A NEUROECONOMIC ANALYSIS OF INTERTEMPORAL DECISION-MAKING: EEG SOURCE LOCALIZATION

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DECLARATION OF ORIGINALITY

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ABSTRACT

A Neuroeconomic Analysis of Intertemporal Decision-Making: EEG Source Localization

Using EEG, we studied the neural correlates of intertemporal decision making when subjects made binary choices between smaller/earlier and larger/later money amounts for 40 trials. We analyzed EEG data by using preprocessing and source localization. Then, we used multiple logit models with neural data or behavioral data to explain participants' responses. In behavioral analysis, we got expected results which is consistent with economic literature and previous studies. When early (late) reward increases, people are more likely to choose early (late) reward. Also, we found that when if early option is today, people are more likely to choose early option. In neural analysis, we observed that there exist two separate systems like McClure et al. (2004) fMRI study. In addition to some regions (lateral prefrontal cortex, posterior parietal cortex, primary visual and motor cortices) which McClure et al. (2004) identified in their study, we found that activations (or deactivations) of superior temporal gyrus, supramarginal gyrus, anterior prefrontal cortex, orbitofrontal cortex, fusiform gyrus, angular gyrus, and middle temporal gyrus are significantly correlated with the responses for at least one epoch of the pre-decision period.

ÖZET

Zaman Kavramı İçeren Ekonomik Karar Alma Süreçlerinin EEG Kaynak Belirlemesi Metodu Kullanılarak Nöroekonomik Açıdan İncelenmesi

EEG makinesi kullanarak 10 öğrencinin beyinlerindeki elektriksel aktivasyonu onlar 40 ayrı az/yakın ve çok/uzak iki para miktarı arasında seçimler yaparken gözlemleyip kaydettik. Bu EEG datasını inceleyerek kullanılabilir hale getirdik. Elde ettiğimiz bu beyinsel bilgileri veya deneyde elde ettiğimiz davranışsal bilgileri kullanarak Logit regresyon modelleri yardımıyla kişilerin seçimlerini açıklamaya çalıştık. Deneysel analizlerimizde; beklediğimiz ve günümüz ekonomi modelleri ile uygun sonuçlar elde ettik. Eğer yakın (uzak) zaman seçeneğindeki paranın miktarı artarsa, kişilerin yakın (uzak) olanı seçmeye meyilleri daha artmaktadır. Ayrıca, eğer yakın zaman seçeneğindeki paranın bugün ödenmesi öngörülüyorsa, kişiler yakın olan seçeneği seçmeye daha meyilli olmaktadırlar. Beyinsel analizlerimizde; McClure et al. (2004) fMRI deneyinde bulduğu gibi karar alma mekanizmasında ikili bir sistemin olduğunu bulduk. Ayrıca, McClure et al. (2004) tarafından tespit edilen beyin bölgelerinden başka superior temporal gyrus, supramarginal gyrus, anterior prefrontal cortex, orbitofrontal cortex, fusiform gyrus, angular gyrus, ve middle temporal gyrus gibi bölgelerdeki elektriksel aktivasyonun artmasının ya da azalmasının da kişilerin karar alma sürecinde kararlarına etki ettiğini bulduk.

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CHAPTER 1

INTRODUCTION

Life is made of waiting; therefore, almost all human actions include intertemporal decision making.

In order to model intertemporal decision mathematically, Paul Samuelson (1937) proposed discounted utility model. Although Samuelson did not support the DU model as a normative model of intertemporal decision, the DU model was accepted instantly and has dominated economic analyses of intertemporal choice because of the simplicity and elegance of formulation. This model is also called exponential discounting function. DU model has time consistency property. If a person has time consistent utility function, he always obeys his earlier decision about future.

$U_t = u_t + \delta u_{t+1} + \delta^2 u_{t+2} + \delta^3 u_{t+3} + \delta^4 u_{t+4} ...$

$\delta \in [0, 1]$. δ exponentially discounts all periods.

However, over the years, empirical studies on intertemporal choice showed that DU model does not represent real world cases accurately. There exist some anomalies such as discount rates are not constant over time and preference reversals.

In his study, Richard Thaler (1981) asked that ”You won some money in a lottery. You can take the money now or wait until later. How much money you would require to make waiting just as attractive as getting the money now?” to subjects. He showed that people’s discount rates decrease when time horizon increase. This means that people do not have exponential discounting functions.

Benzion, Rapoport, and Yagil (1989) conducted economic experiments with 208 university economics or finance students which were well familiar with the basic of economic theory of discount rate. They found that people’s discount rates decrease when time horizon increase.

Similarly, Kirby (1997) made economic experiments in the context of a sealed, second-bid auction. His study showed that people's discount rates decrease when time horizon increase, and hyperbolic discounting function fit the bids better than exponential discounting function.

Kirby and Herrnstein (1995) made series of experiments to test preference reversals which is someone may prefer 110 TL in 31 days over 100 TL in 30 days, but also prefer 100 TL now over 110 TL tomorrow. They offered choices between delayed rewards, while manipulating the delays to those rewards. They observed that most of the subjects (34 out of 36) reversed their preferences. They concluded that exponential discounting function is not appropriate to model intertemporal human decisions.

Strotz (1955) stated that people are often willing to pay a price to pre-commit future actions. If people have exponential discounting function, they do not need pre-commitments because they follow what they decide earlier. This shows that maybe we should consider alternatives to exponential discounting. However, he did not propose any specific alternative functional forms.

To incorporate the significance of immediate utilities, Laibson (1997) proposed the quasi-hyperbolic discounting model (or Beta-Theta model). This functional form was originally proposed by Phelps and Pollak (1968) to study intergenerational altruism. Later, O'Donoghue and Rabin (1999) simplified the Beta-Theta model. This model simply says that today is more valuable than future. Quasi-hyperbolic discounting model has time inconsistency property. If a person has time inconsistent utility function, whether he obeys his earlier decision about future or not. For example, assume that a student has two days until final exam and he has two options which are studying and watching movie for each day. Also, assume that watching movie gives higher utility than studying. In day 1, he made decisions which he will watch movie today but he will study tomorrow. If a student has time consistent utility function, he will study in day 2. However, if a student has time inconsistent utility function, he will watch movie in day 2. Since watching movie gives higher utility than studying.

$U_t = u_t + \beta\delta u_{t+1} + \beta\delta^2 u_{t+2} + \beta\delta^3 u_{t+3} + \beta\delta^4 u_{t+4} \ldots$

$\delta, \beta \in [0, 1]$. δ exponentially discounts all periods. β uniformly discounts all future periods.

McClure, Laibson, Loewenstein, and Cohen (2004) conducted fMRI experiments to examine the neural correlates of time discounting. They monitored brain activations of subjects while they made a series of choices between monetary reward options that varied by delay to delivery. They demonstrated that two separate systems are involved in such decisions. Parts of the limbic system associated with the midbrain dopamine system, including paralimbic cortex, are preferentially activated by decisions involving immediately available rewards. In contrast, regions of the lateral prefrontal cortex and posterior parietal cortex are engaged uniformly by intertemporal choices irrespective of delay.

McClure, Ericson, Laibson, Loewenstein, and Cohen (2007) replicated McClure et al. (2004) fMRI study by using primary rewards such as water and juice. Also, they used time delays of minutes instead of weeks. Thirsty subjects made a series of choices between small volumes of drinks delivered at precise times during the experiment. They recorded activations of subjects' brains during experiment by using fMRI. They found similar and consistent results with their previous study.

In our study, we replicated McClure et al. (2004) paper by using EEG instead of fMRI. We tried to answer the question that ”Do other brain regions, which McClure et al. (2004) could not detect in their study, engage in intertemporal decision making?” Since EEG has higher temporal resolution than fMRI.

In section 2, we explained our experimental design. In section 3, we clarified how we analyzed EEG data. In section 4, we detailed all of our analyses and results. In section 5, we stated limitations of our study. In section 6, we discussed our results comprehensively.

CHAPTER 2

EXPERIMENTAL DESIGN

The EEG experiments were conducted by Prof. Burak Güçlü in a sound- and vibration-proof booth in the Institute of Biomedical Engineering, Bogaziçi University, Istanbul. Ten participants made binary choices between smaller/earlier and larger/later money amounts (e.g. 11.19 TL to be received today versus 16.79 TL to be received after two weeks) for 40 trials (see Appendix A). Every participant encountered with same question for each trial. We especially chose decimal numbers for money amounts in order to prevent instant answers.

