A** and methods). Temporal discounting rates were log transformed to ensure that they follow a normal distribution.

We then estimated a linear model with log discounting rate as the dependent variable and income shock as the independent variable controlling for all demographics (age, gender, education and income). More specifically, we estimated the following equation:

$$\log(k)_{i1} = \beta_0 + \beta_1 \text{Age}_{i1} + \beta_2 \text{Gender}_{i1} + \beta_3 \text{Education}_{i1} + \beta_4 \text{Income}_{i1} + \beta_5 \text{IncomeShock}_{i1}.$$

The subscript i refers to each individual, while 1 refers to time I. This revealed a significant relationship between income shock and log discounting rate ($\beta = 0.13 \pm 0.03$, $t_{1139} = 4.6$, $p < 10^{-5}$; see **figure 2B**), with greater shock leading to greater discounting rates. The same effect is observed when not controlling for demographics ($\beta = 0.16 \pm 0.029$, $t_{1143} = 5.6$, $p < 10^{-7}$).

We also replicate previous findings (de Wit et al., 2007; Dohmen et al., 2018; Mischel et al., 2011; Reimers et al., 2009; Schlam et al., 2013), showing that greater delay discounting rate is related to less education ($\beta = -0.14 \pm 0.03$, $t_{1139} = -4.6$, $p < 10^{-5}$) and lower income ($\beta = -0.15 \pm 0.03$, $t_{1139} = -5.0$, $p < 10^{-6}$), with a trend relationship to younger age ($\beta = -0.6 \pm 0.03$, $t_{1139} = -1.9$, $p = 0.054$). There was no relationship with gender ($\beta = -0.14 \pm 0.001$, $t_{1139} = -0.33$, $p = 0.74$).

Figure 2. Income shock is related to temporal discounting rates. **A:** For illustration purposes participants were split into those experiencing high income shock in orange (that is those that reported income shock higher than 3, which is the middle of the scale) and low income shock in cyan (<3). Displayed are the proportion of trials in which participants selected the immediate reward over the delayed reward (Y axis) as a function of the days associated with the delayed reward. The orange line is above the cyan line indicating that those experiencing higher income shock were more likely to select immediate rewards over delayed rewards for the same temporal delays. The lines represent the prediction of the hyperbolic model and dots represent observed data. Error bars and shaded areas represents the standard error of the mean. $N = 1,145$. **B:** There was a strong relationship between income shock and the log temporal discounting rate in a model controlling for all demographic variables. In addition, greater temporal discounting rate was also related to less education, low income and a trend relationship with age. Figures show standardized coefficients from a linear model predicting the logged temporal discounting rates. Gender: 1 corresponds to male and 0 to female. $N = 1,145$. **C:** Temporal changes in discounting rates (Y axis) are related to temporal changes in income shock (X axis). The orange line corresponds to the regression line controlling for demographic variables. Error bars correspond to the standard deviation of the mean. $N = 184$. † $p < 0.1$, *** $P < 0.001$

Two hundred of the above participants (103 males, age = 47 ± 15 (mean $\pm$ SD), median yearly income = \$52,500) completed the study again on June 6-7, 2020 as markets were recovering. Collecting data across two timepoints allowed us to (1) test for the replicability of the results observed at time I in an environment which was slightly different, and (2) to test for the effect of income shock longitudinally.

As expected, income shock was significant lower in June (2.9 ± 0.11 , mean $\pm$ SE) relative to March (3.2 ± 0.11 , mean $\pm$ SE; difference = 0.27 ± 0.1 , $t_{183} = 2.6$, $p < 0.01$; **supplementary figure 2D**). There was still a wide range of responses in June, with participants reporting income shock from none (0) to extremely high (6) (see **supplementary figure 2 A and B**). This variance of income shock across individuals and timepoints allowed us to study the effect of income shock on delay discounting cross-sectionally and longitudinally.

Note, that at the second timepoint we asked participants whether the income shock was positive or negative. The vast majority of the participants (92%, $N = 184$) reported a negative shock or no shock with only 8% ($n = 16$) reporting a positive shock. We excluded data from the participants who reported the positive shock as our research question was focused on negative income shock. All results detailed below remain the same regardless of whether these participants were included or not, unless otherwise specified.

