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Measuring intertemporal preferences using response times

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ABSTRACT

We use two different approaches to measure intertemporal preferences. First we employ the classical method of inferring preferences from a series of choices (subjects choose between \$X now or \$Y in days). Second we adopt the novel approach of inferring preferences using only response time data from the same choices (how long it takes subjects to choose between \$X now or \$Y in days). In principle, the inference from response times should work, since choices between items of nearly equivalent value should take longer than choices between items with substantially different values. We find that choice-based analysis and response-time-based analysis yield nearly identical discount rate estimates. We conclude that response time data sheds light on both our revealed (choice-based) preferences and on the cognitive processes that implement those preferences.

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1. Introduction

Following Samuelson (1938), economists have adopted the theory of revealed preferences: Economic analysis uses choice data to infer underlying preferences (or tastes). However, there are many observable phenomena other than choices that could in principle be used to infer latent preferences.

For example, one could try to infer preferences using physiological measurements (Edgeworth, 1881). Observers could determine which flavor of ice cream produces the greatest anticipatory salivation, or the sharpest spike in skin conductance, or the greatest blood flow in the brain's reward systems. These physiological responses could then be inverted to impute the underlying preferences that evoked them. A growing body of work in neuroeconomics has followed such strategies, concluding that preferences inferred from neurophysiological measurements closely match those inferred from choices (e.g., de Quervain et al., 2004).

Social scientists could also try to infer latent preferences from response time (i.e., the amount of time subjects take to make decisions) in choice tasks, which is the approach taken in the current paper.¹ In theory, response time should be relatively long when agents choose among goods that have similar value (Gabaix and Laibson, 2005; Gabaix et al., 2006). If an agent has a noisy estimate of the value of a good but the good almost surely dominates its alternatives, then it is not worth taking the time to refine that noisy estimate. However, if an agent has a noisy estimate of the value of a good that seems to be close in value to the next best alternative, then it is optimal to take additional time to refine the noisy estimate. If such theorized mechanisms operate in practice, then it should be possible to use only response times to impute preferences. Long response times imply near indifference between items in a binary choice set. Short response times imply a strong preference for one of the items in a binary choice set.

In psychology, a similar relationship between response time and quantities under comparison has been observed in a variety of domains as early as the work of Henmon (1906). In perception, Johnson (1939) had subjects decide which of two simultaneously presented lines was longer, and found that response time was a negative linear function of the logarithm of the difference in length. This has been found with other perceptual quantities like area and luminance, with the size of visualized objects, and even with the magnitudes of abstract numbers (Moyer and Landauer, 1967). Brain imaging studies suggest that many, if not all, of these comparison tasks invoke a common cognitive process localized in the parietal lobes (Pinel et al., 2001, 2004).

In this paper we find that response times can be used to infer economic preferences. Specifically, we use laboratory data to measure temporal discount

¹ Rubinstein (2007) measures response times during a wide range of games, but does not use them to infer underlying preference parameters.

rates in two ways. First, we measure intertemporal preferences using data from 27 binary choices, each of which has an immediate reward option and a mutually exclusive delayed reward option (Kirby et al., 1999). Second, we infer intertemporal preferences using *only* response times measured in the same experiment. With this second approach, we infer that subjects are indifferent between two mutually exclusive alternatives—an immediate reward and a delayed reward—when the observed response time in the choice task is relatively long compared to other intertemporal choices in our experiment.

Remarkably, the parametric discount function that we infer directly from the choice data closely matches the parametric discount function that we infer indirectly from the response time data. We also find that response time analysis predicts subsequent *choice* data almost as well as choice data predict subsequent choice data. We conclude that response time is an operational and effective measure of preferences. Response time data appear to reveal preferences by revealing key attributes of the cognitive processes that implement those preferences.

This paper is divided into five sections. Following this introduction, Section 2 discusses our data, which are taken from three different experiments involving 712 total subjects. Section 3 presents our modeling framework, and explains how we infer intertemporal preferences first from choice data and second from response time data. Section 4 reports our results comparing the preference estimates derived from choice data and the preference estimates derived from response time data. Section 5 concludes.

