Appendix for Online Publication
Waiting to Choose: The Role of Deliberation in Intertemporal Choice
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A. Relationship between Deliberation Time and Intertemporal Choice

In this section, we derive predictions of a simplified version of the imperfect foresight model of Gabaix and Laibson (2017) for our setting.

Hypothesis 3: Consider a decision-maker (DM) chooses between (u_0^E, u_1^L) and (u_0^L, u_1^E). For all $i \in \{E, L\}$, u_0^i, is received immediately and u_1^i is received in the following period. The DM knows the value of u_0^i with certainty, but lacks perfect information on the 'true' value of u_1^i and must generate simulations to forecast it. In the context of the first two studies, let (u_0^L, u_1^E) represent the utility from choosing to have only leisure time in WP1 such that all effort tasks are allocated to WP2, and (u_0^E, u_1^L) represent the utility of having only leisure in WP2 such that all effort tasks are allocated to WP1. We consider the case where the DM faces a tradeoff of allocating tasks to WP2, such that she has to do more total tasks when she chooses (u_0^L, u_1^E) than (u_0^E, u_1^L). Thus, $u_0^L = u_1^L > u_0^E > u_1^E$. We refer to the (u_0^E, u_1^L) as the patient choice and (u_0^L, u_1^E) as the impatient choice.

Following Gabaix and Laibson (2017), normalize the DM's prior on u_1^i to zero such that $u \sim N(0, \sigma_u^2)$. This can be interpreted as the average utility that could be realized in WP2 given the choice set available to the DM. We consider the case where waiting periods prompt additional simulations relative to when no waiting periods. When the DM performs her first simulation of u_1^i, she draws an unbiased signal of its value $s_{1,1}^i = u_1^i + \epsilon_{1,1}$, where the first term in the subscript $(1,1)$ corresponds to the time horizon and the second to the order of the signal drawn. The simulation noise $\epsilon_{1,1}$ is drawn from $\epsilon_1 \sim N(0, \sigma_{\epsilon_1}^2)$. Since we only consider a one-period time horizon, $\sigma_{\epsilon_1}^2 = \sigma_\epsilon^2$.[42] As a Bayesian, she integrates this signal with her prior. The DM's posterior forecast of u_1^i can be represented as $Ds_{1,1}^i$, where $D = \frac{1}{1+\sigma_\epsilon^2/\sigma_u^2}$. Integrating over the distribution of signals, we get $E_1(u_1^i) = Du_1^i$.

Before the initial simulation, the DM values the patient choice as u_0^E and the impatient choice as u_0^L, and thus prefers the impatient choice. After the first simulation, the average DM values the patient choice as $u_0^E + Du_1^L$ and the impatient choice as $u_0^L + Du_1^E$. Because $u_1^L > u_1^E$, it is straightforward to show that the DM's valuation of the patient choice increases after the initial simulation.

To illustrate how successive simulations increase the valuation of the patient choice relative to the impatient choice, let the DM draw a second signal $s_{1,2}^i = u_1^i + \epsilon_{1,2}$. She again updates her beliefs and obtains the posterior

$$Ds_{1,1}^i + D(s_{1,2}^i - Ds_{1,1}^i) = D(1-D)s_{1,1}^i + Ds_{1,2}^i \tag{A1}$$

[42] This is consistent with a one-period simulation under the proportional variance assumption of Gabaix and Laibson (2017), $\sigma_{\epsilon_t} = t \cdot \sigma_\epsilon$.

from Proposition 1 of Gabaix and Laibson (2017). Integrating over the distribution of signals, we get

$$E_2(u_1^i) = D(1-D)u_1^i + Du_1^i = D(2-D)u_1^i \quad . \tag{A2}$$

To illustrate the result, take a DM who is indifferent between the two choices after an initial simulation, such that her forecasted utility in expectation can be represented as

$$u_0^E + E_1(u_1^L) = u_0^L + E_1(u_1^E) \tag{A3}$$

After the second simulation, the left hand side becomes $u_0^E + E_2(u_1^L)$ and the right hand side becomes $u_0^L + E_2(u_1^E)$. The change in valuation of the patient choice is thus the change in the expectation of u_1^L: $D(2-D)u_1^L - Du_1^L = D(1-D)u_1^L$. Correspondingly, the change in the value of the impatient choice is $D(1-D)u_1^E$. The difference in changes between the patient and impatient choices is $D(1-D)(u_1^L - u_1^E)$. Because $D \in (0,1)$, and $u_1^L > u_1^E$, the expression is positive, meaning that relative preference for the patient choice has increased. Therefore, the DM who was indifferent after one simulation – and thus preferred the impatient choice before any simulations – selects the patient option after two simulations.