Within this smaller subset the delay discounting model still provided a good fit to participants' choices (Time I: pseudo- $R^2 = 0.692 \pm 0.016$ (mean $\pm$ SE); balanced accuracy = 0.883 ± 0.008 (mean $\pm$ SE); Time II: pseudo- $R^2 = 0.875 \pm 0.017$; balanced accuracy = 0.941 ± 0.006 ; see

supplementary figure 3A & B and methods). As above, temporal discounting rates were log transformed to ensure that they follow a normal distribution.

We then estimated a linear model with log discounting rate as the dependent variable and income shock as the independent variable controlling for all demographics (age, gender, education and income) in this subset of participants in each timepoint as done previously. This revealed a significant relationship between income shock and log discounting rate at both timepoints (time I: $\beta = 0.22 \pm 0.072$, $t_{173} = 3.1$, $p = 0.002$; time II: $\beta = 0.31 \pm 0.075$, $t_{173} = 4.2$, $p < 0.0001$; see **supplementary figure 3A, B** for illustration), with greater shock leading to greater discounting rates. The same effect is observed when not controlling for demographics (time I: $\beta = 0.23 \pm 0.071$, $t_{173} = 3.2$, $p = 0.002$; time II: $\beta = 0.31 \pm 0.075$, $t_{173} = 4.1$, $p < 0.0001$). Thus, the results were replicated at time 2. Next, we examined whether changes in income shock across time were related to temporal changes in delay discounting. More specifically, we estimated the following equation:

$$\log(k)_{\Delta t} = \beta_0 + \beta_1 Age_{j1} + \beta_2 Gender_{j1} + \beta_3 Education_{j1} + \beta_4 Income_{j1} + \beta_5 IncomeShock_{j\Delta t}.$$

The subscript j refers to each individual from the subset, while Δt corresponds to the difference of the variable between time II and time I.

Indeed, we found that the greater the increase in income shock an individual experienced, the greater the increase in temporal discounting rates the individual displayed correcting for demographics ($\beta = 0.14 \pm 0.060$, $t_{178} = 2.3$, $p = 0.02$) or not ($\beta = 0.13 \pm 0.055$, $t_{182} = 2.3$, $p = 0.02$; **figure 2C**). Including participants with positive income shock leads to the same results when correcting for demographics ($\beta = 0.12 \pm 0.06$, $t_{194} = 2.1$, $p = 0.04$), and to a trend in the same direction when not correcting for demographics ($\beta = 0.097 \pm 0.053$, $t_{198} = 1.8$, $p = 0.067$).

Thus far, we have shown that income shock led to a highly significant increase in temporal discounting rates across participants, and that temporal changes in income shock were linked to temporal changes in delay discounting, in support of our prediction. Given that income shock was due to an external event (a pandemic) it is more likely that income shock led to greater delay discounting than the other way around.

Negative affect is related to greater delay discounting

Participants reported their emotions (fear, sadness, anger) in the last 24 hours on a Likert scale ranging from 0 (none) to 100 (extremely high). We found that negative emotions were strongly correlated with one another (fear, sadness, anger; all Spearman $\rho > 0.5$, all $p < 10^{-20}$; see **supplementary figure 4A**). We therefore averaged the ratings for negative emotions as a measure of ‘negative affective state’. The mean response in negative affect was 43 ± 25 (Mean $\pm$ SD), suggesting that participants were experiencing negative emotions (see **supplementary figure 4B**). There was large individual variability in participants’ negative affect with individual averaged ratings varying from 0 to 95 (100 being the maximum).

To test whether negative affect was related to temporal discounting rates we conducted a linear regression with log delay discounting as the dependent measure and negative affect as the independent measure, controlling for demographics as above. More specifically, we estimated the equation below:

$$\log(k)_{i1} = \beta_0 + \beta_1 \text{Age}_{i1} + \beta_2 \text{Gender}_{i1} + \beta_3 \text{Education}_{i1} + \beta_4 \text{Income}_{i1} + \beta_5 \text{NegativeAffect}_{i1}.$$

The subscript i refers to each individual, and 1 to time 1.

