games

Online Appendix

O1. An extend model

In the main text we solved a model where past dilemma decisions affect subsequent dilemma decisions but the DM does not take into account how her actions will affect future dilemma decisions. In this appendix we provide numerical simulations of an extended model where the DM foresees future consequences of her decisions. As in our basic model we show that the consumption path is characterized by compensatory temptation and self-control cycles.

Technically, if the DM is forward looking she maximizes her overall utility given by the sum of the extended utilities plus the continuation value:

$$W_t(M) = \max_{x \in M}[U(x, e_t) + V(x, g_t) + \delta W_{t+1}(M)]$$

where $\delta \in [0,1]$ is the DM's discount factor.

Therefore, the difference with respect to the analysis we present in the main text is that we now solve the model for any $\delta \in [0,1]$. We relegate all the technical details to the next section (Section O2), where we solve the dynamic programming problem and obtain the optimal consumption path. Here we present graphical simulations that allow us to explain the intuition of the results and provide comparative statics analyses.[1] The parameters chosen for the simulations do not intend to be representative of normal real-world phenomenon, but instead emphasize several noteworthy qualitative results of the model.

In the main text we showed that the myopic DM alternates between periods of indulgence, and hence high regret, with periods of restraint, and hence high effort (Proposition 1). We also showed that consumption cycles tend to a steady state when the impact of emotions (ρ) and/or the depreciation rate (λ) are sufficiently high, but increase in amplitude over time otherwise (Corollary 1). Moreover, we showed that the amplitude of these cycles increases with the shift of the available set of alternatives ($|\mu|$) (Corollary 2). In Figure O1 below we can observe the effects of emotions on the consumption path when the DM is forward looking and the available set of alternatives is temptation shifted ($\mu > 0$). In red we have a model where emotions play no role ($\rho = 0$) and in blue we have the case with emotion effects ($\rho > 0$). As we can see, emotions create a non-stationary consumption path.

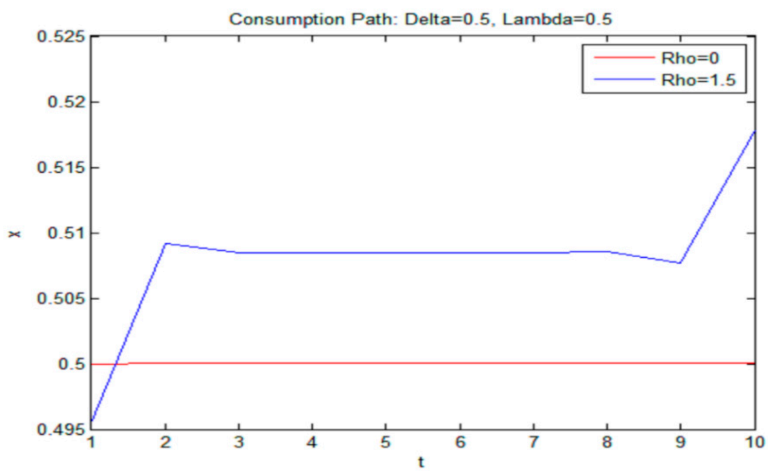

Figure O1. Non-stationary consumption path with emotions ($\rho > 0$) and stationary consumption path with no emotions ($\rho = 0$).

[1] Simulations are done using Matlab 7 software. Matlab codes are available upon request.

This path is affected by the available set of alternatives. When the available set of alternatives is temptation shifted ($\mu > 0$) the effort emotion has a comparatively larger effect, in turn up-regulating the relative power of the temptation preference such that consumption will tend to be closer to one. As we observe in Figure O2 below, if the available set of alternatives is self-control shifted ($\mu < 0$) we have the symmetric effect. Under self-control shifted conditions, the guilt emotion is more important, favoring the self-control preference and driving consumption closer to zero. Whereas, if the available set of alternatives is neutral ($\mu = 0$), both emotions are equally important and consumption is stationary.

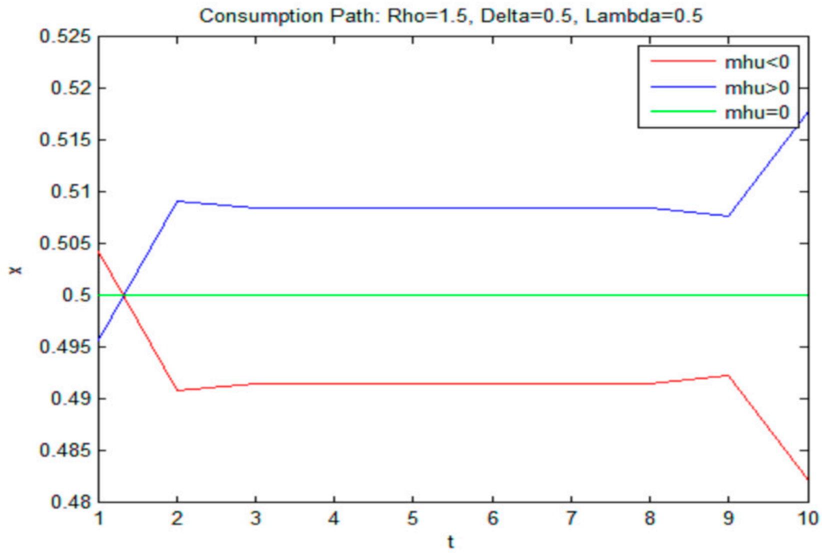

Figure O2. Ecological effects under a self-control shifted ($\mu < 0$), a temptation shifted ($\mu > 0$), and a neutral set of available alternatives ($\mu = 0$).

In the following Figure O3, we compare a myopic DM ($\delta = 0$) with a forward-looking DM ($\delta = 1$) who both have short emotional memories (i.e., remembering only their most recently produced emotions) and a temptation shifted set of available alternatives.

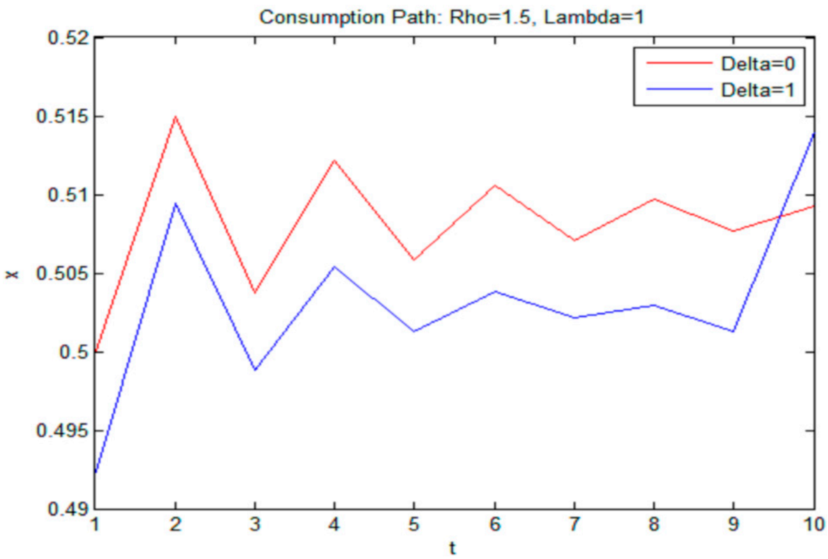

Figure O3. Decision paths under short emotional memory for a myopic DM ($\delta = 0$) and a forward looking DM ($\delta = 1$).

We observe that the consumption path in Figure O3 above follows compensatory indulgence and self-control cycles. Note that a forward-looking DM manages her emotions by keeping guilt low (across all periods but the last) so as to minimize the costs that would otherwise prevent him from yielding to temptation in the last period. In other words, if the DM expects to yield to temptation (increasing x) tomorrow, she practices self-control and minimizes today's consumption (decreasing x) to keep tomorrow's guilt low, thereby making tomorrow's indulgence less costly. Moreover, the difference between consumption in the last and first periods increases with δ, so the more a DM anticipates the future, the larger the change in amplitude between serial consumption choices.

Finally, in Figure O4 we compare a myopic ($\delta = 0$) with a forward-looking ($\delta = 1$) DM. We assume that both have long emotional memories and a temptation shifted alternatives.

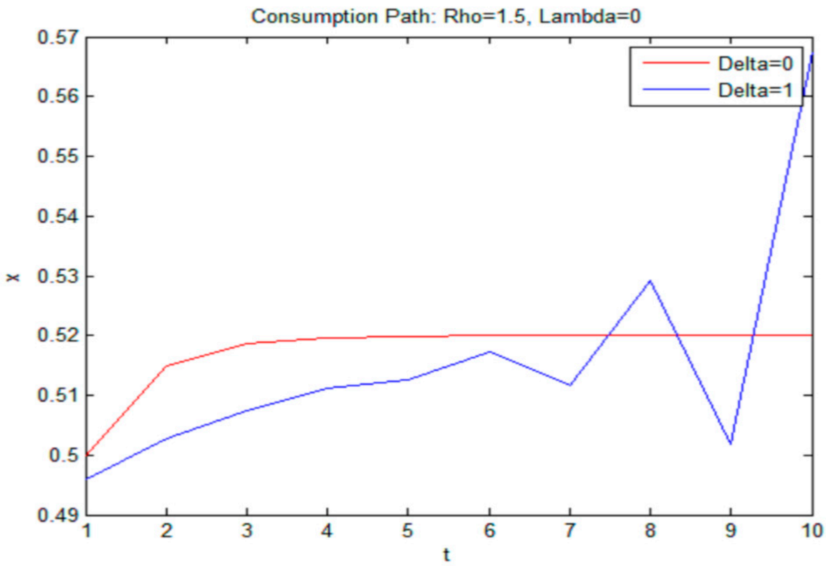

Figure O4. Last period craving effect under long emotional memory for a myopic DM (δ = 0) and a forward looking DM (δ = 1).

In this case, the last period craving effect for the forward-looking DM is even more intense. If the available set of alternatives is temptation shifted, the effort has a greater effect than guilt, so B_T will be high, and hence last period consumption will be close to the temptation preference. As we mentioned before, forward-looking DM tries to minimize the cost of last period guilt by restraining in $T-1$. Here we can see that this effect increases with $(1-\lambda)$ since the higher the emotional memory, the higher the weight of previous emotions on present decisions.

O2. Computation of the Optimal Consumption Path

We know that consumption in the last period is given by $x_T = \frac{1}{2} + \frac{\rho}{4} B_T$. Where B_T is the consequence of previous self-control decisions. Moving backwards and solving $\max_{x \in M} U(x, e_t) + V(x, g_t) + \delta W_{t+1}$ recursively we get the following result summarized in Lemma O1.

Lemma O1. Let us consider $\boldsymbol{\rho} \in [\mathbf{0}, \mathbf{2}]$. Solving the problem recursively we get that for all $\boldsymbol{t} < \boldsymbol{T}$:

$$\boldsymbol{x_1} = \boldsymbol{\beta_1 x_2} + \boldsymbol{\gamma_1} \tag{O1}$$

$$\boldsymbol{x_t} = \boldsymbol{\alpha_t}[\boldsymbol{x_{t-1}} + (\mathbf{1}-\boldsymbol{\lambda})\boldsymbol{x_{t-2}} + \cdots + (\mathbf{1}-\boldsymbol{\lambda})^{\boldsymbol{t-2}}\boldsymbol{x_1}] + \boldsymbol{\beta_t x_{t+1}} + \boldsymbol{\gamma_t} \text{ for all } \boldsymbol{t} \in \{\mathbf{2}, \dots, \boldsymbol{T}-\mathbf{2}\} \tag{O2}$$

$$\text{and } \boldsymbol{x_{T-1}} = \boldsymbol{\alpha_{T-1}}[\boldsymbol{x_{T-2}} + (\mathbf{1}-\boldsymbol{\lambda})\boldsymbol{x_{T-3}} + \cdots + (\mathbf{1}-\boldsymbol{\lambda})^{\boldsymbol{T-3}}\boldsymbol{x_1}] + \boldsymbol{\gamma_{T-1}} \tag{O3}$$

where α_t, β_t and γ_t are recursive functions defined in the proof below.

Proof.

Consumption in period $\boldsymbol{T}$ is given by $\mathbf{x_T} = \underset{\mathbf{x \in M}}{\mathbf{argmax}}\, \mathbf{W_T} = \frac{1}{2} + \frac{\rho}{4}\mathbf{B_T}$. The first order condition (FOC) of the maximization problem in period $\boldsymbol{t} < \boldsymbol{T}$ is given by

$$\frac{dW_t}{dx_t} = 2 - 4x_t + \rho B_t + \delta \frac{dW_{t+1}}{dx_t} = 0 \tag{O4}$$

Plugging x_T in W_{T-1} and taking derivatives we get:

$$\frac{dW_T}{dx_{T-1}} = -\rho\left[\frac{\rho}{2}\left((1-\lambda)B_{T-1} + \mu\right) - (1 - 2x_{T-1})\left(1 - \frac{\rho}{2}\right)\right] \tag{O5}$$

Solving the FOC in period T − 1 we obtain:

$$x_{T-1} = \frac{1}{2} + \left(\frac{\rho\left(B_{T-1}\left(1 - (1-\lambda)\frac{\delta\rho}{2}\right) - \frac{\delta\rho}{2}\mu\right)}{4 + 2\delta\rho\left(1 - \frac{\rho}{2}\right)}\right) \tag{O6}$$

If we keep moving backwards we get that for all t < T

$$x_t = \frac{1}{2} + \left(\frac{\rho\left(B_t\left(1 - (1-\lambda)\frac{\delta\rho}{2}\right) - \frac{\delta\rho}{2}\mu f_t - \delta(1-f_t)(1-2x_{t+1})\right)}{4 + 2\delta\rho\left(1 - \frac{\rho}{2}f_t\right)}\right) \tag{O7}$$

where $f_{T-1} = 1$ and $f_t = \left(\frac{1-(1-\lambda)\frac{\delta\rho}{2}f_{t+1}}{1+\frac{\delta\rho}{2}\left(1-\frac{\rho}{2}f_{t+1}\right)}\right)$ for all $t < T - 1$.

Given the initial emotional balance, B_1=0, we can write emotional balance in period t > 2 as a function of previous consumption decisions:

$$B_t = (1+\mu)\left[\frac{1-(1-\lambda)^{t-1}}{\lambda}\right] - 2\left[x_{t-1} + (1-\lambda)x_{t-2} + \cdots + (1-\lambda)^{t-2}x_1\right] \tag{O8}$$

Therefore, we can rewrite the recursive equations O1 and O2 as:

$$x_1 = \beta_1 x_2 + \gamma_1 \tag{O9}$$

$$x_t = \alpha_t\left[x_{t-1} + (1-\lambda)x_{t-2} + \cdots + (1-\lambda)^{t-2}x_1\right] + \beta_t x_{t+1} + \gamma_t \text{ for all } t \in \{2, \ldots, T-2\} \tag{O10}$$

where $\alpha_t = -\frac{\rho(1-(1-\lambda)\frac{\delta\rho}{2}f_t}{2+\delta\rho\left(1-\frac{\rho}{2}f_t\right)}$, $\beta_t = -\frac{\delta\rho(1-f_t)}{2+\delta\rho\left(1-\frac{\rho}{2}f_t\right)}$ and $\gamma_t = \frac{1}{2} - \frac{\delta\rho\left(\frac{\rho}{2}\mu f_t - (1-f_t)\right)}{4+2\delta\rho\left(1-\frac{\rho}{2}f\right)} - \frac{\alpha_t}{2}(1+\mu)\left[\frac{1-(1-\lambda)^{t-1}}{\lambda}\right]$.

The second order condition (SOC) of the maximization problem in period $t < T$ is given by

$$\frac{d^2W_t}{d^2x_t} = -4 - 2\delta\rho\left[1 - \frac{\rho}{2}\left(\frac{1-(1-\lambda)\frac{\delta\rho}{2}f_t}{1+\frac{\delta\rho}{2}\left(1-\frac{\delta\rho}{2}\left(1-\frac{\rho}{2}f_t\right)\right)}\right)\right] < 0 \tag{O11}$$

Therefore, a sufficient condition for SOC to be satisfied is $\rho \in [0,2]$.

The function contained in Lemma O1 is not a solution in itself but a relation between optimal decisions in different periods: Today´s decision (x_t) is a linear function of past decisions ($x_1, \ldots, x_{t-1}$) and tomorrow´s decision (x_{t+1}). It implies that, consumption in two adjacent periods are substitutes. Hence, an increase in a DM's current consumption decreases their future consumption.

In order to get the solution, note that we can plug $x_1(x_2)$ in $x_2(x_1, x_3)$ and solve the resulting equation to get $x_2(x_3)$. If we keep doing this we get x_t as a function of x_{t+1}:

$$\boldsymbol{x_t} = \frac{\boldsymbol{k_t} + \boldsymbol{\gamma_t} + \boldsymbol{\beta_t x_{t+1}}}{\mathbf{1} - \boldsymbol{\alpha_t \beta_{t-1} h_t}} \text{ for all } \boldsymbol{t} \in \{\mathbf{2}, \dots, \boldsymbol{T} - \mathbf{2}\} \tag{O12}$$

where $h_t = \left(\frac{1+\beta_{t-2}(1-\lambda)h_{t-1}}{1-\alpha_{t-1}\beta_{t-2}h_{t-1}}\right)$ and $k_t = \alpha_t\left(h_t(k_{t-1}+\gamma_{t-1}) + (1-\lambda)\left(\frac{k_{t-1}}{\alpha_{t-1}}\right)\right)$

Now we can use $x_{T-1} = \frac{k_{T-1}+\gamma_{T-1}}{1-\alpha_{T-1}\beta_{T-2}h_{T-2}}$ which is a known scalar, and find the optimal decision path following the transition.