All participants were university students and the experiments adhered to the tenets of the Declaration of Helsinki for testing humans. We obtained approvals from the ethics committees of Bogaziçi University and the University of Chicago. Also, we took informed consent from each participant.

In our experiment; possible earlier times are today, after two weeks and after four weeks. Possible later times are after two weeks, after four weeks and after six weeks. Possible time duration between earlier and later times are two weeks and four weeks.

We started EEG acquisition with the presentation of the offer and ended with the response. We measured scalp potentials by 19 gold-plated, 9-mm disk electrodes placed according to the standard 10 - 20 system. In order to correct for ocular artifacts, we placed 7 additional electrodes around the eyes (Croft & Barry, 2000).

The responder viewed the computer monitor through a window and entered behavioral responses by pressing keys. We amplified the scalp potentials by a clinical EEG/polysomnography system (model L59b; Sagura Medizintechnik GmbH, Mhlheim am Main Germany) and recorded on a computer. We performed experimental control, data acquisition, and preprocessing in MATLAB (The MathWorks, Natick, MA, USA). We used standard personal computers for the analyses including source localization. We also recorded response time of each trial.

At the end of the experiment, we randomly selected three trials, and we paid their payments based on their earnings and time preferences from these trials.

CHAPTER 3

EEG DATA ANALYSIS

In EEG data analyses, we followed same procedure which Güçlü, Ertaç, Hortaçsu, and List (2012) applied in their study.

We applied preprocessing and source localization to EEG data successively. Preprocessing was the first step to prepare the raw scalp-potential data for source localization. We held a calibration session on a different day before experiment to obtain data which we used to eliminate eye movements from EEG data. We corrected ocular artifacts by the technique described in Croft and Barry (2000). We band-pass filtered (1 - 70 Hz) the resulting EEG time series with a zero-phase, non-causal digital filter to discarding unwanted frequency components. Also, we eliminated first and last few ms of EEG data. Since opening and closing of EEG machine causes signal pollution. We segmented EEG data into 125-ms intervals.

Next, we put segmented EEG time series into independent component analysis (ICA) in EEGLAB (Delorme & Makeig, 2004). We found nineteen independent components by using the JADE algorithm (Cardoso & Souloumiac, 1993), which has been previously helpful for clinical EEG studies (Iriarte et al., 2005). JADE does not apply stochastic gradient descent, and heuristic tuning of parameters is not required; therefore, it produces identical results (i.e., deterministic) if a run is repeated. We performed source localization on independent components by the DIPFIT plug-in of EEGLAB based on the standard boundary-element model from the Montreal Neurological Institute (Oostendorp & van Ooestrom, 1989). The source localization found the locations and moments of the dipoles which generated the independent components of preprocessed scalp potentials. These dipoles correspond to the gross electrical activity of large populations of neurons and show regions of the brain which activated or deactivated during the task. We saved only dipoles with residual variance lower than 15 percent for further analyses. We normalized magnitudes of the dipole moments by dividing each by the mean dipole moment magnitude of a given participant. We identified each dipoles anatomical region by Talairach coordinates. We excluded dipoles (2 %) localized in subcortical structures (e.g., thalamus, caudate nucleus) from subsequent analyses. If we found less than 500 dipoles from one brain region from all participants, we excluded dipoles from this brain region. Remaining dipoles (72,433) represented time averaged brain activity in every 125-ms segment of each acquisition. They were spread across 12 different anatomical regions.

CHAPTER 4

RESULTS

4.1 Behavioral Results

In order to modeling behavioral results, we used multiple logit model which is utilized as a special type of statistical model when dependent variable is binary.

$$r = f(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \gamma_4 x_4 + \sum_{j=1} \alpha_j t_j)$$

where r is response (if agent chooses early reward, r = 0. Similarly, if agent chooses late reward, r = 1.); x_1 is dummy variable for today (if early option is today in a trial, x_1 = 1) ; x_2 is amount of early reward ; x_3 is amount of late reward ; x_4 is dummy variable for delay between early reward and late reward (if delay is 4 weeks in a trial, x_4 = 1) ; t_j is the time period indexed by j (i.e., early, middle, and late trials within an experimental session). γ_0 is the intercept, and γ, α are the coefficients of parameters. We clustered standard errors for each subject in a regression.

We observe that coefficients of today (-0.775), early reward (-0.539) and late reward (0.496) are statistically significant at 0.05 confidence level (see Table 1).

Therefore, as we expected, if early option is today, people are more likely to choose early option. When early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. However, we cannot find any significant relationship between delay difference and responses.

When we removed nuisance variables which are periodphase parameters from regression, we observe that coefficients of early reward (-0.533) and late reward (0.489) are statistically significant at 0.05 confidence level.

Table 1. Behavioral Results

	(1)	(2)
VARIABLES	response	response
today_dummy	-0.775**	-0.493
	(0.363)	(0.473)
early_reward	-0.539***	-0.533***
	(0.0766)	(0.0736)
late_reward	0.496***	0.489***
	(0.0690)	(0.0669)
delay_dummy	-0.773	-0.650
	(0.503)	(0.473)
periodphase_2	0.636*	
	(0.376)	
periodphase_3	0.252	
	(0.258)	
Constant	-2.541***	-2.325***
	(0.505)	(0.468)
Observations	400	400
Pseudo R-squared	0.374	0.369

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2 Simulation

We wanted to know that can we obtain our behavioral results from using parameter values which are mainly accepted in mainstream economic theory. We assume that people have CRRA utility function.

$U(C) = (C^{1-r} - 1)/(1 - r)$

The parameter r measures the degree of relative risk aversion in the utility function.

Arrow et al. (1996) found that reasonable estimate of r value is 1.5 or less.

Layard, Mayraz, and Nickell (2008) used four large cross-sectional surveys of subjective happiness and two panel surveys to estimate r value. Their data collected from over 50 countries in between 1972 and 2005. Their overall estimated r value is 1.26 (their highest estimation is 1.34 and their lowest estimation is 1.19).

Gandelman and Hernandez-Murillo (2015) used data on self-reports of personal well-being from the 2006 Gallup World Poll for 75 countries to estimate r values at country level. Their estimated r values are in between 0 and 3. For example; they found that r=1.39 for US, r=1.21 for Switzerland, r=1.43 for France, r=1.55 for Belgium, r=0.77 for Germany, r=0.27 for South Korea, r=0.10 for Netherlands, r=1.85 for Azerbaijan, r=1.13 for Chile, r=0.65 for Russia, r=1.29 for South Africa, r=0.63 for Brazil, r=0.04 for Zimbabwe, r=2.95 for Uzbekistan.

Many empirical studies found that annual discount factor (δ) is between 0.02 and 0.99 (Frederick, Loewenstein, & Odonoghue, 2002). When we converted these annual discount rates to weakly discount rates, we found that δ is between 0.93 and 0.99.

Laibson, Repetto, and Tobacman (2007) estimated β value as 0.703 using a structural buffer stock consumption model and the Method of Simulated Moments.

We observed that participants chose later options in only 76 out of 400 trials. Therefore, if simulation always chooses early option, it can predict %81 of total responses. We observed that when r = 2, our model always chooses early option. Similarly, when r = 1.5 or 1.2 and $\gamma < 0.99$, our model always chooses early option. Although it seems that our model predicts well, it does not have any predictive power in these cases. Also, when r = 0.1, our model has poor predictive power. Our model has highest predictive power when γ = {0.93, 0.96} and r = {0.3, 0.6, 0.9} or γ = {0.99} and r = {1.2, 1.5} (see Table 2) .

Table 2. Simulation Results

	$r = 2$	$r = 1.5$	$r = 1.2$	$r = 0.9$	$r = 0.6$	$r = 0.3$	$r = 0.1$
$\beta = 0.6$, $\delta = 0.99$	0.81	0.775	0.705	0.665	0.62	0.545	0.545
$\beta = 0.6$, $\delta = 0.96$	0.81	0.81	0.81	0.83	0.795	0.745	0.705
$\beta = 0.6$, $\delta = 0.93$	0.81	0.81	0.81	0.81	0.84	0.83	0.795
$\beta = 0.7$, $\delta = 0.99$	0.81	0.775	0.705	0.665	0.62	0.545	0.54
$\beta = 0.7$, $\delta = 0.96$	0.81	0.81	0.81	0.83	0.795	0.745	0.705
$\beta = 0.7$, $\delta = 0.93$	0.81	0.81	0.81	0.81	0.84	0.83	0.795
$\beta = 0.8$, $\delta = 0.99$	0.81	0.775	0.705	0.665	0.615	0.565	0.55
$\beta = 0.8$, $\delta = 0.96$	0.81	0.81	0.81	0.83	0.795	0.74	0.7
$\beta = 0.8$, $\delta = 0.93$	0.81	0.81	0.81	0.81	0.84	0.83	0.79
$\beta = 0.9$, $\delta = 0.99$	0.81	0.775	0.705	0.66	0.625	0.515	0.5
$\beta = 0.9$, $\delta = 0.96$	0.81	0.81	0.81	0.83	0.79	0.77	0.7
$\beta = 0.9$, $\delta = 0.93$	0.81	0.81	0.81	0.81	0.84	0.825	0.795

4.3 Neural results from all trials

If a given anatomical region included more than one dipole in a 125-ms segment, we summed the normalized moment magnitudes of the dipoles to make up one stronger dipole instead. We entered regions with no activity as zero. This resulted in 13498 dipole entries including all participants and trials.

We took average of 125-ms segment dipoles magnitudes for each people and each trial. This resulted 400 dipole entries (10 people * 40 trials).

In order to explain peoples responses, we used multiple logit model.

$$r = f(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \gamma_4 x_4 + \sum_{i=1} \beta_i y_i + \sum_{j=1} \alpha_j t_j)$$

where r is response (if agent chooses early reward, r = 0. Similarly, if agent chooses late reward, r = 1.); x_1 is dummy variable for today (if early option is today in a trial, x_1 = 1) ; x_2 is amount of early reward ; x_3 is amount of late reward ; x_4 is dummy variable for delay between early reward and late reward (if delay is 4 weeks in a trial, x_4 = 1) ; y_i denotes the moment magnitude of the dipole associated with the region indexed by i; t_j is the time period indexed by j (i.e., early, middle, and late trials within an experimental session). γ_0 is the intercept, and γ, β, α are the coefficients of parameters. We clustered standard errors for each subject in a regression.

We observe that coefficients of today (-1.481), early reward (-0.912), late reward (0.848), anterior prefrontal cortex (0.885), somatosensory association cortex (2.262), supramarginal gyrus (-1.465) and angular gyrus (6.741) are statistically significant at 0.05 confidence level (see Appendix B).

Therefore, as we expected, if early option is today, people are more likely to choose early option. When early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. When, on average, electrical activations in anterior prefrontal cortex, somatosensory association cortex and angular gyrus increase, people are more likely to choose late reward. When, on average, electrical activation in supramarginal gyrus increases, people are more likely to choose early reward.

4.4 Neural results from trials which early option is today

If a given anatomical region included more than one dipole in a 125-ms segment, we summed the normalized moment magnitudes of the dipoles to make up one stronger dipole instead. We entered regions with no activity as zero. This resulted in 13498 dipole entries including all participants and trials.

We took average of 125-ms segment dipoles magnitudes for each people and each trial. This resulted 400 dipole entries (10 people * 40 trials). Then, we excluded trials which early option is not today.

In order to explain peoples responses, used multiple logit model.

$$r = f(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \sum_{i=1} \beta_i y_i + \sum_{j=1} \alpha_j t_j)$$

where r is response (if agent chooses early reward, r = 0. Similarly, if agent chooses late reward, r = 1.); x_1 is amount of early reward ; x_2 is amount of late reward ; x_3 is dummy variable for delay between early reward and late reward (if delay is 4 weeks in a trial, x_3 = 1) ; y_i denotes the moment magnitude of the dipole associated with the region indexed by i; t_j is the time period indexed by j (i.e., early and other trials within an experimental session).

γ_0 is the intercept, and γ, β, α are the coefficients of parameters. We clustered standard errors for each subject in a regression.

We observe that coefficients of delay difference (-2.713), somatosensory association cortex (1.700), supramarginal gyrus (-2.911), fusiform gyrus (-3.822) and angular gyrus (4.336) are statistically significant at 0.05 confidence level (see Appendix B).

Therefore, when early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. When delay difference increases, people are more likely to choose early reward.

When, on average, electrical activations in somatosensory association cortex and angular gyrus increase, people are more likely to choose late reward.

When, on average, electrical activations in supramarginal gyrus and fusiform gyrus increases, people are more likely to choose early reward.

4.5 Temporal dynamic neural results from all trials

If a given anatomical region included more than one dipole in a 125-ms segment, we summed the normalized moment magnitudes of the dipoles to make up one stronger dipole instead. We entered regions with no activity as zero. This resulted in 13498 dipole entries including all participants and trials.

In order to study the temporal dynamics, we divided the dipole data into sixteen epochs in a trial with average median epoch duration of 240 ms. We took average of 125-ms segment dipoles magnitudes for each people, each trial and each epoch. This resulted 400 dipole entries (10 people * 40 trials) for each epoch. We run independent multiple logit regression for each epoch.

In order to explain people's responses, used multiple logit model.

$$r = f(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \gamma_4 x_4 + \sum_{i=1} \beta_i y_i + \sum_{j=1} \alpha_j t_j)$$

where r is response (if agent chooses early reward, r = 0. Similarly, if agent chooses late reward, r = 1.); x_1 is dummy variable for today (if early option is today in a trial, x_1 = 1) ; x_2 is amount of early reward ; x_3 is amount of late reward ; x_4 is dummy variable for delay between early reward and late reward (if delay is 4 weeks in a trial, x_4 = 1) ; y_i denotes the moment magnitude of the dipole associated with the region indexed by i; t_j is the time period indexed by j (i.e., early, middle, and late trials within an experimental session). γ_0 is the intercept, and γ, β, α are the coefficients of parameters. We clustered standard errors for each subject in all regressions.

We observe that coefficients of today are -1.445, -1.791, -0.878, -1.008, -0.928, -1.225 and -1.034 are statistically significant with responses at 0.05 confidence level in third, fourth, sixth, eighth, ninth, fifteenth, sixteenth regressions respectively (see Appendix C).

We observe that coefficients of early reward are always negative. They are statistically significant with responses at 0.05 confidence level in all regressions.

We observe that coefficients of late reward are always positive. They are statistically significant with responses at 0.05 confidence level in all regressions.

We observe that coefficients of Dorsolateral Prefrontal Cortex are always negative. They are statistically significant with responses at 0.05 confidence level in all regressions.

We observe that coefficients of Somatosensory Association Cortex are always positive. They are statistically significant with responses at 0.05 confidence level in all regressions.

We observe that coefficients of Primary Somatosensory Cortex are -0.780, -0.898, -0.996, -0.734, -0.884, -0.776 and -0.616 are statistically significant with responses at 0.05 confidence level in first, third, eighth, ninth, tenth, fifteenth and sixteenth regressions respectively.

We observe that coefficients of Supramarginal Gyrus are -0.492, -0.399, -0.475, -0.283 and -0.336 are statistically significant with responses at 0.05 confidence level in fifth, sixth, seventh, tenth and sixteenth regressions respectively.

We observe that coefficient of anterior prefrontal cortex is 0.327 is statistically significant with responses at 0.05 confidence level in eleventh regression.

We observe that coefficient of Superior Temporal Gyrus is 0.376 is statistically significant with responses at 0.05 confidence level in third regression.

We observe that coefficients of Middle Temporal Gyrus are -1.298 and 0.620 are statistically significant with responses at 0.05 confidence level in second and fourth regressions respectively.

We observe that coefficients of Associative Visual Cortex are -0.534 and -0.456 are statistically significant with responses at 0.05 confidence level in tenth and eleventh regressions respectively.

We observe that coefficient of fusiform Gyrus is 0.531 is statistically significant with responses at 0.05 confidence level in eighth regression.

We observe that coefficients of Angular Gyrus are 1.290, 0.784 and 0.546 are statistically significant with responses at 0.05 confidence level in fourth, fifth and sixth regressions respectively.

We observe that coefficients of Premotor Cortex are -1.124, -1.695, 0.635 and -1.693 are statistically significant with responses at 0.05 confidence level in second, fourth, eighth and thirteenth regressions respectively.

Therefore, as we expected, when early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward.

Although today variable is not significant in all epochs, still we can say that if early option is today, people are more likely to choose early option.

When electrical activation in somatosensory association cortex increases in any epoch, people are more likely to choose late reward.

When electrical activation in dorsolateral prefrontal cortex increases in any epoch, people are more likely to choose early reward.

Since Primary somatosensory cortex is negatively correlated with response in most of epochs, we can say that When electrical activation in Primary somatosensory cortex increases in any epoch, people are more likely to choose early reward.

When electrical activation in supramarginal gyrus increases in middle epochs, people are more likely to choose early reward.

When electrical activation in superior temporal gyrus increases in early epochs, people are more likely to choose late rewards.

Since middle temporal gyrus is negatively correlated with response in second epoch, but it is positively correlated with response in fourth epoch. It is hard to explain overall relation between response and middle temporal gyrus.

When electrical activation in associative visual cortex increases in middle epochs, people are more likely to choose early reward.

When electrical activation in angular gyrus increases in middle epochs, people are more likely to choose late reward.

When electrical activation in premotor cortex increases in early or late epochs, people are more likely to choose early reward.

When electrical activation in fusiform gyrus increases in middle epochs, people are more likely to choose late reward.

When electrical activation in anterior prefrontal cortex increases in middle epochs, people are more likely to choose late reward.

4.6 Temporal dynamic neural results from trials which early option is today

If a given anatomical region included more than one dipole in a 125-ms segment, we summed the normalized moment magnitudes of the dipoles to make up one stronger dipole instead. We entered regions with no activity as zero. This resulted in 13498 dipole entries including all participants and trials.

In order to study the temporal dynamics, we divided the dipole data into sixteen epochs in a trial with average median epoch duration of 240 ms. We took average of 125-ms segment dipoles magnitudes for each people, each trial and each epoch. This resulted 400 dipole entries (10 people * 40 trials) for each epoch. Then, we excluded trials which early option is not today. We run independent multiple logit regression for each epoch.

In order to explain peoples responses, used multiple logit model.

$$r = f(\gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \sum_{i=1} \beta_i y_i + \sum_{j=1} \alpha_j t_j)$$

where r is response (if agent chooses early reward, r = 0. Similarly, if agent chooses late reward, r = 1.); x_1 is amount of early reward ; x_2 is amount of late reward ; x_3 is dummy variable for delay between early reward and late reward (if delay is 4 weeks in a trial, x_3 = 1) y_i denotes the moment magnitude of the dipole associated with the region indexed by i; t_j is the time period indexed by j (i.e., early and other trials within an experimental session).

γ_0 is the intercept, and γ, β, α are the coefficients of parameters. We clustered standard errors for each subject in all regressions.

We observe that coefficients of early reward are always negative. They are statistically significant with responses at 0.05 confidence level in all regressions except second and sixth regressions (see Appendix D).

We observe that coefficients of late reward are always positive. They are statistically significant with responses at 0.05 confidence level in all regressions except second and sixth regressions.

We observe that coefficients of delay difference are always negative. They are statistically significant with responses at 0.05 confidence level in all regressions except second, fourth, seventh and eleventh regressions.

We observe that coefficients of dorsolateral prefrontal cortex are -1.033, -1.162, -1.899, -0.655, -0.550 and -0.430 are statistically significant with responses at 0.05 confidence level in third, fifth, eighth, ninth, thirteenth and sixteenth regressions respectively.

We observe that coefficients of anterior prefrontal cortex are -2.625 and -0.905 are statistically significant with responses at 0.05 confidence level in eighth and ninth regressions respectively.

We observe that coefficients of primary somatosensory cortex are -1.640, -5.496, -4.289, -9.000, -2.402, -1.287 and -2.691 are statistically significant with responses at 0.05 confidence level in first, second, fifth, eighth, ninth, fourteenth and fifteenth regressions respectively.

We observe that coefficients of somatosensory association cortex are 0.640, 1.076, 2.815, 0.595, 1.737, 1.096, 1.657, 1.240, 2.782 and 1.209 are statistically significant with responses at 0.05 confidence level in first, fourth, sixth, seventh, eighth, eleventh, twelfth, thirteenth, fifteenth and sixteenth regressions respectively.

We observe that coefficients of orbitofrontal cortex are -5.299, -11.99, -8.463 and -1.852 are statistically significant with responses at 0.05 confidence level in third, fifth, eighth and thirteenth regressions respectively.

We observe that coefficients of supramarginal gyrus are -3.290, -2.770, -1.540, -0.537, -2.169 and -1.272 are statistically significant with responses at 0.05 confidence level in fifth, eighth, eleventh, twelfth, thirteenth and sixteenth regressions respectively.

We observe that coefficients of superior temporal gyrus are 1.154, -2.390, -3.237 and -2.940 are statistically significant with responses at 0.05 confidence level in third, fifth, sixth and ninth regressions respectively.

We observe that coefficients of middle temporal gyrus are -13.64, 0.982 and -8.709 are statistically significant with responses at 0.05 confidence level in third, fourth and eighth regressions respectively.

We observe that coefficients of associative visual cortex are 1.162, -2.747, -1.395, -0.681 and -0.662 are statistically significant with responses at 0.05 confidence level in sixth, eighth, ninth, tenth and thirteenth regressions respectively.

We observe that coefficients of fusiform gyrus are -1.416 and 1.152 are statistically significant with responses at 0.05 confidence level in sixth and fourteenth regressions respectively.

We observe that coefficients of angular gyrus are -2.494, 2.919 and 1.963 are statistically significant with responses at 0.05 confidence level in eighth, thirteenth and sixteenth regressions respectively.

We observe that coefficients of premotor cortex are -27.63, -15.27 and 3.169 are statistically significant with responses at 0.05 confidence level in third, thirteenth and fifteenth regressions respectively.

Therefore, as we expected, when early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward.

When delay difference increases, people are more likely to choose early reward.

Since dorsolateral prefrontal cortex is negatively correlated with response in some of epochs, we can say that when electrical activation in dorsolateral prefrontal cortex increases in any epoch, people are more likely to choose early reward.

When electrical activation in anterior prefrontal cortex increases in early or middle epochs, people are more likely to choose early reward.

Since primary somatosensory cortex is negatively correlated with response in most of epochs, we can say that When electrical activation in primary somatosensory cortex increases in any epoch, people are more likely to choose early reward.

Since somatosensory association cortex is positively correlated with response in most of epochs, we can say that When electrical activation in somatosensory association cortex increases in any epoch, people are more likely to choose late reward.

When electrical activation in Orbitofrontal cortex increases in early epochs, people are more likely to choose early reward.

Since supramarginal gyrus is negatively correlated with response in middle or late epochs, we can say that when electrical activation in supramarginal gyrus increases in middle or late epochs, people are more likely to choose early reward.

Although superior temporal gyrus is positively correlated in third epoch, we may say that When electrical activation in superior temporal gyrus increases in middle epochs, people are more likely to choose early reward.

When electrical activation in middle temporal gyrus increases in early epochs, people are more likely to choose early reward. However, when electrical activation in middle temporal gyrus increases in late epochs, people are more likely to choose late reward.

Although associative visual cortex is negatively correlated in sixth epoch, we may say that When electrical activation in associative visual cortex increases in middle or late epochs, people are more likely to choose early reward.

When electrical activation in fusiform gyrus increases in middle epochs, people are more likely to choose early reward. However, when electrical activation in fusiform gyrus increases in late epochs, people are more likely to choose late reward.

When electrical activation in angular gyrus increases in late epochs, people are more likely to choose late reward.

When electrical activation in premotor cortex increases in early or middle epochs, people are more likely to choose early reward. However, when electrical activation in premotor cortex increases in late epochs, people are more likely to choose late reward.

CHAPTER 5

LIMITATIONS

There are three major weaknesses of this study.

Firstly, although EEG measures neural activity more directly than fMRI, EEG data needs more sophisticated analysis to became usable data. There exist several methods for preprocessing and source localization of EEG data. We used one of the most popular and accepted methods which we explained in previous sections exhaustively for preprocessing and source localization. If we used other methods, we might find slightly different dipole results.

Secondly, subject number is ten in our experiment. Ten people seems very low number of people for economic experiment, but ten participants are higher than typical for neuroscience experiments. Also, our experiment consisted of 40 trials. Therefore, our sample size (400) is enough for making econometric analysis.

Finally, there exists asymmetry in our dipole data. We found that some brain regions are activated mostly in one participant. In this case, the neat solution is to increase number of participants, but we could not increase number of subjects. However, we took several averages before making regressions. This method solves asymmetry problem partly.

CHAPTER 6

DISCUSSION

Since we took several averages of dipole data before regressions, values of coefficients are not meaningful, but signs of coefficients are meaningful for our analyses.

In behavioral analysis, we get expected results which is consistent with economic literature and previous studies. When early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. Since mainstream economic theory assumes that people have increasing and locally non-satiated utility functions. When offer's monetary value increases, it becomes more attractive to people.

Also, we found that if early option is today, people are more likely to choose early option. This is very important finding for our assumption which people have hyperbolic discounting functions because it supports our assumption.

We put brain regions as independent parameters into our regression analyses. However, all brain regions are connected with each other. This may cause multicollinearity in our regressions. Since interconnection of brain regions is biological phenomena, we cannot solve multicollinearity problem.

Our knowledge about functions of brain regions are not complete. To date, researchers found that dorsolateral prefrontal cortex is related with cognitive control of behavior, decision making and working memory; anterior prefrontal cortex is related with strategy; primary somatosensory cortex is related with tactile stimulation of the skin surface; somatosensory association cortex is related with visuo-motor coordination ; orbitofrontal cortex is related with reward and emotion aspects of decision making; supramarginal gyrus is related with processing and perception of language; superior temporal gyrus is related with auditory processing and comprehension of language; middle temporal gyrus is related with face recognition and understanding meaning of words; associative visual cortex is related with processing of visual information; fusiform gyrus is related with recognition of word, number and face and processing of color information; angular gyrus is related with mathematical calculations, spatial recognition and language related complex functions such as reading, writing and interpretation; premotor cortex is related with direct control of behavior and movement (Kandel, Schwartz, & Jessell, 2000).

In neural analyses, we made two different econometrical analysis for average neural dipoles and finer temporal resolution neural dipoles.

In average neural analyses, when we put all dipoles into regression, we found same results with our behavioral analysis. When early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. When if early option is today, people are more likely to choose early option. Also, we found that anterior prefrontal cortex, somatosensory association cortex, supramarginal gyrus and angular gyrus are significantly correlated with responses.

When we put only dipoles which early option is today into regression, we found that when delay difference increases, people are more likely to choose early reward. However, we found that somatosensory association cortex, supramarginal gyrus, fusiform gyrus, and angular gyrus are significantly correlated with responses.

In these two regressions, signs of somatosensory association cortex, supramarginal gyrus, and angular gyrus do not change.

In finer temporal resolution neural analyses, we divided all dipoles and only dipoles which early option is today into 16 epochs for each. We did 16 independent regressions for these two dipole types.

When we put all dipoles into regressions, we found same results with our previous analysis. When early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. We found these results for each epoch. If early option is today, people are more likely to choose early option. However, we found this result for most of the epochs. Also, we found that dorsolateral prefrontal cortex and somatosensory association cortex are significantly correlated with responses for all or most of the epochs on the other hand supramarginal gyrus, primary somatosensory cortex, anterior prefrontal cortex, fusiform gyrus, superior temporal gyrus, middle temporal gyrus, associative visual cortex, angular gyrus and premotor cortex are significantly correlated with responses for at least one of the epochs. Signs of significant coefficients are mostly same in these regressions for each brain region. However, we observed that sign of one significant coefficient of premotor cortex and middle temporal gyrus changed.

When we put only dipoles which early option is today into regressions, still we found that when early reward increases, people are more likely to choose early reward. Similarly, when late reward increases, people are more likely to choose late reward. We found these results for each epoch except two epochs. If delay difference increases, people are more likely to choose early reward for most of the epochs. Also, we found that dorsolateral prefrontal cortex, somatosensory associationc cortex, supramarginal gyrus and primary somatosensory cortex are significantly correlated with responses for most of the epochs on the other hand anterior prefrontal cortex, orbitofrontal cortex, superior temporal gyrus, middle temporal gyrus, associative visual cortex, fusiform gyrus, angular gyrus and premotor cortex are significantly correlated with responses for at least one of the epochs. Signs of significant coefficients are mostly same in these regressions for each brain region. However, we observed that sign of one significant coefficient of superior temporal gyrus, angular gyrus, fusiform gyrus, premotor cortex, associative visual cortex and middle temporal gyrus changed.

We found that orbitofrontal cortex, superior temporal gyrus and associative visual cortex are significantly correlated with responses for more epochs when we put only dipoles which early option is today into regressions than when we put all dipoles into regressions. Similarly, We found that dorsolateral prefrontal cortex, and somatosensory associationc cortex are significantly correlated with responses for more epochs when we put all dipoles into regressions than when we put only dipoles which early option is today into regressions.

We may say that when early option is today, cognitive control of behavior aspects of subjects' brains engages in decision making less. Since, they already are more willing to choose early option. However, strategy aspects of their brains engage more in middle epochs. When they start to think more strategically, they are more likely to choose early option.

When early option is today, reward and emotion aspects of subjects' brains engage in decision making. Otherwise, it does not engage in. When they start to think more emotionally or materialistically, they are more likely to choose early option.

We may say that subjects made mathematical calculations in early epochs when early option is today or not, but they made mathematical calculations in late epochs when early option is today. Since, when early option is today, emotional temptation of taking money today may delay making calculations in decision making process. However, when they start to make calculations, they are more likely to choose late option. Since late reward is much bigger than early reward and this may tempt subjects to choose late option.

Since brain regions which are related with visuo-motor coordination, tactile stimulation of skin surface, language, processing of auditory information, processing of visual information and direct control of movement reflect nonspecific aspects of intertemporal decision making, we do not pay attention to these regions.

Additionally, although we observed that dorsolateral prefrontal cortex and primary somatosensory cortex are significantly correlated with responses for most of the epochs in finer temporal resolution neural analyses, we did not observe that these regions are significantly correlated with responses for average neural analyses. Since we did different statistical treatments which we explained earlier to these two different econometric analyses.

We showed that our experimental results can be mostly reachable with parameters' values which are accepted in modern economic theory by using simulation.

We were particularly interested in comparing our results with McClure et al. (2004) fMRI study, which has become a reference standard in the neuroeconomics literature.

They demonstrated that two separate systems are involved in intertemporal decisions. Parts of the limbic system associated with the midbrain dopamine system, including paralimbic cortex, are preferentially activated by decisions involving immediately available rewards. In contrast, regions of the lateral prefrontal cortex and posterior parietal cortex are engaged uniformly by intertemporal choices irrespective of delay. Also, they found that regions of the primary visual and motor cortices are engaged uniformly by intertemporal choices irrespective of delay, but they thought that these regions more likely reflect nonspecific aspects of task performance engaged during the decision-making epoch, such as visual processing and motor response.

By comparison with their study, we used different econometric methods (General Linear Model vs Logit) and we put behavioral parameters such as amounts of offers to our regressions. Additionally, we could not observe activations of limbic system since limbic system is in the deeper part of the brain and EEG cannot detect electrical activations of deeper brain regions well.

However, we observe that there exist two separate systems like their study. In addition to some regions (lateral prefrontal cortex, posterior parietal cortex, primary visual and motor cortices) which McClure et al. (2004) identified in their study, we found that activations (or deactivations) of superior temporal gyrus, supramarginal gyrus, anterior prefrontal cortex, orbitofrontal cortex, fusiform gyrus, angular gyrus, and middle temporal gyrus are significantly correlated with the responses for at least one epoch of the pre-decision period.

As a conclusion, our findings support the hyperbolic discounting models, and also show that EEG source localization may indicate fast dynamics in some brain regions which may not be captured by fMRI.

APPENDIX A

LIST OF ALL TRIALS

Trials	Time of Early Reward	Amount of Early Reward	Time of Late Reward	Amount of Late Reward
1	0	32.46	4	34.08
2	2	29.08	4	39.26
3	4	13.75	6	15.12
4	2	13.18	4	16.48
5	0	12.31	4	15.38
6	4	19.23	6	25.96
7	4	16.01	6	16.49
8	2	25.52	4	25.78
9	4	31.88	6	47.82
10	2	33.99	4	35.01
11	2	11.50	6	11.67
12	0	22.20	2	27.75
13	4	19.19	6	22.07
14	0	24.90	2	33.61
15	2	7.54	6	7.76
16	2	23.78	4	27.35
17	0	27.50	4	28.32
18	0	5.40	2	5.67
19	0	34.62	4	39.81
20	0	9.86	4	13.31

Trials	Time of Early Reward	Amount of Early Reward	Time of Late Reward	Amount of Late Reward
21	2	25.20	6	27.72
22	0	11.19	2	16.79
23	0	29.52	2	32.48
24	0	29.10	2	33.46
25	0	31.83	4	47.74
26	4	13.70	6	13.83
27	2	8.74	6	11.80
28	2	7.63	6	9.54
29	0	16.26	2	16.75
30	4	13.12	6	13.77
31	2	22.19	6	25.52
32	0	27.45	4	27.72
33	2	12.53	4	13.78
34	2	8.74	6	11.80
35	2	17.00	6	25.50
36	4	14.18	6	17.72
37	2	21.67	4	22.75
38	0	9.78	2	9.88
39	0	21.02	4	23.12
40	2	9.65	6	10.13

APPENDIX B

NEURAL RESULTS FROM ALL TRIALS AND TRIALS WHICH EARLY OPTION IS TODAY

VARIABLES	(1) response	(2) response
today	-1.481**	
	(0.619)	
early_reward	-0.912***	-1.746*
	(0.179)	(1.019)
late_reward	0.848***	1.662*
	(0.175)	(0.966)
delay_diff	-1.335*	-2.713**
	(0.791)	(1.274)
Dorsolateral_Prefrontal_Cortex	-0.0769	-0.644
	(0.130)	(0.533)
Anterior_Prefrontal_Cortex	0.885***	-0.690
	(0.238)	(0.843)
Primary_Somatosensory_Cortex	0.0475	-1.108*
	(0.712)	(0.643)
Somatosensory_Association_Cortex	2.262***	1.700***
	(0.309)	(0.381)
Orbitofrontal_Cortex	0.292	-2.535
	(0.892)	(1.894)
Supramarginal_Gyrus	-1.465***	-2.911**
	(0.344)	(1.411)
Superior_Temporal_Gyrus	0.757	-2.378
	(1.275)	(3.308)

VARIABLES	(1) response	(2) response
Middle_Temporal_Gyrus	1.473	-0.769
	(1.458)	(5.535)
Associative_Visual_Cortex	0.927	-0.608
	(0.571)	(2.069)
Fusiform_Gyrus	-2.786*	-3.822**
	(1.678)	(1.614)
Angular_Gyrus	6.741***	4.336***
	(1.574)	(1.645)
Premotor_Cortex	-1.453	-4.800
	(3.048)	(6.672)
periodphase_2	0.935	
	(0.712)	
periodphase_3	0.830	
	(0.752)	
phase2		0.882
		(2.398)
Constant	-7.057***	-5.793*
	(1.275)	(2.994)
Observations	400	160
Pseudo R-squared	0.602	0.814

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX C

TEMPORAL DYNAMIC RESULTS FROM ALL TRIALS

VARIABLES	(1) response	(2) response	(3) response	(4) response
today	-0.600	-0.916	-1.445**	-1.791***
	(0.596)	(0.596)	(0.579)	(0.609)
early_reward	-0.631***	-0.780***	-0.767***	-0.831***
	(0.134)	(0.162)	(0.161)	(0.139)
late_reward	0.596***	0.721***	0.704***	0.761***
	(0.136)	(0.156)	(0.162)	(0.144)
delay_diff	-0.669	-0.953	-0.785	-1.056*
	(0.666)	(0.628)	(0.670)	(0.558)
Dorsolateral_Prefrontal_Cortex	-0.199**	-0.262**	-0.239**	-0.208**
	(0.0893)	(0.111)	(0.110)	(0.0951)
Anterior_Prefrontal_Cortex	0.0573	0.109	0.110	0.300*
	(0.194)	(0.171)	(0.237)	(0.162)
Primary_Somatosensory_Cortex	-0.780**	-0.602*	-0.898**	-0.427*
	(0.354)	(0.313)	(0.409)	(0.245)
Somatosensory_Association_Cortex	0.517***	0.451***	0.644***	0.957***
	(0.141)	(0.122)	(0.169)	(0.127)
Orbitofrontal_Cortex	-0.0882	-0.580	-0.743	-0.316
	(0.435)	(0.503)	(0.674)	(0.671)
Supramarginal_Gyrus	-0.0825	-0.238*	-0.345*	-0.450
	(0.163)	(0.142)	(0.196)	(0.276)
Superior_Temporal_Gyrus	-0.166	0.378	0.376**	-0.350
	(0.342)	(0.295)	(0.175)	(0.489)

VARIABLES	(1) response	(2) response	(3) response	(4) response
Middle_Temporal_Gyrus	0.335	-1.298**	-1.022	0.620**
	(0.417)	(0.552)	(0.730)	(0.277)
Associative_Visual_Cortex	-0.229	-0.164	-0.308	-0.459*
	(0.277)	(0.215)	(0.228)	(0.249)
Fusiform_Gyrus	0.181	-1.006*	-0.395	-0.396
	(0.496)	(0.577)	(0.622)	(0.676)
Angular_Gyrus	0.00431	0.435	-0.0526	1.290**
	(0.451)	(0.757)	(0.624)	(0.545)
Premotor_Cortex	0.0853	-1.124***	0.710	-1.695***
	(0.391)	(0.320)	(0.550)	(0.592)
periodphase_2	0.566	0.567	0.957	0.788
	(0.503)	(0.413)	(0.587)	(0.550)
periodphase_3	0.557	0.237	0.219	0.315
	(0.404)	(0.279)	(0.448)	(0.391)
Constant	-3.094***	-2.453***	-2.512***	-3.284***
	(0.575)	(0.458)	(0.684)	(0.531)
Observations	332	396	383	379
Pseudo R-squared	0.467	0.544	0.533	0.570

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(5)	(6)	(7)	(8)
VARIABLES	response	response	response	response
today	-1.021	-0.878**	-1.176*	-1.008**
	(0.640)	(0.443)	(0.644)	(0.442)
early_reward	-0.759***	-0.753***	-0.845***	-0.685***
	(0.156)	(0.156)	(0.152)	(0.125)
late_reward	0.710***	0.687***	0.794***	0.640***
	(0.156)	(0.149)	(0.152)	(0.129)
delay_diff	-0.866	-0.965	-0.799	-0.972
	(0.631)	(0.769)	(0.735)	(0.661)
Dorsolateral_Prefrontal_Cortex	-0.240**	-0.209**	-0.290**	-0.206**
	(0.118)	(0.103)	(0.118)	(0.0951)
Anterior_Prefrontal_Cortex	0.160	0.240	0.119	0.116
	(0.197)	(0.153)	(0.240)	(0.250)
Primary_Somatosensory_Cortex	-0.450	-0.748*	-0.641	-0.996***
	(0.330)	(0.424)	(0.415)	(0.386)
Somatosensory_Association_Cortex	0.565***	0.655***	0.432**	0.468***
	(0.154)	(0.110)	(0.216)	(0.152)
Orbitofrontal_Cortex	-0.687	-0.383	-0.751	-0.293
	(0.905)	(0.696)	(0.735)	(0.585)
Supramarginal_Gyrus	-0.492**	-0.399**	-0.475***	-0.181
	(0.207)	(0.200)	(0.149)	(0.115)
Superior_Temporal_Gyrus	0.0691	-0.434	-0.489	-0.264
	(0.362)	(0.371)	(0.534)	(0.315)

	(5)	(6)	(7)	(8)
VARIABLES	response	response	response	response
Middle_Temporal_Gyrus	-0.191	0.718	0.143	0.276
	(0.509)	(0.509)	(0.378)	(0.240)
Associative_Visual_Cortex	-0.302	-0.0886	-0.0159	-0.370
	(0.283)	(0.230)	(0.127)	(0.246)
Fusiform_Gyrus	-0.542	-0.472	-0.294	0.531**
	(0.425)	(0.459)	(0.428)	(0.250)
Angular_Gyrus	0.784**	0.546**	0.740*	0.0389
	(0.378)	(0.261)	(0.435)	(0.425)
Premotor_Cortex	-1.989	-0.364	-1.463	0.635**
	(1.364)	(0.308)	(0.960)	(0.323)
periodphase_2	0.799	0.785	0.706	0.752
	(0.668)	(0.695)	(0.644)	(0.483)
periodphase_3	0.430	0.509	0.612	0.307
	(0.432)	(0.526)	(0.383)	(0.354)
Constant	-3.080***	-3.029***	-3.123***	-2.918***
	(0.627)	(0.637)	(0.689)	(0.681)
Observations	375	374	381	392
Pseudo R-squared	0.541	0.527	0.551	0.499

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

VARIABLES	(9) response	(10) response	(11) response	(12) response
today	-0.928**	-1.077	-1.049*	-0.812
	(0.445)	(0.682)	(0.636)	(0.638)
early_reward	-0.695***	-0.720***	-0.724***	-0.722***
	(0.144)	(0.150)	(0.113)	(0.120)
late_reward	0.641***	0.672***	0.697***	0.675***
	(0.143)	(0.158)	(0.112)	(0.118)
delay_diff	-0.878	-0.873	-1.146**	-1.182*
	(0.588)	(0.722)	(0.539)	(0.684)
Dorsolateral_Prefrontal_Cortex	-0.241**	-0.259**	-0.195**	-0.194**
	(0.107)	(0.123)	(0.0938)	(0.0879)
Anterior_Prefrontal_Cortex	0.102	0.0418	0.327**	0.266*
	(0.170)	(0.246)	(0.155)	(0.137)
Primary_Somatosensory_Cortex	-0.734**	-0.884**	-0.471	-0.559*
	(0.317)	(0.428)	(0.360)	(0.290)
Somatosensory_Association_Cortex	0.419**	0.456**	0.870***	0.760***
	(0.175)	(0.219)	(0.263)	(0.179)
Orbitofrontal_Cortex	-0.568	-0.863	-0.0906	-0.185
	(0.652)	(0.708)	(0.462)	(0.614)
Supramarginal_Gyrus	-0.213	-0.283**	-0.421*	-0.184
	(0.186)	(0.135)	(0.217)	(0.127)
Superior_Temporal_Gyrus	-0.154	-0.589	-0.229	0.175
	(0.308)	(0.582)	(0.456)	(0.385)

	(9)	(10)	(11)	(12)
VARIABLES	response	response	response	response
Middle_Temporal_Gyrus	-0.488	-0.165	0.636*	-0.144
	(0.421)	(0.388)	(0.361)	(0.248)
Associative_Visual_Cortex	0.00421	-0.534**	-0.456***	-0.0306
	(0.276)	(0.251)	(0.156)	(0.131)
Fusiform_Gyrus	-0.374	-0.241	0.390	-0.103
	(0.397)	(0.264)	(0.340)	(0.392)
Angular_Gyrus	-0.638	-0.651	0.309	0.652
	(0.757)	(0.883)	(0.946)	(0.616)
Premotor_Cortex	-0.910	-0.732	-1.253	-0.710
	(0.673)	(1.006)	(1.462)	(0.471)
periodphase_2	0.761	0.756	0.969*	0.585
	(0.604)	(0.566)	(0.544)	(0.389)
periodphase_3	0.295	0.471	0.872*	0.522
	(0.374)	(0.378)	(0.476)	(0.497)
Constant	-2.216***	-2.279***	-4.365***	-3.528***
	(0.596)	(0.850)	(1.047)	(0.762)
Observations	364	373	376	393
Pseudo R-squared	0.499	0.543	0.550	0.521

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(13)	(14)	(15)	(16)
VARIABLES	response	response	response	response
today	-0.926	-1.014*	-1.225***	-1.034**
	(0.574)	(0.522)	(0.423)	(0.489)
early_reward	-0.719***	-0.828***	-0.718***	-0.712***
	(0.113)	(0.149)	(0.120)	(0.141)
late_reward	0.669***	0.772***	0.669***	0.666***
	(0.119)	(0.142)	(0.115)	(0.144)
delay_diff	-0.993*	-1.051	-0.942*	-0.967
	(0.585)	(0.692)	(0.561)	(0.663)
Dorsolateral_Prefrontal_Cortex	-0.200**	-0.230**	-0.184**	-0.231**
	(0.0953)	(0.0898)	(0.0826)	(0.102)
Anterior_Prefrontal_Cortex	0.264	0.243	0.251	0.0418
	(0.171)	(0.174)	(0.164)	(0.244)
Primary_Somatosensory_Cortex	-0.392	-0.611*	-0.776**	-0.616**
	(0.261)	(0.353)	(0.346)	(0.301)
Somatosensory_Association_Cortex	0.609***	0.792***	0.750***	0.622***
	(0.155)	(0.150)	(0.136)	(0.144)
Orbitofrontal_Cortex	-0.227	-0.0338	-0.212	-0.248
	(0.368)	(0.577)	(0.594)	(0.694)
Supramarginal_Gyrus	-0.330	-0.440*	-0.0323	-0.336**
	(0.223)	(0.255)	(0.129)	(0.149)
Superior_Temporal_Gyrus	0.0198	-0.0277	0.0766	-0.523*
	(0.395)	(0.311)	(0.384)	(0.279)

	(13)	(14)	(15)	(16)
VARIABLES	response	response	response	response
Middle_Temporal_Gyrus	0.00863	0.191	0.388	0.206
	(0.541)	(0.265)	(0.492)	(0.385)
Associative_Visual_Cortex	-0.297	-0.105	-0.532	-0.249
	(0.207)	(0.239)	(0.442)	(0.247)
Fusiform_Gyrus	0.386	0.168	0.428	-0.716
	(0.494)	(0.246)	(0.344)	(0.609)
Angular_Gyrus	0.688*	0.497	0.191	0.332
	(0.363)	(0.799)	(0.701)	(0.488)
Premotor_Cortex	-1.693***	-1.771	0.158	-0.496
	(0.583)	(1.101)	(0.355)	(0.365)
periodphase_2	0.649	0.606	1.126*	0.702
	(0.452)	(0.581)	(0.666)	(0.581)
periodphase_3	0.369	0.262	0.601	0.495
	(0.405)	(0.621)	(0.561)	(0.455)
Constant	-3.266***	-3.716***	-3.718***	-2.745***
	(0.733)	(0.676)	(0.428)	(0.533)
Observations	369	383	393	400
Pseudo R-squared	0.522	0.569	0.520	0.512

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

APPENDIX D

TEMPORAL DYNAMIC RESULTS FROM TRIALS WHICH EARLY OPTION IS TODAY

VARIABLES	(1) response	(2) response	(3) response	(4) response
early_reward	-1.418**	-8.912	-2.453***	-1.248***
	(0.600)	(5.527)	(0.941)	(0.479)
late_reward	1.358**	7.815*	2.395***	1.256***
	(0.565)	(4.719)	(0.887)	(0.468)
delay_diff	-1.388**	-13.61	-4.745**	-1.487
	(0.548)	(9.353)	(2.022)	(1.408)
Dorsolateral_Prefrontal_Cortex	-0.524*	-3.357*	-1.033**	-0.461*
	(0.277)	(1.883)	(0.472)	(0.242)
Anterior_Prefrontal_Cortex	-0.617	-5.324	-0.761	-0.246
	(0.408)	(3.270)	(0.585)	(0.283)
Primary_Somatosensory_Cortex	-1.640**	-5.496***	-0.774	-1.134*
	(0.761)	(1.411)	(0.588)	(0.619)
Somatosensory_Association_Cortex	0.640**	2.464*	0.723	1.076***
	(0.275)	(1.422)	(0.463)	(0.253)
Orbitofrontal_Cortex	-1.974	-10.93	-5.299***	-1.968*
	(1.324)	(7.246)	(1.718)	(1.041)
Supramarginal_Gyrus	-1.046	-12.25	-2.033*	-1.676*
	(0.769)	(8.095)	(1.208)	(0.987)
Superior_Temporal_Gyrus	-1.800	2.364*	1.154***	-3.366*
	(1.177)	(1.280)	(0.202)	(1.808)

VARIABLES	(1) response	(2) response	(3) response	(4) response
Middle_Temporal_Gyrus	2.852	-21.30*	-13.64**	0.982**
	(1.837)	(11.90)	(6.368)	(0.382)
Associative_Visual_Cortex	0.252	-6.415	-1.277	0.0703
	(0.392)	(4.061)	(1.554)	(0.677)
Fusiform_Gyrus	-4.830*	-15.16	2.159	-3.441
	(2.811)	(13.94)	(1.328)	(2.168)
Angular_Gyrus	-0.183	6.330	-9.463*	-0.385
	(1.521)	(5.151)	(5.360)	(1.148)
Premotor_Cortex	-0.0619	-19.27	-27.63**	-4.116*
	(0.496)	(34.18)	(11.15)	(2.449)
phase2	0.270	-0.575	3.573	0.284
	(1.471)	(2.773)	(2.734)	(1.765)
Constant	-4.763*	4.022	-10.32***	-6.884**
	(2.671)	(8.274)	(2.516)	(3.421)
Observations	127	159	155	149
Pseudo R-squared	0.700	0.896	0.845	0.813

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(5)	(6)	(7)	(8)
VARIABLES	response	response	response	response
early_reward	-2.752***	-2.099*	-1.112**	-4.249**
	(0.508)	(1.150)	(0.534)	(1.866)
late_reward	2.648***	2.024*	1.068**	4.174**
	(0.502)	(1.115)	(0.497)	(1.827)
delay_diff	-4.350***	-4.526**	-1.308	-5.625***
	(0.714)	(2.055)	(0.824)	(2.096)
Dorsolateral_Prefrontal_Cortex	-1.162***	-0.541	-0.427	-1.899**
	(0.251)	(0.412)	(0.281)	(0.879)
Anterior_Prefrontal_Cortex	-0.190	-0.446	-0.591	-2.625**
	(0.431)	(0.393)	(0.558)	(1.171)
Primary_Somatosensory_Cortex	-4.289***	-1.286*	-1.631	-9.000***
	(0.941)	(0.674)	(1.140)	(2.314)
Somatosensory_Association_Cortex	0.705	2.815**	0.595**	1.737**
	(0.624)	(1.127)	(0.269)	(0.713)
Orbitofrontal_Cortex	-11.99***	-1.629*	-1.298	-8.463**
	(2.914)	(0.899)	(1.105)	(3.567)
Supramarginal_Gyrus	-3.290***	-1.627	-0.986*	-2.770**
	(1.079)	(1.194)	(0.510)	(1.151)
Superior_Temporal_Gyrus	-2.390**	-3.237**	-1.504	-1.596
	(0.932)	(1.523)	(1.043)	(1.353)

	(5)	(6)	(7)	(8)
VARIABLES	response	response	response	response
Middle_Temporal_Gyrus	-2.769	2.691	-0.140	-8.709**
	(2.639)	(2.507)	(0.803)	(3.936)
Associative_Visual_Cortex	-0.890	1.162**	0.267	-2.747**
	(1.249)	(0.458)	(0.284)	(1.214)
Fusiform_Gyrus	-3.840	-1.416***	-0.664	-0.223
	(3.246)	(0.537)	(0.620)	(0.589)
Angular_Gyrus	0.714	1.771	0.0382	-2.494***
	(0.779)	(1.911)	(0.741)	(0.931)
Premotor_Cortex	3.765	-2.239	0.531	4.949
	(3.267)	(4.813)	(0.752)	(3.441)
phase2	1.451	-0.963	2.215	0.237
	(3.462)	(1.757)	(3.183)	(2.199)
Constant	-6.789*	-9.668	-5.673*	-10.95*
	(3.529)	(6.358)	(3.079)	(6.380)
Observations	145	150	149	160
Pseudo R-squared	0.812	0.843	0.713	0.891

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

	(9)	(10)	(11)	(12)
VARIABLES	response	response	response	response
early_reward	-1.325***	-1.247**	-1.235***	-1.161***
	(0.453)	(0.547)	(0.453)	(0.314)
late_reward	1.300***	1.220**	1.202***	1.118***
	(0.421)	(0.543)	(0.452)	(0.310)
delay_diff	-2.493**	-1.705**	-1.021	-3.196***
	(1.016)	(0.851)	(0.860)	(0.799)
Dorsolateral_Prefrontal_Cortex	-0.655**	-0.438	-0.447*	-0.272*
	(0.265)	(0.359)	(0.239)	(0.159)
Anterior_Prefrontal_Cortex	-0.905**	-0.0980	-0.222	-0.0933
	(0.377)	(0.499)	(0.318)	(0.235)
Primary_Somatosensory_Cortex	-2.402**	-0.275	-0.644*	-0.890
	(1.056)	(0.418)	(0.370)	(0.564)
Somatosensory_Association_Cortex	0.166	1.289*	1.096**	1.657***
	(0.198)	(0.680)	(0.547)	(0.511)
Orbitofrontal_Cortex	-2.948*	-1.480	-0.429	0.0682
	(1.572)	(1.894)	(0.294)	(0.790)
Supramarginal_Gyrus	-1.056*	-1.385	-1.540**	-0.537***
	(0.547)	(1.068)	(0.729)	(0.166)
Superior_Temporal_Gyrus	-2.940**	-1.557	-1.503*	-0.0490
	(1.240)	(2.624)	(0.893)	(0.685)

VARIABLES	(9) response	(10) response	(11) response	(12) response
Middle_Temporal_Gyrus	-0.505	-0.785	-0.909	-0.696
	(0.788)	(1.210)	(1.140)	(0.929)
Associative_Visual_Cortex	-1.395**	-0.681***	-1.049	0.242
	(0.596)	(0.232)	(0.844)	(0.257)
Fusiform_Gyrus	0.247	-0.528	0.610	-0.399
	(0.849)	(0.717)	(0.764)	(0.725)
Angular_Gyrus	-2.528	0.331	-0.381	1.090
	(1.545)	(0.665)	(1.789)	(0.702)
Premotor_Cortex	-0.431*	-3.526	-3.493	-1.358
	(0.244)	(2.640)	(2.543)	(1.238)
phase2	-0.449	1.194	0.755	-0.552
	(1.601)	(2.359)	(1.888)	(1.244)
Constant	-1.762	-6.553**	-6.130*	-5.470**
	(1.382)	(3.057)	(3.471)	(2.137)
Observations	144	148	150	156
Pseudo R-squared	0.754	0.737	0.725	0.741

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

	(13)	(14)	(15)	(16)
VARIABLES	response	response	response	response
early_reward	-1.577***	-1.052***	-1.280***	-1.218***
	(0.392)	(0.209)	(0.284)	(0.359)
late_reward	1.573***	1.002***	1.277***	1.209***
	(0.374)	(0.185)	(0.279)	(0.363)
delay_diff	-2.342**	-1.832***	-3.116***	-2.593***
	(1.028)	(0.501)	(0.732)	(0.918)
Dorsolateral_Prefrontal_Cortex	-0.550***	-0.287*	-0.254	-0.430**
	(0.171)	(0.153)	(0.196)	(0.200)
Anterior_Prefrontal_Cortex	-0.102	-0.225	0.519	-0.360
	(0.368)	(0.410)	(0.357)	(0.269)
Primary_Somatosensory_Cortex	-0.130	-1.287***	-2.691***	-1.277*
	(0.136)	(0.325)	(0.858)	(0.694)
Somatosensory_Association_Cortex	1.240***	0.986*	2.782***	1.209***
	(0.436)	(0.568)	(1.016)	(0.272)
Orbitofrontal_Cortex	-1.852***	-0.206	-0.520	-1.391
	(0.553)	(0.947)	(1.552)	(1.597)
Supramarginal_Gyrus	-2.169***	-0.520	-0.483*	-1.272**
	(0.596)	(0.375)	(0.273)	(0.550)
Superior_Temporal_Gyrus	-1.289	-0.109	-0.0350	-0.0398
	(2.554)	(0.480)	(0.767)	(0.360)

	(13)	(14)	(15)	(16)
VARIABLES	response	response	response	response
Middle_Temporal_Gyrus	-0.412	-1.134	1.416*	-2.212*
	(3.652)	(1.310)	(0.854)	(1.279)
Associative_Visual_Cortex	-0.662***	-0.0686	0.324	-0.741
	(0.243)	(0.559)	(0.725)	(0.561)
Fusiform_Gyrus	0.749*	1.152***	-1.969*	-2.589
	(0.437)	(0.395)	(1.011)	(1.729)
Angular_Gyrus	2.919***	-0.709	1.777*	1.963***
	(0.692)	(0.748)	(0.969)	(0.438)
Premotor_Cortex	-15.27**	0.329	3.169***	0.217
	(7.708)	(1.167)	(0.442)	(1.491)
phase2	-0.377	-0.385	1.224	0.484
	(1.368)	(1.392)	(1.580)	(1.657)
Constant	-7.658***	-4.550**	-10.81***	-5.990**
	(2.746)	(2.265)	(3.342)	(2.633)
Observations	148	153	159	160
Pseudo R-squared	0.773	0.725	0.780	0.753

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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