Replicating previous reports (e.g., Lerner et al., 2013) we found that greater negative emotion was related to greater delay discounting rate ($\beta = 0.07 \pm 0.029$, $t_{1139} = 2.5$, $p = 0.012$; see **figure 3A** for illustration), failing to control for demographics led to a trend: $\beta = 0.055 \pm 0.30$, $t_{1143} = 1.8$, $p = 0.065$). As before in this model delay discounting was greater in participants with less education ($\beta = -0.14 \pm 0.03$, $t_{1139} = -4.6$, $p < 10^{-5}$), lower income ($\beta = -0.17 \pm 0.03$, $t_{1139} = -5.7$, $p < 10^{-7}$) and younger individuals ($\beta = -0.07 \pm 0.03$, $t_{1139} = -2.5$, $p = 0.01$). There was no relationship between gender and delay discounting rate ($\beta = -0.01 \pm 0.03$, $t_{1139} = -0.2$, $p = 0.84$).

Figure 3. Temporal discounting is related to negative affect. **A:** For illustration purposes participants were split to those experiencing high negative affective state in red (≥ 50) and low negative affective state in green (< 50). Displayed are the proportion of trials in which participants selected the immediate reward over the delayed reward (Y axis) as a function of the days associated with the delayed reward. The lines represent the prediction of the hyperbolic model and dots represent observed data. Error bars and shaded areas represents the standard error of the mean. **B:** Figure shows standardized coefficients from a linear model predicting the logged temporal discounting rates when both affect and income shock compete for variance. Logged temporal discounting rate was related to greater negative affect and greater income shock, suggesting both variables independently influence temporal discounting. Gender: 1

corresponds to male and 0 to female. **C:** Figure illustrates the link between income shock and temporal discount rate when negative affective state and demographics are regressed out. Orange line refers to the regression line; dashed lines represent the confidence interval. **D:** Temporal changes in discounting rate (Y axis) are not related to temporal changes in negative affective state (X axis). The red line corresponds to the regression line, controlling for demographic variables (each of the 6 error bars corresponds to a bin of 30 participants). Dashed lines around represent the confidence interval. * $P < 0.05$, *** $P < 0.0001$

Interestingly, in the subset of participants there was no association between affect and temporal discounting in June ($\beta = 0.04 \pm 0.08$, $t_{178} = 0.55$, $p = 0.58$; **supplementary figure 5A and B** for illustration) and only a trend in March ($\beta = 0.14 \pm 0.07$, $t_{178} = 1.9$, $p = 0.063$). Not controlling for demographics led to similar results (March: $\beta = 0.15 \pm 0.07$, $t_{182} = 2.0$, $p = 0.046$; June: $\beta = 0.06 \pm 0.08$, $t_{182} = 0.8$, $p = 0.44$). The lack of relationship in June may be due to the lower overall negative affect participants were feeling or to the relatively smaller N in this sample. Neither was the temporal change in delay discounting related to the temporal change in affect controlling for demographics ($\beta = 0.40 \pm 0.34$, $t_{178} = 1.2$, $p = 0.24$; see **figure 3D**) or not ($\beta = 0.39 \pm 0.32$, $t_{182} = 1.2$, $p = 0.23$).

Thus far, our results suggest that income shock was linked to delay discounting rate across participants in both the full sample and the sub-set, as well as longitudinally, whereas the link between negative affect and delay discounting was only observe across participants in the full sample. This suggest that income shock has a greater impact on temporal discounting than negative affective state and that the effect of negative affect on delay discounting may be driven by an observed variable.

The relationship between income shock and delay discounting is independent of affect

We next ask whether the relationship between income shock and temporal discounting was dependent or independent from affect. To answer this question, we first examined the relationship between negative affect and income shock. To that end, we ran a linear regression with negative affective state as the independent measure, income shock as the dependent measure. More specifically, we estimated the equation below:

$$IncomeShock_{i1} = \beta_0 + \beta_1 Age_{i1} + \beta_2 Gender_{i1} + \beta_3 Education_{i1} + \beta_4 Income_{i1} + \beta_5 NegativeAffect_{i1}.$$

The subscript i refers to each individual, and 1 to time I.