2. Data description

We created a computerized version of a 27-question delay-discounting task developed by Kirby et al. (1999). Each question asks the subject to choose between a smaller, immediate reward (SIR) and a larger, delayed reward (LDR), both denominated in U.S. dollars. For example, the first question asks “Would you prefer \$54 today, or \$55 in 117 days?” Rewards range from \$11 (the smallest SIR) to \$85 (the largest LDR). Delays range from 7 to 186 days. Nine trials involve “small” LDRs (\$25–35), nine involve “medium” LDRs (\$50–60), and nine involve “large” LDRs (\$75–85). Following Kirby et al. (1999), we refer to these sets of nine trials as reward size categories.

We administered the questions as described by Kirby et al. (1999), except that we also recorded the time that each subject took to answer each question, starting from the time it was displayed on the screen. Responses were entered by pressing the B key for the SIR or the N key for the LDR.

This task was included in three separate studies that yielded data from a total of 712 subjects: (1) The *Weight* study examined associations between body mass index (BMI) and discounting, as well as other measures of reward-related behavior. (2) The *Cognition* study examined individual differences in cognitive abilities, decision-making, and personality. (3) The *Web* study

examined differences in cognition and personality that may be associated with differences in academic disciplines and career choices.²

In all three studies, each subject had a 1-in-6 chance of having one randomly-selected question played out for real stakes. In the Weight and Cognition studies, the subject rolled a six-sided die at the end of the testing session. If a 6 was rolled, the subject blindly drew a card from a box containing cards labeled 1–27, corresponding to the 27 trials of the discounting task. If the subject chose the SIR on the randomly-drawn trial, the amount of the SIR was added to the subject’s show-up fee for participating, and a check request for the total was submitted to the research administration office within one business day. If the subject chose the LDR, a separate check request for the LDR amount was made after the specified delay. In the Web study, a spreadsheet was used to generate the necessary random numbers, and “winning” subjects received payment through an Amazon.com gift certificate, which was e-mailed by the next business day (SIRs) or after the specified delay (LDRs).

In the Weight and Cognition studies, the questions were presented, and choices and response times recorded, using PsyScope 1.2.5 (Cohen et al., 1993) running under OS 9 on Apple Macintosh computers. For the Web study, this PsyScope implementation was converted into a Flash movie that ran in each subject’s web browser on his or her own computer and transmitted data back to a central server. Because the three studies varied in recruitment strategies, participant characteristics, payment methods, and apparatus used to measure response time, we analyze them separately in this paper.

3. Models and estimation techniques

3.1. Discount function

We use a generalized hyperbola to model time preferences. We assume that the discounted value of a one unit reward delayed τ days is

$$D(\tau) = \frac{1}{1 + \alpha\tau}.$$

Previous studies linking discount rates to behavior have adopted this function as well (e.g., Mazur, 1987; Kirby & Marakovic, 1996; Kirby et al., 1999; de Wit et al., 2007; Myerson & Green, 1995; Rachlin et al., 1991).

² In total 751 subjects were tested, but 18 subjects were excluded from the Weight study and 16 subjects were excluded from the Cognition study for one or more of the following reasons: reported brain injury; reported mental illness; reported drug use; had difficulty understanding directions; was unable to complete the protocol; was previously tested. Additionally, any subject who had three or more responses faster than 200 milliseconds on the discounting task was excluded; a total of five subjects from the Web study were excluded based on this criterion. The average ages of remaining participants in the Weight, Cognition, and Web studies were, respectively, 32, 27, and 31 years; the average numbers of years of education were 15.0, 14.3, and 18.4; the percentages of female participants were 50%, 52%, and 67%. Complete details of the study procedures can be found in Chabris et al. (2008).

This discount function $D(\tau)$ is a special case in the family of hyperbolic discount functions derived by Loewenstein and Prelec (1992):

$$D(\tau) = (1 + \alpha\tau)^{-\gamma/\alpha}.$$

In this family of discount functions, the discount rate—the rate of decline of the discount function—is given by

$$\frac{\partial D(\tau) / \partial \tau}{D(\tau)} = \frac{\gamma}{1 + \alpha\tau}.$$

Hence, the discount rate is decreasing with horizon τ . The falling discount rate generates dynamically inconsistent preferences (Strotz, 1957; Ainslie, 1992).

Our specification imposes the common restriction $\gamma = \alpha$. Thus at horizon $\tau = 0$, the discount rate is α . To simplify notation, we sometimes refer to parameter α as the “discount rate,” though it is actually the instantaneous discount rate at horizon $\tau = 0$.