More generally, define $\gamma(N) \in [0,1]$ as the relationship between deliberation time, N, and simulation noise γ, with $\gamma'(N) < 0$. The Bayesian updating factor becomes an "as-if" discount factor $D(N) = \frac{1}{1+\gamma(N)\alpha}$ where $\alpha = \frac{\sigma_\epsilon^2}{\sigma_u^2}$. Because $\gamma(N)$ is decreasing in N, $D(N)$ is decreasing in N, and additional simulations lead the decision maker closer to forecasting $u_1^L = u_0^L > u_0^E > u_1^E$ without noise, implying $(u_0^E, u_1^L) \succ (u_0^L, u_1^E)$.[43]

B. Structural Estimation in the Online Effort Allocation Study

In this section, we discuss estimates of the utility parameters from equations (1), (2) and (3). Since participants make allocation decisions between two periods, each treatment on its own only reveals their one-hour discount factor for task effort. Because the timing of the work periods and the allocation decision differs by treatment, the variation in the theoretical interpretation of that discount factor allows us to identify the parameters of interest. Specifically, the treatments were designed to separately identify aggregate estimates of the exponential discount factor δ, the present bias parameter β, and the simulation parameter $S_k(t)$. The parameter $S_k(t)$ is meant to capture the effect of additional simulations of the decision problem prompted by the waiting period. In the application of the Gabaix and Laibson (2017) framework outlined in Section I.A, the parameter can be represented as $S_k(t) = \frac{D_k(t)}{D_{k+1}(t)}$. Given the short horizon and the fact that

[43] Sincere thanks to an anonymous referee for helpful, detailed comments on this section.

our experiment manipulates the waiting period over only one interval, we drop the subscripts for the analysis, setting $S_k(t) = S$.

Our identification strategy is as follows. Participants in the Waiting Period treatment solve the optimization problem in equation (2), as laid out in Section I.A. We allow for present bias, such that the discount factor between periods is equal to $\frac{D_1(1)}{D_1(0)} = \beta\delta$. Participants in the Immediate treatment solve a similar problem, shifted back by one period as in equation (1). The parameter S identifies any additional discounting that occurs in the Immediate treatment that does not occur in the Waiting Period treatment. Therefore, the discount factor in the Immediate treatment can be represented as $\frac{D_0(1)}{D_0(0)} = S\beta\delta$. We obtain an estimate of S as the ratio of the Immediate discount factor to the Waiting Period discount factor.

Participants in the Commit treatment maximize equation (3). At $t = 0$, subjects allocate tasks between $t = 1$ and $t = 2$. Because choices are made in the absence of a waiting period, the discount factor can be represented as $\frac{D_0(2)}{D_0(1)} \approx S\delta$.[44] In turn, we obtain an estimate of β as the ratio of the Immediate discount factor to the Commit discount factor.

Call z_1 tasks allocated to Work Period 1 and z_2 tasks allocated to Work Period 2 and r the the interest rate by which undone tasks grow. The general convex intertemporal allocation decision in our study is

$$\text{(B1)} \qquad \min_{z_1,z_2} U(z_1, z_2) = z_1^\gamma + \delta_T z_2^\gamma \quad \text{s.t.} \quad z_1 + \frac{z_2}{1+r} = 40 \quad .$$

γ is the instantaneous disutility of effort parameter, and δ_T is a treatment-specific discount factor (constructed linearly using indicator variables), which we map to the parameters of interest with the across-treatment comparisons mentioned above.

We make two additional adjustments to allow for more flexibility in our model of effort cost. First, we add background parameters ω_1 and ω_2 to the tasks required in each period to represent other effort that might need to be expended during those time periods. Second, we allow for the possibility of less-than complete recovery after Work Period 1 with another background effort parameter, ω_3, that enters as a coefficient on z_1 in the Work Period 2 effort level. The utility function is thus

$$\text{(B2)} \qquad U(z_1, z_2) = (z_1 + \omega_1)^\gamma + \delta_T(z_2 + \omega_2 + \omega_3 z_1)^\gamma \quad .$$

[44]This is an approximation. Since the variance in forecasts of future utility is increasing in their time horizon, the as-if discounting that occurs in the Commit treatment is between one and two periods in the future, whereas in the Immediate treatment, it is between one period in the future and the present, which is subject to no uncertainty. Assuming a linear increase in simulation variance and time period, which leads to a hyperbolic as-if discount factor, the S in Commit is slightly closer to one than the S in Immediate. Our estimate of β is thus a lower bound on the quasi-hyperbolic discount factor.