This revealed a marginal positive effect controlling for all demographics as above ($\beta = 0.06 \pm 0.03$, $t_{1139} = 1.9$, $p = 0.05$) or not ($\beta = 0.06 \pm 0.03$, $t_{1139} = 2.0$, $p = 0.04$). Given the association between income shock and affective state we examined if the two are related to delay discounting when entered together in a model to compete for variance. To that end, we conducted a linear regression with temporal discounting rate as the dependent variable, both income shock and affective states as the independent variables and controlling for demographics. More specifically, we estimated the equation below:

$$\log(k)_{i1} = \beta_0 + \beta_1 Age_{i1} + \beta_2 Gender_{i1} + \beta_3 Education_{i1} + \beta_4 Income_{i1} + \beta_5 IncomeShock_{i1} + \beta_6 NegativeAffect_{i1}.$$

The subscript i refers to each individual, and 1 to time I .

Income shock was significantly associated with temporal discounting rate ($\beta = 0.13 \pm 0.03$, $t_{1138} = 4.5$, $p < 10^{-5}$, see **figure 3B&C**) as was affective state ($\beta = 0.07 \pm 0.03$, $t_{1138} = 2.3$, $p = 0.020$; see **figure 3B**). The same patterns are observed when not controlling for demographics (income shock: $\beta = 0.16 \pm 0.03$, $t_{1138} = 5.5$, $p < 10^{-7}$) although here the effect of affect was only a trend ($\beta = 0.05 \pm 0.03$, $t_{1142} = 1.6$, $p = 0.10$). This indicates that the two variables may impact temporal discounting independently, with the strength of the relationship between income shock and delay discounting rate more than double that of the link between negative affect and delay discounting rate.

We next conducted a formal mediation to test whether negative affective state was mediating the effect of income shock on temporal discounting rate. Using a Sobel test on the product of the weight between income shock and affective state and the weight from affective state to temporal discounting rate (denoted α and β respectively), we found that negative affective state did not mediate the effect of income shock on temporal delay discounting regardless of whether we controlled for demographics (Sobel test on $\alpha \cdot \beta = 0.004 \pm 0.002$, $t_{1138} = 1.5$, $p = 0.13$) or not (Sobel test on $\alpha \cdot \beta = 0.003 \pm 0.002$, $t_{1142} = 1.3$, $p = 0.20$).

Finally, we turned to the data from our second timepoint to examine how affect changed between March and June and whether those changes were related to changes in temporal discounting and income shock. As expected, participants experienced significantly less negative emotions in June (median $\pm$ SE: 25.5 ± 1.8), as markets were recovering and unemployment rate decreasing, relative to the same participants in March (median $\pm$ SE: 40.1 ± 2.03 ; difference in timepoints 15.5 ± 1.8 , $t_{183} = 8.6$, $p < 10^{-14}$; **supplementary figure 4C-G**). As in timepoint I , negative emotions were also strongly correlated with one another (fear, sadness, anger; all Spearman $\rho > 0.6$, all $p < 10^{-20}$; see **supplementary figure 4H**) and there was large individual variability in participants' negative affective state. We then examined whether this change in affective state mediated the relationship between the change in income shock and temporal discounting rate. The mediation analysis revealed that it was not – regardless of whether we controlled for demographics (Sobel test on $\alpha \cdot \beta = 0.00008 \pm 0.00098$, $t_{177} = 0.09$, $p = 0.93$) or not (Sobel test on $\alpha \cdot \beta = 0.00087 \pm 0.0055$, $t_{181} = 0.16$, $p = 0.87$). Taken together, these results suggest that the relationship between income shock and delay discounting is not mediated by affect.

Discussion

In this study, we examined how a naturally occurring income shock, which impacted a large diverse population, influenced temporal discounting rate, affect, and their interactions. In particular, we looked at the effect of a real life-threatening situation - the 2020 pandemic - and its actual economic impact at two timepoints. We tested a large representative population in the US in late March 2020 when markets were crashing, and in early June 2020 when markets were recovering.

We found that this naturally occurring income shock was related to larger temporal discounting rates in a diverse population. In particular, individuals reporting greater income shock exhibited higher temporal discounting rates. Moreover, greater negative change in income shock within an individual over time was related to greater increase in discounting rate over time. These results are in line with previous work in which decrease in income was either measured in

specific populations (e.g. Ethiopian famers) or manipulated in the lab (Haushofer et al., 2013; Tanaka et al., 2010; Di Falco et al., 2019).