3.2. Choice data model

We assume that time preferences are homogeneous within each of our three datasets.³ A subject chooses delayed reward Y in τ days over an immediate reward X if and only if the net present value of Y exceeds X :

$$\frac{Y}{1 + \alpha\tau} - X \geq 0.$$

We assume that subjects experience preference shocks with the logistic distribution, so subjects choose the delayed reward with probability

$$F_{\text{Logit}}\left(\frac{Y}{1 + \alpha\tau} - X\right) = e^{\frac{\omega Y}{1 + \alpha\tau}} / \left(e^{\omega X} + e^{\frac{\omega Y}{1 + \alpha\tau}}\right), \quad (1)$$

where $1/\omega$ is the variance of the logistic distribution. The estimated discounting parameters, $\hat{\alpha}$ and $\hat{\omega}$, are obtained in each dataset by maximizing the likelihood function

$$\mathcal{L}(\alpha | d) = \prod_{i=1}^N \prod_{t=1}^T \left[F_{\text{Logit}}\left(\frac{Y_t}{1 + \alpha\tau_t} - X_t\right) \right]^{d_{it}} \left[1 - F_{\text{Logit}}\left(\frac{Y_t}{1 + \alpha\tau_t} - X_t\right) \right]^{1 - d_{it}} \quad (2)$$

³ Even though the choice data allow us to estimate a distinct discount rate for each subject as in Chabris et al. (2008), we were not able to do the same with the response time data. Because the response time model contains many more parameters and because the response time data is naturally noisier than the choice data, there are not enough observations per subject to estimate the model well. Accordingly, all analysis in this paper is at the group level.

where T is the number of trials, N is the number of subjects, and $d = \{d_{it}\}_{1 \leq i \leq N, 1 \leq t \leq T}$ is the set of the NT binary decisions made by the N subjects. In trial t , dummy variable $d_{it} = 1$ if subject i chose the delayed reward Y_t in τ_t days over the immediate reward X_t (otherwise $d_{it} = 0$).

3.3. Response time (RT) model

Following the framework in Gabaix and Laibson (2005) and Gabaix et al (2006) we assume that subjects take longest to decide when the two options are most similar in their *discounted values*. For example, a choice between \$10 immediately or \$40 in a week would not be difficult, whereas a choice between \$10 immediately or \$15 in a week would take more time.

Formally, subjects should take longest on those trials t for which the difference in the discounted values of the choices on trial t ,

$$\Delta_t \equiv \left| \frac{Y_t}{1 + \alpha \tau_t} - X_t \right|, \quad (3)$$

is closest to 0. The proxy for decision difficulty, $\Gamma(\Delta_t) \in [0, 1]$, that we actually use is given by the transformation

$$\Gamma(\Delta_t) \equiv 2 / (1 + e^{\omega \Delta_t}). \quad (4)$$

This transformation has three desirable properties. First, Γ is convex and decreasing, which means that as the difference between the discounted values of the options grows larger, Γ exhibits less sensitivity to changes in Δ . Second, this transformation is based on the logit distribution function (1); another interpretation of Γ is that subjects take longest to decide when the probability of choosing one or the other reward is close to $1/2$. Third, the precision parameter ω incorporates the effect of the variance of taste shocks on response time—greater variance in taste shocks corresponds to a smaller precision parameter ω , which corresponds to larger response times.

The response time model is

$$RT_{it} = b_0 + b_1 t + b_2 \Gamma(\Delta_t) + \varepsilon_{it} \quad (5)$$

where t is trial number, RT_{it} is the response time of subject i on trial t , and ε_{it} is the subject and trial specific noise term (section 4.1 motivates the $b_1 t$ term). We make no assumptions about the errors except that the random vectors $\varepsilon_i = (\varepsilon_{i1}, \dots, \varepsilon_{iT})$ are mutually independent. Our approach to estimating the model is simply to minimize the sum of squared residuals; in other words, we seek the vector $(\hat{b}_0, \hat{b}_1, \hat{b}_2, \hat{\alpha}, \hat{\omega})$ that minimizes

$$\sum_{it} [RT_{it} - (\hat{b}_0 + \hat{b}_1 t + \hat{b}_2 \Gamma(\hat{\Delta}_t))]^2, \quad (6)$$

where

$$\hat{\Delta}_t = \frac{2}{1 + e^{\hat{\omega} \left| \frac{Y_t - X_t}{1 + \hat{\alpha} \tau_t} \right|}}.$$