We use the solution to the utility maximization problem to set up a maximum-likelihood estimation. The supply of tasks in Work Period 1 is

$$z_1^* = \frac{40A(1+r) + \omega_2 A - \omega_1}{1 + A(1+r) - \omega_3 A} \quad , \tag{B3}$$

where $A = \left(\delta_T(1+r-\omega_3)\right)^{\frac{1}{\gamma-1}}$. Individuals, i, solve this problem for each choice, j, and select the nearest available option subject to a standard normal error term, $\epsilon_{i,j}$, such that

$$z_{1,(i,j)} - \frac{40A_t(1+r_j) + \omega_2 A_j - \omega_1}{1 + A_j(1+r_j) - \omega_3 A_j} + \epsilon_{i,j} = 0 \quad , \tag{B4}$$

where $z_{1,(i,j)}$ is our observed choice for period 1 tasks by person i on task j. The likelihood associated with that observation is

$$\phi\left(z_{1,(i,j)} - \frac{40A_j(1+r_j) + \omega_2 A_j - \omega_1}{1 + A_j(1+r_j) - \omega_3 A_j}\right) \tag{B5}$$

When subjects select corner solutions from the convex choice sets, the convex first order conditions may poorly approximate choices. Therefore, we assume censoring at each corner as in a Tobit model. If $z_{1,(i,j)} = 0$, then we assume that

$$\epsilon_{i,j} > \frac{40A_j(1+r_j) + \omega_2 A_j - \omega_1}{1 + A_j(1+r_j) - \omega_3 A_j} \quad , \tag{B6}$$

and the likelihood contribution is

$$\Phi\left(-\frac{40A_j(1+r_j) + \omega_2 A_j - \omega_1}{1 + A_j(1+r_j) - \omega_3 A_j}\right) \quad . \tag{B7}$$

If $z_{1,(i,j)} = 40$, then we assume that

$$\epsilon_{i,j} < \frac{40A_j(1+r_j) + \omega_2 A_j - \omega_1}{1 + A_j(1+r_j) - \omega_3 A_j} - 40 \quad , \tag{B8}$$

and the likelihood contribution is

$$\Phi\left(\frac{40A_j(1+r_j) + \omega_2 A_j - \omega 1}{1 + A_j(1+r_j) - \omega_3 A_j} - 40\right) \quad . \tag{B9}$$

In our two binary choice tasks, subjects simply select the smaller value between

$(40{+}\omega_1)^\gamma$ and $\delta_T(40(1{+}r){+}\omega_2)^\gamma$. We make the standard Probit model assumption that the difference between the two utilities is subject to a normal distribution. Thus the probability of observing all work in the first period is

$$Pr(z_{1,(i,j)} = 40) = Pr((40 + \omega_1)^\gamma - \delta_T(40(1 + r_j) + \omega_2)^\gamma + \epsilon_{i,j} < 0) = \Phi(\delta_T(40(1 + r_j) + \omega_2)^\gamma - (40 + \omega_1)^\gamma) \tag{B10}$$

and the probability of observing all work in the second period is

$$Pr(z_1 = 0) = Pr((40 + \omega_1)^\gamma - \delta_T(40(1 + r_t) + \omega_2)^\gamma + \epsilon_{i,j} > 0) = \Phi((40 + \omega_1)^\gamma - \delta_T(40(1 + r_j) + \omega_2)^\gamma). \tag{B11}$$

These probabilities are used to construct the likelihood function. In the estimation, we impose the restrictions that $\gamma > 0$ and that $\omega_1, \omega_2, \omega_3 > 0$ to prevent degenerate results (by replacing these parameters with $exp()$ of themselves). With these constraints in place, we also specify the "nonrtolerance" option in order to permit convergence when the parameter vector and/or likelihood become stable near the boundary of the restriction, rather than search for a global maximum. One consequence of this is that minor differences in the standard errors of the estimated parameters may emerge across machines using different numbers of processors, operating systems, and versions of Stata, as documented by StataCorp.[45] Please see our replication package Imas, Kuhn and Mironova (2021) for more detail. We initialize the estimation at values of 0.95 for all treatment-specific discount factors, $ln(\gamma)$ at 0.25 ($\gamma \approx 1.28$), and all ω values at $ln(\omega) = -1$ ($\omega \approx 0.37$).