We were specifically interested in examining whether both income shock and negative affect influenced temporal discounting, and if they do so independently. To study this, we first examined for a relationship between negative affect and delay discounting. Using a real-life threatening situation that impacted a large diverse population, we observe a link between negative affect and greater temporal discounting, in line with studies in which affect was manipulated in the lab (e.g., Lerner et al., 2013). Importantly, however, a mediation analysis revealed that negative affect was not mediating the relationship between income shock and temporal discounting rate. Moreover, when both negative affect and income shock were entered into one model to compete for variance they both predicted temporal discounting rate. This suggest that these two factors independently impact financial temporal discounting rates. That is, changes in affect that are not directly caused by income changes likely alter temporal discounting rates and equivalently changes in income that are not accompanied by an emotional response can alter discounting rates. Note, that we tested temporal discounting in the domain of finance. Future studies are needed to examine whether similar results are observed for temporal choices in other domains such as food or other consumables (Mellis et al., 2018).

Together, our results suggest that income shock leads to an increase in temporal discounting rate independently of negative affect. That is, people directly adapt delay discounting to environmental constraints, without the need of input from the affective system. This may be adaptive as affect is a noisy reflection of environmental constraints, and as such could introduce noise to the decision problem leading to suboptimal behaviour. Instead of being influenced by negative affective state, delay discounting could be primarily determined by liquidity constraints.

Methods

Participants. We tested 1166 individuals between March 26-29, 2020, representative of the US population in terms of age, gender, education, income and ethnicity (see **supplementary figure 1A-D**). The individuals were residing in 30 US states at the time of testing. They completed an online questionnaire on Prolific Academic. We tested participants' engagement and attention by asking them to select a particular answer to various "catch trials" throughout the Survey (for example: *Please select 'strongly disagree'*). Participants who did not select the required response more than once were excluded from analysis (N=21). Thus, data of 1145 participants were analysed (mean age=44.00, SD=15.59; females=52.3%, Democrats=69%, Republicans=31%).

We tested 200 individuals a second time between June 6-7, 2020. Participants from this subsample were representative of the US population in terms of age, gender, education, income, and ethnicity (see **supplementary figure 1E-H**). Participants who reported positive income shock in June were excluded from that analysis. Thus, data of 184 participants were analysed (age=44.00, SD=15.61; females=52.1%). Participants provided informed consent and received £3.75 for their participation. Ethical approval was provided by the Research Ethics Committee at University College London.

Participants completed an online survey which lasted approximately 30 minutes. In addition to the questions that formed this study, additional information was gathered as part of parallel studies conducted by members of our lab (e.g., Globig et al., 2020). These focused mostly on

habits, personality, psychopathology and other opinions regarding the crisis. We detail the additional information gathered in **supplementary material**. Below we detail the information gathered via the online survey which is part of the current study.

Demographics: Participants indicated their age, gender, household income, and education level. Gender was coded as 1 for male and 0 for female.

Negative income shock. We measure negative income shock by asking participants to indicate “What is the impact of COVID-19 on your income?” on the following scale: None (1), Extremely low (2), Low (3), Medium (4), High (5), Extremely high (6).

Negative affective states. Participants indicated on a continuous visual analogue scale ranging from 0 (not at all) to 100 (very much), the emotion they felt in the last 24 hours (fear, sad, angry). For example, “In the last 24 hours have you felt: fear?”.

Delay discounting. We measured delay discounting using the 27-item Kirby questionnaire that has been used with success many times (Kirby et al., 1999). The range of temporal discounting rate this questionnaire is sensitive to varies from 0.00001 to 1. For example, a typical question was “Would you prefer: \$55 today or \$75 in 61 days”.

Additional measures at time II. We added the BIS-BAS questionnaire to test whether income shock affected specifically temporal discounting rate or impulsivity more broadly (Beck et al., 1996). We asked whether income shock was negative, neutral, or positive.

Data analyses. Delay discounting models were fitted to experimental data by minimizing the negative log likelihood of the predicted choice probability given different model parameters using the `fmincon` function in MATLAB (Mathworks Inc.). More specifically, choice probability was computed as follows (using the softmax function (Luce, 1958)):

$$P_{\text{immediate reward}} = \frac{1}{1 + \exp(-\beta(U_{\text{delayed reward}} - U_{\text{immediate reward}}))}$$

where β is a reversed temperature parameter that adjusts the stochasticity of choices.