4. Results

4.1. Using choice data to predict response times

Table 1 shows the estimates $\hat{\alpha}$ obtained by using choice data to estimate the discount function. Specifically, we maximize the choice-based likelihood function in equation (2) for each of our three studies. We also estimate separately the discount rates for each of the three different reward size categories. Consistent with others (e.g., Kirby et al., 1999; Kirby and Marakovic, 1996; Jaroni et al., 2004) we find that subjects' discount rates decrease with reward size category. Moreover, we find that subjects in the Weight study have higher discount rates than subjects in the Cognition study, and that subjects in the Cognition study have slightly higher discount rates than subjects in the Web study. This is probably at least partially due to demographic differences between the samples.⁴

We find that we can use the discount function estimates from choice data to predict response times. Specifically, for each study we use the estimated parameters $\hat{\alpha}$ and $\hat{\omega}$ to define $\hat{\Delta}_t$ as in equation (3), apply Γ as in equation (4) to get our proxy for decision difficulty, $\Gamma(\hat{\Delta}_t)$, and then show that $\Gamma(\hat{\Delta}_t)$ correlates with response times.

We also control for the effect of experience—as subjects become accustomed to the format of the discounting task, they answer the questions more quickly. We find that subjects take a disproportionate amount of time on the first two trials but that the effect of experience is approximately linear for the subsequent trials. Therefore, we leave the first two trials out of the response time analysis and control for the linear learning effect in the remaining 25 trials. Finally, we trim our dataset by cutting observations with extremely high response times—we demean response times at the subject level and drop

⁴ For example, the Weight study recruited subjects with high BMI whereas the Web study recruited college graduates. The differences in the group-level discount rates are reduced when we exclude overweight and obese subjects ($BMI \geq 25$) from the estimation samples. Chabris et al. (2008) estimate discount rates at the individual level and show statistically significant relationships between the estimated discount rates and composites of variables such as BMI, smoking, and exercising.

observations that are in the top 2% of the distribution of the demeaned response times.⁵ We apply these exclusions to all subsequent analysis.

The columns labeled *choice data* in Tables 2 and 3 show the estimated discounting parameters when the model is estimated with choice data that is taken from the trimmed sample.⁶ We form the decision difficulty measure, $\Gamma(\hat{\Delta}_t)$, using these parameters.

To test our hypothesis that $\Gamma(\hat{\Delta}_t)$ predicts response time, we estimate the linear regression model

$$RT_{it} = b_0 + b_1t + b_2\Gamma(\hat{\Delta}_t) + \varepsilon_{it}.$$

The effect of $\Gamma(\hat{\Delta}_t)$ is highly significant ($p < 0.001$) and positive in the regression. Figure 1 shows, for each of the three datasets, a plot of $RT_{it} - b_1t$ (averaged by trial) against $\Gamma(\hat{\Delta}_t)$, and the corresponding regression lines. When we average by trial and control for the learning effect, $\Gamma(\hat{\Delta}_t)$ accounts for 51.2%, 49.8%, and 61.3% of the variance, respectively, in the Weight, Cognition, and Web studies. When we estimate a different α for each of the different reward categories, the results are even more statistically significant—the corresponding R^2 values are 74.8%, 64.1%, and 70.8%.

4.2. Using response times to predict choice

We also estimate the discount function using only the response time data. Specifically, we estimate equation (5) by minimizing the sum of squared residuals (6). Table 2 shows the estimates of $\hat{\alpha}$ and $\hat{\omega}$ for each of the three datasets, with the *choice data* columns showing estimates obtained by estimating the choice data model (2) and the *RT data* columns showing estimates obtained by estimating the RT model (5). Overall, the estimates based on choice data covary closely with the estimates based on response times. The correlation between the $\hat{\alpha}$'s estimated from choice data and the $\hat{\alpha}$'s estimated from response time data is 0.97.⁷

⁵ Response time is a very noisy variable because of the many ways in which it can be affected on any given trial. An example of an outlier is a 59-second response in the Weight study (compared to a mean of 3.4 and SD of 2.8 seconds in this dataset). In other analyses, varying the cutoff point from 2% yielded similar results to those reported here.

⁶ These estimates are nearly identical to those in Table 1.

⁷ In contrast, the $\hat{\omega}$ estimates do not move together because of a discrepancy that arises in the Weight study. The correlation between the $\hat{\omega}$'s estimated from choice data and the $\hat{\omega}$'s estimated from response time data is -0.66.