We estimate $\gamma = 1.255$ (S.E. = 0.047), indicating increasing marginal disutility of performing the counting task. There is no evidence on any background effort level in Work Period 1 ($\omega_1 = 0$), but there is evidence of background effort in Work Period 2 ($\omega_2 = 4.711$, S.E. = 2.455). Additionally there is some evidence of effort spillover across period ($\omega_3 = 0.253$, S.E. = 0.017). We estimate treatment-specific discount factors of $D_I = 0.968$ (S.E. = 0.071), $D_{WP} = 1.151$ (S.E. = 0.113), $D_C = 1.062$ (S.E. = 0.087), and $D_{DC} = 0.878$ (S.E. = 0.061). The very short time horizon means that we should expect very little discounting. Indeed, discount factors D_I, D_W, D_C do not significantly differ from one ($p = 0.65, 0.18$ and 0.48, respectively); only the Delay Control estimate D_{DC} does ($p = 0.05$). Estimates of S and β are discussed in the text.

C. Tables

[45] `https://www.stata.com/support/faqs/windows/results-in-different-versions/`

Table C1—Effects of Treatments on Doing All Tasks in Work Period 1 on Convex Task Allocations, Probit Models, Online Study

Sample:	Convex Choices					Binary Choices	
Interest rate:	50%	25%	12.5%	0%	All	-12.5%	2.5%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Waiting Period	0.284	0.346	0.346	0.155	0.274	-0.133	-0.008
	(0.142)	(0.134)	(0.134)	(0.117)	(0.111)	(0.126)	(0.058)
Commit	0.000	0.031	0.062	-0.000	0.023	-0.062	0.040
	(0.125)	(0.125)	(0.125)	(0.122)	(0.114)	(0.123)	(0.084)
Delay Control	0.002	0.031	0.031	-0.115	-0.011	-0.269	-0.085
	(0.127)	(0.127)	(0.127)	(0.133)	(0.112)	(0.123)	(0.032)
Constant	0.531	0.469	0.469	0.375	0.461	0.562	0.938
	(0.089)	(0.089)	(0.089)	(0.086)	(0.082)	(0.088)	(0.043)
$\chi^2_1(H_0 : \text{WP} = \text{C})$	4.20	5.18	4.20	1.53	4.84	0.30	0.43
$\chi^2_1(H_0 : \text{WP} = \text{DC})$	4.03	5.04	5.04	4.22	6.50	1.02	1.26
$\chi^2_1(H_0 : \text{C} = \text{DC})$	0.00	0.00	0.06	0.82	0.10	2.54	1.86
N	122	122	122	122	488	122	122

Note: Coefficients are the marginal effects of each treatment on the probability a subject allocates all tasks to WP1. In columns (1)-(4) and (6)-(7), robust standard errors are reported in parentheses below each estimate. In column (5), standard errors clustered at the individual level are reported in parentheses below each estimate. The hypothesis tests report the chi-square statistics associated with tests of equality between the treatment effects, where WP stands for Waiting Period, C stands for Commit and DC stands for Delay Control.

Table C2—Effect of Treatment on Doing All Tasks in Work Period 1 on Convex Task Allocations, Probit Models, Lab Study

Sample:	Convex Choices					Binary Choices	
Interest rate:	50%	25%	12.5%	0%	All	-12.5%	2.5%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Waiting Period	0.259	0.338	0.250	0.171	0.258	-0.105	-0.029†
	(0.098)	(0.070)	(0.093)	(0.097)	(0.044)	(0.086)	
Constant	0.342	0.237	0.316	0.316	0.303	0.763	1.000†
	(0.078)	(0.069)	(0.076)	(0.076)	(0.037)	(0.069)	
N	72	72	72	72	288	72	72

Note: Coefficients are the marginal effects of each treatment on the probability a subject allocates all tasks to WP1. In columns (1)-(4) and (6)-(7), robust standard errors are reported in parentheses below each estimate. In column (5), standard errors clustered at the individual level are reported in parentheses below each estimate.
† : All subjects in the Immediate treatment allocated 40 tasks to WP1 on this budget, versus 97.1% in Waiting Period. The marginal effect estimation fails due to a lack of variation. We instead place the IT mean in the constant row, and the difference in means between WPT and IT in the Waiting Period coefficient row.