The utility of each option assumes that reward is discounted by time in a hyperbolic fashion:

$$U_{\text{delayed reward}} = \frac{\text{delayed reward}}{1 + k \times \text{delay}}$$

where k is a free parameter corresponding to the temporal discounting rate. The higher the discount rate, the lower the utility of the discounted reward. Note that for the immediate reward the delay is null and therefore the utility is just equal to the reward. Lower and upper boundaries for temporal discounting rate were 0.0001 and 0.25, respectively, corresponding to the range of recoverable values for such a design.

Parameter recovery analyses were performed to ensure that these model parameters were recoverable given the current experimental design.

All the regressions were estimated using robust regressions (with the MATLAB (Mathworks Inc.) `robustfit` function), which are designed to be robust to violations heteroscedasticity and outliers. The t-tests performed on the parameters were two tailed. Rank correlations were tested following Spearman approach using the MATLAB ‘`corr`’ function.

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Supplementary material

Supplementary figures

Supplementary figure 1. Overview of demographics. Sample (N = 1145) is representative of the US population in terms of (a) Age, (b) Gender, and (c) Education, and (d) Income, as well as the subsample (N = 200, e-h). Participants resided in 30 US States at time of testing.

Supplementary figure 2. A. Income shock, whole dataset at time 1 (N = 1,145). Distribution of the reported income shock on a scale from 1 (no income shock) via 3 (moderate income shock) to 6 (high income shock). The black vertical lines correspond to the median (M = 3). **B-E. Income shock in the data subset (N = 182).** **B & C.** Distribution of the reported income shock on a scale from 1 (no income shock) via 3 (moderate income shock) to 6 (high income shock). The black vertical lines correspond to the median (M = 3). **D.** Temporal correlation of income shock across participants. Income shock at time I is represented on the x axis, while income shock at time II is represented on the y axis. Each dot represents the proportion of participants at the coordinates. The legend represents the sizes corresponding to the minimal, the median and the maximal frequency, respectively. Dashed line the equality line. **E.** average income shock decreased between each timepoint (March 2020 and June 2020 respectively). Error bars correspond to the standard error of the mean. **P<0.01

Supplementary figure 3. Income shock is related to temporal discounting rates in the subset of participants at time I and time II. The left panel corresponds to data collected at time I, and the right panel to data collected at time II. **A&B:** For illustration purposes participants were split to those experiencing high income shock in orange (that is those that reported income shock higher than 3, which is the middle of the scale) and low income shock in cyan (<3). Displayed are the proportion of trials in which participants selected the immediate reward over the delayed reward (Y axis) as a function of the days associated with the delayed reward. The orange line is above the cyan line indicating that those experiencing higher income shock were more likely to select immediate rewards over delayed rewards for the same delays. The lines represent the prediction of the hyperbolic model and dots represent observed data. Error bars and shaded areas represents the standard error of the mean.

Supplementary figure 4. Affective states. **A, C, E:** Self-reported negative emotions for the whole dataset at time I (**A**), for the subsample at time I (**C**), and for the subsample at time II (**E**) are correlated with each other (all Spearman ρ are displayed, all $p < 10^{-20}$). These were averaged, creating a single construct which we refer to as negative affective state. **B, D, F:** Distribution of negative affective state in the population for the whole dataset at time I (**B**), for the subsample at time I (**D**), and for the subsample at time II (**F**). The vertical black line corresponds to the median. **G:** Average negative affective state was reduced over time. Error bars correspond to the standard error of the mean. **H:** Most participants experienced more negative affective states at time 1 than at time 2 although both were correlated, with approximately 70 participants who experienced no or almost no negative affective state at Time 2. **** $p < 10^{-14}$

Supplementary figure 5. Temporal discounting rate is related to negative affect in the subset of participants in Time 1 but not Time 2. A: data collected at time 1 of the subset. **B:** data collected at time 2. For illustration purposes participants were median split into those experiencing high negative affective state in red (≥ 50) and low negative affective state in green (< 50). Displayed are the proportion of trials in which participants selected the immediate reward over the delayed reward (Y axis) as a function of the days associated with the delayed reward (X axis). The lines represent the prediction of the hyperbolic model and dots represent observed data. Error bars and shaded areas represents the standard error of the mean.

Additional information obtained in questionnaire at time 1 (which are part of parallel studies conducted in our lab):

Behavioural Changes. To assess behavioural changes participants were asked to indicate the frequency of face-to-face interaction, online/telephone interaction, physical activity, outdoor activity, visiting places of religious worship before and after the restrictions.

Addictive behaviours. Participants reported frequency of habitual and addictive behaviours including smoking, alcohol consumption, gambling, eating before and after the restrictions.

Psychopathology. Participants completed the Obsessive-Compulsive Inventory – Revised (OCI-R, (Foa et al., 1998), Patient Health Questionnaire (PHQ-9, Kroenke et al., 2001) Apathy Evaluation Scale (AES, (Mann, 1990).

Psychosocial Questionnaires: Participants completed a series of psychosocial questionnaires assessing empathic concern (Davis, 1983), resilience (Smith et al., 2008), narcissism (Leckelt et al., 2018), risk-taking propensity (GRiPS, (Zhang et al., 2019).

Stress Coping. Participants responded on a 5-point Likert Scale from 1 (strongly disagree) to 5 (strongly agree) to the following items: 1) The effects of stress are negative and should be avoided. 2) The effects of stress are positive and should be utilized.

Health Anxiety. Participants were asked to indicate health anxiety on a 5-point Likert Scale from 1 (very inaccurate) to 5 (very accurate): Often I am concerned about diseases I might have.

Non-Conformity. Participants were asked to indicate conformity on a 5-point Likert Scale from 1 (very strong disagreement) to 5 (very strong agreement): I prefer to make my own way in life rather than find and follow.

Social Support and Connectedness. Participants were asked to indicate on a 7-point Likert Scale from 1 (strongly disagree) to 7 (strongly agree): My friends/family give me the support I need. We presented participants with a modified version of the “inclusion of others in the self” scale (Aron et al., 1991).

Anxiety about possible implications of COVID-19. Participants indicated how anxious they were on a scale of 0 (not at all) to 100 (very much): a) “Are you anxious about your own health in light of COVID-19?”; b) “Are you anxious about the health of your loved ones in light of COVID-19?”; c) “Are you anxious about dealing with lockdown in your area?”; d) “Are you anxious about the consequence to your income/savings in light of COVID-19?”; e) “Are you anxious about home-schooling in light of COVID-19?”; f) “Are you anxious about not being able to exercise?”; g) “Are you anxious about not having access to food/medicine/other supplies?”; h) “Are you anxious about not being able to socialize?”

Anxiety. We assessed general anxiety using the short version of the State-Trait Anxiety Inventory (STAI(Marteau & Bekker, 1992)

Happiness. Participants were asked two question to assess their happiness: (i) “Taken all together, how happy are you with your life these days? Mark your rating relative to the least and most happy time of your life.” Participants were asked to respond on a continuous visual analogue scale ranging from 0 (least happy time of your life) to 100 (most happy time of your life). (ii) “Think about right now. How happy are you at this moment?” to respond on a continuous visual analogue scale ranging from 0 (very unhappy) to 100 (very happy).

Relative Private Optimism. Participants were asked to indicate: “Relative to others of your age and gender do you think you are less/more likely to get COVID-19?” on a scale from 1 (much less likely) to 5 (much more likely). Assessing one’s risk relative to others has often been used in the literature as a measure of optimism (Weinstein, 1980). For regressions, mediations and graphs we reverse scored participants’ responses such that high numbers will

indicate high private optimism and low numbers low private optimism (that is a 1 became a 5, a 2 became 4 and so on).

Public Pessimism. Participants were asked to indicate: “Do you think COVID-19 presents a real danger to the health of the human population?” using continuous visual analogue scale from 0 (not really) to 100 (extreme danger). High numbers indicate public pessimism.

Compliance measures. Participants rated on a continuous visual analogue scale ranging from 0 (none at all) to 100 (a lot): a) “How much effort do you make to wash your hands regularly?”; b) “How much effort do you make to socially distance yourself from others?”; c) “How much effort do you make to avoid touching your face?”, as well on a continuous visual analogue scale ranging from 0 (zero) to 100 (many times) d) “In the past week how many times have you been to another person's house ?”; e) How many days this week have you been closer than 1 meter to another person (except those you live with)?”. Items d) and e) were reverse coded to compute a mean score of compliance.

Sense of agency. Participants completed a questionnaire assessing sense of agency(Lachman & Weaver, 1998).