Additionally, we estimate α and ω for each of the three reward categories. We simply estimate the choice model separately for each reward size category. The response time model is similar to expression (6), except that we allow a distinct discount rate, $\hat{\alpha}_k$, and precision parameter, $\hat{\omega}_k$, for each of the three reward size categories—small, medium, large. Therefore, we seek the vector $(\hat{b}_0, \hat{b}_1, \hat{b}_2, \hat{\alpha}_s, \hat{\alpha}_m, \hat{\alpha}_l, \hat{\omega}_s, \hat{\omega}_m, \hat{\omega}_l)$ that minimizes

$$\sum_{it} [RT_{it} - (\hat{b}_0 + \hat{b}_1 t + \hat{b}_2 \Gamma(\hat{\Delta}_{tk}))]^2,$$

where

$$\hat{\Delta}_{tk} = \frac{2}{1 + e^{\hat{\omega}_k \left| \frac{Y_t}{1 + \hat{\alpha}_k \tau_t} - X_t \right|}},$$

and $k \in \{s, m, l\}$ indexes the reward size categories.

Table 3 shows the estimates of $\hat{\alpha}$ and $\hat{\omega}$ for each of the three reward categories in each of the three studies. Again, the estimates based on choice data covary closely with the estimates based on response times. The correlation between the $\hat{\alpha}$'s estimated from choice data and the $\hat{\alpha}$'s estimated from response time data is 0.82.⁸

4.3. Monte-Carlo horse race

As a final test, we compare the predictive power of models estimated using choice data and models estimated using RT data. The idea of the procedure is to estimate α and ω on a subsample of the data using the choice model and also using the RT model, and then compare the out-of-sample predictions for *choice* data of the two estimated models. This places the RT model at a disadvantage because we are using RT data to make predictions about subsequent choice behavior.

We run Monte Carlo simulations with 1000 trials for each of the three studies. On each trial, we choose M subjects randomly and without replacement from the N subjects in the study. Using data from those M subjects we find $\hat{\alpha}_{choice}$ and $\hat{\omega}_{choice}$ by maximizing expression (2) and we find $\hat{\alpha}_{RT}$ and $\hat{\omega}_{RT}$ by minimizing expression (6).

For the other N–M subjects, we first calculate the mean squared residual from the choice-estimated and RT-estimated parameters. We define the squared residual on trial t of subject i induced by parameters α and ω as

⁸ The correlation between the $\hat{\omega}$'s estimated from choice data and the $\hat{\omega}$'s estimated from response time data is 0.94.

$$\hat{\eta}_{it}^2 = \left[d_{it} - F_{\text{Logit}} \left(\frac{Y}{1 + \alpha\tau} - X \right) \right]^2,$$

where the variance of the logistic distribution is $1/\omega$ and where d_{it} is a binary 0-1 variable that equals 1 if and only if subject i chooses the delayed reward on trial t . Next, we calculate the fraction of responses predicted correctly by the two sets of parameters. We say that a response d_{it} is predicted correctly by the discounting parameters α and ω if the probability of that response is at least $1/2$ under the choice model:

$$\left| d_{it} - F_{\text{Logit}} \left(\frac{Y_t}{1 + \alpha\tau_t} - X_t \right) \right| \leq 1/2.$$

For each study, we run the Monte Carlo procedure for $M = 25$, $M = 50$, and $M = 75$ and we compute the average of the mean squared residual and the fraction of responses predicted correctly across the 1000 trials. Table 4 shows the mean squared residual and the fraction of responses predicted correctly for the two sets of parameters estimated from choice and RT data, respectively. The discounting parameters estimated using RT data predict out of sample responses almost as well as the parameters estimated using choice data.

When we estimate the discounting parameters for each of the three reward categories, the results are qualitatively similar. The difference is that the discounting parameters estimated using RT data do not predict out of sample responses very well when the sample size is small ($M = 25$). This could be due to the addition of more parameters to the model and the inherently noisy nature of response time data.

5. Conclusion

We have used two different approaches to measure preferences. First we adopted the classical approach of inferring preferences from choices. Second we adopted the novel approach of inferring preferences using only response time data. Remarkably, these two approaches yielded nearly identical preference estimates for our aggregated subjects. We conclude that response time data sheds light on both our preferences and on the cognitive processes that execute those preferences.

Future work should extend this analysis by asking related questions at the individual subject level. Can response time data also predict variation in preferences at the subject level? Are there sources of data, whether response times or other indices of information processing such as neural activity, that can be used to improve our ability to predict an individual's choice behavior? Fully exploiting all of the behavioral and physiological information that we can measure during intertemporal choice should enable us to construct more accurate models that yield more novel and precise predictions.

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Table 1: Discount rates estimated using choice data

	Weight	Cognition	Web
Alpha	0.0090	0.0060	0.0050
	[0.0005]	[0.0003]	[0.0001]
Alpha small	0.0248	0.0143	0.0104
	[0.0021]	[0.0011]	[0.0005]
Alpha medium	0.0129	0.0063	0.0056
	[0.0010]	[0.0005]	[0.0002]
Alpha large	0.0065	0.0045	0.0037
	[0.0006]	[0.0003]	[0.0001]

Notes: Standard errors in brackets.

Table 2: Estimated discounting parameters

	Weight		Cognition		Web	
	Choice	RT	Choice	RT	Choice	RT
Alpha	0.0094	0.0112	0.0060	0.0043	0.0050	0.0051
	[0.0005]	[0.0013]	[0.0003]	[0.0003]	[0.0001]	[0.0003]
Omega	0.0837	0.1545	0.1111	0.0845	0.1199	0.12457
	[0.0028]	[0.0339]	[0.0039]	[0.0158]	[0.0024]	[0.0121]

Notes: Standard errors in brackets. For the RT model, observations are clustered by subject and robust standard errors are reported.

Table 3: Estimated discounting parameters for each reward category

	Weight		Cognition		Web	
	Choice	RT	Choice	RT	Choice	RT
Alpha	0.0207	0.0116	0.0147	0.0089	0.0106	0.0065
small	[0.0018]	[0.0017]	[0.0012]	[0.0012]	[0.0005]	[0.0006]
Alpha	0.0102	0.0106	0.0061	0.0042	0.0057	0.0066
medium	[0.0009]	[0.0020]	[0.0005]	[0.0006]	[0.0002]	[0.0006]
Alpha	0.0061	0.0073	0.0043	0.0040	0.0035	0.0055
large	[0.0006]	[0.0013]	[0.0004]	[0.0005]	[0.0002]	[0.0005]
Omega	0.1509	0.0945	0.1917	0.1345	0.1898	0.1144
small	[0.0079]	[0.0368]	[0.0106]	[0.0262]	[0.0059]	[0.0176]
Omega	0.0804	0.0435	0.1125	0.0773	0.1195	0.0547
medium	[0.0046]	[0.0156]	[0.0066]	[0.0152]	[0.0040]	[0.0082]
Omega	0.0699	0.0395	0.0892	0.0682	0.0979	0.0471
large	[0.0038]	[0.0154]	[0.0053]	[0.0140]	[0.0034]	[0.0076]

Notes: Standard errors in brackets. For the RT model, observations are clustered by subject and robust standard errors are reported.

Table 4: Monte-Carlo results

Estimation Sample Size	Study	Mean SR (Choice)	Mean SR (RT)	Correct (Choice)	Correct (RT)
75	Weight	0.1344	0.1347	0.8338	0.8315
		[0.0002]	[0.0003]	[0.0004]	[0.0005]
	Cognition	0.1163	0.1242	0.8471	0.8352
		[0.0002]	[0.0002]	[0.0005]	[0.0003]
	Web	0.1152	0.1161	0.8390	0.8400
		[0.0000]	[0.0001]	[0.0002]	[0.0002]
50	Weight	0.1349	0.1378	0.8329	0.8263
		[0.0001]	[0.0006]	[0.0003]	[0.0007]
	Cognition	0.1168	0.1252	0.8475	0.8362
		[0.0001]	[0.0002]	[0.0005]	[0.0003]
	Web	0.1155	0.1169	0.8404	0.8414
		[0.0001]	[0.0001]	[0.0002]	[0.0003]
25	Weight	0.1361	0.1490	0.8282	0.8181
		[0.0001]	[0.0018]	[0.0004]	[0.0010]
	Cognition	0.1178	0.1292	0.8477	0.8385
		[0.0001]	[0.0005]	[0.0005]	[0.0004]
	Web	0.1165	0.1204	0.8418	0.8427
		[0.0001]	[0.0003]	[0.0003]	[0.0003]

Notes: Standard errors in brackets.

Figure 1: Plots of $RT - b_1 t$ versus Γ for each of the three studies