Table C3—Effect of Treatment on Convex Task Allocations to Work Period 1, Lab & Field Studies

Interest rate:	50%	25%	12.5%	0%	All
	(1)	(2)	(3)	(4)	(5)
Waiting Period	4.936	5.635	4.796	3.047	4.604
	(1.362)	(1.442)	(1.464)	(1.824)	(1.339)
Constant	31.257	30.171	30.171	28.114	29.929
	(1.125)	(1.100)	(1.084)	(1.217)	(1.014)
N	132	132	132	132	528

Note: All estimates from OLS models. In columns (1)-(4), bootstrapped standard errors from 1000 replications are reported in parentheses below each estimate, to adjust for non-normality of the error distribution. Output is reproducible with a seed of 1. In column (5), standard errors clustered at the individual level are reported in parentheses below each estimate.

Table C4—Observable Balance across Treatments, DRC Study

Variable	Immediate	Waiting Period	Difference
Female	0.41	0.42	-0.01
Age	30.90	30.59	0.31
Secondary education or beyond	0.79	0.77	0.02
Has children	0.69	0.75	-0.05
Employed	0.44	0.39	0.06
Unimportance of religion (1-4 scale)	3.52	3.55	-0.03
Distance from city center (1-3 scale)	1.57	1.61	-0.04
Feels safe at home (1-4 scale)	2.34	2.53	-0.20
Access to food (1-4 scale)	2.39	2.39	0.00
Access to clean water (1-4 scale)	2.40	2.29	0.11
Access to medical care (1-4 scale)	2.05	2.13	-0.08
Access to shelter (1-4 scale)	2.36	2.40	-0.04
Access to phone network (1-4 scale)	2.66	2.40	0.26
Life got better last year (1-5 scale)	3.04	3.14	-0.10
Expects life better next yr. (1-5 scale)	3.72	3.73	-0.01
Not afraid to take risks (1-4 scale)	3.03	3.12	-0.09
Feels in control of life (1-4 scale)	2.32	2.23	0.08
Worries about future (1-4 scale)	2.74	2.88	-0.14
Plans for next week (1-4 scale)	3.10	3.13	-0.04
Trusts others (1-4 scale)	2.38	2.55	-0.17
Close to community (1-4 scale)	2.94	3.05	-0.11
Property damage due to conflict	0.46	0.50	-0.04
Direct exposure to violence during war	0.38	0.30	0.08

Note: The "Feels safe at home" and "Access to phone network" differences have $p < 0.10$. None of the other differences are statistically significant.

Table C5—Impact of Waiting Period on Likelihood of Minimum-value Coupon Redemption, Full Results

Model:	OLS	Probit
	(1)	(2)
Waiting Period	-0.166	-0.243
	(0.048)	(0.082)
Food Access	-0.020	-0.020
	(0.044)	(0.045)
Food Access X Waiting Period	0.013	0.013
	(0.050)	(0.066)
Distance from Store	0.037	0.037
	(0.060)	(0.058)
Distance from Store X Waiting Period	-0.000	0.038
	(0.069)	(0.087)
Trust in Others	-0.003	-0.003
	(0.041)	(0.039)
Trust in Others X Waiting Period	0.014	0.022
	(0.048)	(0.066)
Risk Tolerance	-0.020	-0.020
	(0.044)	(0.042)
Risk Tolerance X Waiting Period	0.067	0.133
	(0.050)	(0.077)
Constant	0.250	0.250
	(0.037)	(0.038)
N	258	252

Note: Coefficients from Probit models are the marginal effects associated with switching from the Immediate to Waiting Period treatment. Robust standard errors are reported in parentheses below each estimate. Food access, trust in others and risk tolerance are all measured on 1-4 scales, and distance from the store is measured on a 1-3 scale. All control variables are de-meaned. We lose six observations with the addition of control variables due to incomplete survey responses.

D. Sample Experiment Instructions

Both the online and laboratory studies were run using the Qualtrics platform. All .qsf files are available in Imas, Kuhn and Mironova (2021) in the AEA Data and Code Repository.

Sample Task

To continue, please complete the two example tasks below.

0	0	0	1	1	0	1	0	1	0	1	1	1	1	0
1	0	0	1	0	1	0	0	0	1	1	1	1	1	1
1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
1	1	1	0	0	0	1	1	0	1	0	0	0	0	1
1	1	1	1	1	0	1	0	1	1	1	1	1	0	1
0	1	0	0	0	0	1	1	0	0	1	1	1	1	0
1	0	0	1	0	0	0	0	1	0	0	1	1	0	1
0	1	1	0	1	0	1	0	1	0	1	0	1	0	1
1	0	0	1	1	0	1	0	0	1	0	0	0	0	1
1	1	1	0	1	1	1	0	0	1	1	1	1	1	1

Example Table 1

How many zeros are in the table above?

0	0	1	0	1	1	0	1	1	1	0	0	1	1	0
0	1	0	0	0	0	1	1	1	0	0	0	0	0	0
1	1	0	0	1	1	0	1	1	0	0	1	1	0	0
0	0	0	1	0	1	1	1	1	0	0	0	0	1	1
1	0	1	1	0	0	1	0	1	1	0	1	0	1	1
0	1	1	1	1	0	1	0	0	0	1	1	0	0	0
0	0	0	1	1	0	0	1	1	1	1	0	1	0	0
0	0	0	0	1	0	0	0	1	0	0	1	0	0	1
0	1	1	0	1	1	1	0	1	1	1	1	1	0	0
1	1	0	1	1	1	0	0	0	0	1	0	1	0	0

Example Table 2

How many zeros are in the table above?

>>

Immediate Treatment

To finish the study and earn your payment, you will be given a choice about how many tasks to do and when to do them. The study is broken up into two work periods. Work Period 1 will begin immediately after you make a choice and will last for approximately 1 hour. Work Period 2 begins directly after that and also lasts for approximately 1 hour.

You will be given a choice of how many tasks to do in each work period.

If you choose not to work during a work period or if you finish your tasks early within a work period, you have free time for the rest of the work period. The program is timed in such a way that you cannot advance to the next work period until the full hour has elapsed. Once you finish the tasks you chose to complete in a work period, you can spend the rest of the time in the period however you want. For example, you can open another browser window and surf the internet, read a book, study, etc. Once the one hour ends, the next work period will begin. Here you will work on the number of tasks you chose to complete in that period.

Once Work Period 2 is over, you will have one additional hour of free time. After this, we will give you a brief survey to complete.

>>

Waiting Period Treatment

To finish the study and earn your payment, you will be given choices about how many tasks to do and when to do them. We will first describe the choices to you. You will then have an hour to think about the choices and are free to do whatever you want to pass the time at your lab station. The one restriction is that you cannot communicate with others.

At the end of the hour you will be asked to make choices of how many tasks to do in each of the two work periods. Work Period 1 will begin after you make a choice and will last for approximately 1 hour. Work Period 2 begins directly after that and also lasts for approximately 1 hour.

You will be given a choice of how many tasks to do in each work period.

For example, you may be faced with a choice between:

Option A) 10 tasks in Work Period 1 and 0 tasks in Work Period 2
Option B) 5 tasks in Work Period 1 and 6 tasks in Work Period 2
Option C) 0 tasks in Work Period 1 and 12 tasks in Work Period 2

If you choose not to work during a work period or if you finish your tasks early within a work period, you have free time for the rest of the work period. The program is timed in such a way that you cannot advance to the next work period until the full hour has elapsed. Once you finish the tasks you chose to complete in a work period, you can spend the rest of the time in the period however you want. For example, you can open another browser window and surf the internet, read a book, study, etc. Once the one hour ends, the next work period will begin. Here you will work on the number of tasks you chose to complete in that period.

Once Work Period 2 is over, you will have a brief survey to complete.

You have a variety of options for how many tasks you need to do in Work Period 1 (starting immediately after your choices) and Work Period 2 (starting in approximately 1 hour).

Each column in the table below represents one option. For example, Option A involves doing 0 tasks in Work Period 1 *and* 60 tasks in Work Period 2. Option B involves doing 4 tasks in Work Period 1 *and* 54 tasks in Work Period 2, etc.

PERIOD	**TASK OPTIONS**										
	A	B	C	D	E	F	G	H	I	J	K
WORK PERIOD 1 - IMMEDIATELY	0	4	8	12	16	20	24	28	32	36	40
WORK PERIOD 2 - IN 1 HOUR	60	54	48	42	36	30	24	18	12	6	0

Please examine the table above and choose your preferred option by putting the letter of the option into the box below.

My preferred option is: