Food Decision-Making under Time Pressure

Samir Huseynov [†] Marco A. Palma [‡]

November 28, 2018

Abstract

Does time pressure affect the cognitive process and subsequently food choices? We use the Drift Diffusion (DD) model and data from a well-controlled experiment to show that the cognitive process behind food choices is subject to significant changes under time pressure. Specifically, we find that subjects tend to accumulate less product information compared to the *no time pressure* condition. Under time pressure, they also spend less time encoding pre-decisional product stimuli and have more information accumulation speed to make food choices. However, faster decisions do not affect the consistency of food choices. Our *post hoc* analysis suggests that subjects manage to use acquired information more efficiently under time pressure. Particularly, with the same amount of accumulated information subjects are more likely to make consistent food choices under time pressure compared to the *no time pressure* condition. Overall, our results indicate that exposing consumers to less, but more crucial food information, may improve the efficiency and consistency of food choices.

Keywords: choice, drift diffusion, food, time pressure.

JEL Codes: C25, D03.

[†]Corresponding author, Research Assistant, Department of Agricultural Economics, Texas A&M University. 2124 TAMU, College Station, Texas, 77843, samirhuseyn@tamu.edu, (979)-777-7173

[‡]Professor, Department of Agricultural Economics, Texas A&M University. 2124 TAMU, College Station, Texas, 77843

1 Introduction

From a conventional economic perspective, consumers maximize a latent utility function based on the decision values of choice alternatives. The rigid concept of a rational economic agent pays little attention to contextual and environmental factors as long as observed choices satisfy the revealed preference framework (Fehr and Rangel, 2011). However, external factors are crucial in value computation, especially when consumers make food choices (Enax et al., 2016, 2015; Hawkes et al., 2015; Jabs and Devine, 2006; Enax et al., 2015; Van Loo et al., 2018). New insights from neuroeconomics provide evidence that the brain assigns different values to choice alternatives depending on various external elements, such as time delay, risk, ambiguity, and decision time (Padoa-Schioppa, 2011; Sokol-Hessner et al., 2012; Barberini et al., 2012). Indeed, previous economic studies also show that factors in a decision environment can change the relative importance of product attributes (Kőszegi and Szeidl, 2012; Bordalo et al., 2013; Grebitus and Roosen, 2018; Van Loo et al., 2018). Time pressure is one of the most critical external cues affecting consumer decisions (Park et al., 1989; Suri and Monroe, 2003). For instance, early in the day, a person may plan for a low sugar meal at lunch, but due to time constraints may end up eating chocolate bars from a vending machine. Time scarcity causes sub-optimal food choices, such as over-consumption of fast food (Jabs and Devine, 2006). In fact, a commonly used sales tactic consists of deliberately expediting a sale so that consumers are rushed to make immature and sub-optimal decisions (Krajbich et al., 2012).

Three intersecting trends motivate our work. First, the number of products in grocery stores has dramatically increased. Ruhlman (2017) documents that the number of items in a typical grocery store almost quintupled from 9,000 in 1975 to over 40,000 in 2008. Second, the complexity of product information has parallelly increased. Food labels have become more complex and there is evidence that consumers are willing to pay a premium to reduce labeling information in nutritional facts (Balcombe et al., 2015). Consumers also prefer more straightforward food labels that require less computational effort. For instance, in the United Kingdom, Guideline Daily Amount (GDA) values provide information about the daily healthy intake values of certain nutrients. Previous studies show that consumers dislike seeing GDA values in percentages as they perceive that it increases the complexity of food labels (Grunert and Wills, 2007). Third, the average shopping time spent inside the grocery store is decreasing. For instance, using the American Time Use Survey, Petrosky-Nadeau et al. (2016) report that the average daily shopping time decreased from 43.1 minutes in the period 2005-2007 to 40.7 minutes in the period 2008-2010. All three trends point out to a more complex landscape for consumers to make food choices (Messer et al., 2017).

Preliminary studies in Psychology show that consumers may alleviate adverse effects of time pressure and the complexity of choice tasks by increasing the speed of information processing (Payne et al., 1988; Zur and Breznitz, 1981), filtering out seemingly less important information (Zur and Breznitz, 1981; Rieskamp and Hoffrage, 2008), and utilizing simplifying decision rules (Payne et al., 1988, 1993; Conte et al., 2016; Spiliopoulos and Ortmann, 2014). However, little has been done in the economics literature in terms of testing the effect of time pressure on the consistency of food choices and the efficiency of using available information to make food choices when agents face incentivized economic decisions. For example, Reutskaja et al. (2011) analyze the impact of time limitations on food choice behavior when subjects complete multi-item decision problems. However, Reutskaja et al. (2011) do not have a control condition that excludes time pressure, as their research question is not to establish a causal link between time pressure and food choices. Furthermore, secondary data sources usually record the choice behavior of consumers without any information about how consumers process food-related cues. Thus, an experimental research framework that randomly assigns a time pressure condition and controls for potential confounding factors has the advantage to elicit the effect of time pressure on the consistency of food choices and efficiency of using food information.

We use data from the experiment of Oud et al. (2016) to analyze the consistency of food choices and the efficiency of information acquisition under time pressure[1]. The experiment of Oud et al. (2016) consists of two parts and offers a well-controlled and unique design for answering our research question. In the first part, subjects reveal their WTP for snack food products using a non-hypothetical experimental auction framework. In the second part, the snacks from the first part are randomly paired, and subjects choose their preferred snack out of two alternatives in five decision blocks. Two blocks impose time pressure, and three blocks do not have a time constraint. Our performance measure is based on subjects' consistency with the WTP measure. If a subject chooses the alternative with higher (lower) self-identified WTP, we label the outcome *time-consistent* (*time-inconsistent*) choice. Since no additional information is provided in the second part, we assume that subjects preserve their preferences revealed in the first part. That is, we assume subjects have time-consistent preferences. It is known that agents' preferences cannot be directly observed by the experimenter, especially when the research interest is in decision accuracy (Fudenberg et al., 2017). Thus, in economic studies, constructing outcome measures based on previous ordinal rankings of choice alternatives is becoming more common (Woodford, 2014; Fudenberg et al., 2017; Fehr and Rangel, 2011; Reutskaja et al., 2011; Armel and Rangel, 2008). WTP measures have also been extensively used to analyze the welfare consequences of changes in food demand (Lusk and Anderson, 2004; Gao and Schroeder, 2009). Thus, based on previous studies a subject's welfare increases if she/he makes time-consistent decisions. Therefore, our study also contributes by studying the impact of time pressure on welfare changes associated with food decisions. In our case, subjects start the second part of the experiment immediately after finishing the first part. This design feature helps us to control for subjects' information set and make the first and second parts reasonably comparable. Nevertheless, it is possible that subjects may learn and become better in experimental tasks as they proceed along the experimental blocks. In our *post hoc* analysis, we show that our results are still robust to the inclusion of possible learning effects. We also control for

[1]We are immensely grateful to Ian Krajbich for his comments and suggestions that greatly contributed to improving this manuscript.

choice difficulty and scrutinize the choice process using the Drift Diffusion (DD) model. We also estimate the information threshold subjects' use to complete their decisions under time pressure. Moreover, we analyze subjects' efficiency in utilizing accumulated information about choice alternatives in making *time-consistent* decisions.

Our results suggest that the cognitive process of food decision-making is subject to changes under time pressure. We document that under time constraints, subjects spend less time encoding external product stimuli, increase the speed of evidence accumulation and also reduce the amount of information needed to make food choices. However, we do not detect a decrease in the number of *time-consistent* choices when subjects face time constraints. Thus, with the help of incentivized experimental choice tasks, we show that consumers may adapt to time pressure without impairing choice performance. Moreover, we observe that *time-inconsistent* choices are slower compared to *time-consistent* choices when subjects face time pressure and also when they do not have task-specific time constraints. This result is aligned with findings in the psychology and economic literature which show that "decision errors" can also be accompanied by longer decision times (Ditterich, 2006; Churchland et al., 2008; Achtziger and Alós-Ferrer, 2013; Fudenberg et al., 2017). We also find that the difficulty of choices matters by showing that larger WTP differences between choice alternatives increase the likelihood of making *time-consistent* choices (i.e., choosing the alternative with the higher WTP). Our analysis shows that under time pressure — with the same amount of information — decision-makers are more likely to make *time-consistent* decisions compared to the control condition which has no time limitations. This result suggests that subjects tend to cope with time pressure by using acquired information more efficiently. Thus, exposing consumers to less complicated food labels with crucial information may increase the consistency of food choices under time pressure. In fact, new rules by the Food and Drug Administration (FDA) on nutrition labeling discuss using larger fonts for calorie information compared to price information (FDA, 2014).

The rest of the article proceeds as follows: A discussion of related studies employing response time is presented in section 2. Next, the *Materials and Methods* section lays out the experimental setup. The *Methodolog*y section presents the Drift Diffusion model and empirical methods, respectively. The *Estimation Results* discusses the results, and the last section concludes.

2 Response time data in choice modeling

Traditional economic models usually omit the time dimension of the choice process; however, as Camerer (1998) suggests, economists should "spend more time in the wild" and should bring new insights into economic modeling to better understand individual behavior. The time limitation is always salient "in the wild." Recently economists have demonstrated high interest in incorporating response time (RT) data into models of consumer choice (Kocher and Sutter, 2006; Fehr and Rangel, 2011; Achtziger and Alós-Ferrer, 2013; Rubenstein, 2013; Spiliopoulos and Ortmann, 2014; Caplin and Martin, 2016; Rubinstein, 2016; Agranov and Ortoleva, 2017).[2] Food choices have received increasing attention in the context of time pressure (Enax et al., 2016; Krajbich and Smith, 2015; Balcombe et al., 2015). Mostly because in the presence of time constraints temptation and other visceral emotions are activated in food decision-making.

DD models have been extensively used to analyze the choice process with the help of RT (Caplin and Martin, 2016; Krajbich et al., 2012; Milosavljevic et al., 2010; Ratcliff and Smith, 2004; Ratcliff and McKoon, 2008). DD models are special cases of sequential sampling models (SSM), initially developed in the experimental psychology literature to analyze speed-accuracy trade-offs in binary choices (Ratcliff, 1978; Ratcliff and Smith, 2004; Ratcliff and McKoon, 2008). Interested readers should consult Ratcliff and Smith (2004) who offer an extensive survey on different types of sequential sampling models, including discrete and continuous time models with relative or absolute stopping rules. The primary building assumption of these models is that while making a decision, the central neural system acquires

[2]See Spiliopoulos and Ortmann (2014) for an extensive survey of the literature.

stimuli signals, which most of the time tend to be very noisy (Ratcliff and Smith, 2004; Sundararajan et al., 2017). Thus, a DM sequentially samples evidence for choice alternatives until a decision criterion favors one of the choice options (Ratcliff and Smith, 2004). The most employed decision criterion is the threshold rule, which assumes that a DM collects signals of all decision alternatives until accumulated evidence goes beyond a threshold favoring one of the options. This rule overlaps with one of the principal premises of Neuroeconomics, which models that neurons transmit all-or-nothing signals (or "action potentials") only after decision values in the neurons reach a certain level (Krajbich et al., 2014).

In DD, one needs to observe the decision outcomes and RT data to understand the evidence accumulation process (Ratcliff and McKoon, 2008; Krajbich et al., 2014; Spiliopoulos and Ortmann, 2014). RT data can also serve to identify how smooth the decision process is, since a slow decision process may hint to more signal sampling due to the difficulty of economic choices (Alós-Ferrer, 2018). Furthermore, one salient attribute can significantly make the decision process very smooth and fast through allocating limited attention to the "right" dimension of choice alternatives (Bordalo et al., 2013; Spiliopoulos and Ortmann, 2014; Masatlioglu et al., 2016; Kőszegi and Szeidl, 2012; Karmarkar and Plassmann, 2017). Usually, conventional economic models describe choice with the help of Random Utility Theory (RUT) type models, which conceptualize the choice process as a mapping of preferences to action space and ignore dynamic information acquisition and comparison aspects of decisions (Krajbich and Smith, 2015). For example, under RUT the variance of decision value signals are time-invariant. Time invariance ignores that the accumulation of evidence is a function of time; but in the real world more decision time results in the collection of more information and eventually changes choice outcomes (Krajbich and Smith, 2015; Gabaix et al., 2006). Thus, DD models offer an extensive framework for analyzing the dynamic structure of economic choice with insights from cognitive psychology (Alós-Ferrer, 2018; Ratcliff and McKoon, 2008; Krajbich and Smith, 2015; Spiliopoulos and Ortmann, 2014; Milosavljevic et al., 2010; Ratcliff, 1978; Ratcliff and Smith, 2004).

RT data can also be useful to inform about the strength of preferences. For example, if a decision maker spends 10 seconds choosing an apple over an orange, and 5 seconds choosing an apple over a banana, with the help of RT data and the DD model, we can predict that the DM will choose the orange over the banana (Krajbich et al., 2014). Since the choice process between the apple and the orange was slower compared to the choice process between the apple and the banana, it suggests that the DM assigns closer values to the alternatives in the former case. Thus she/he will most likely choose the orange over the banana. However, solely relying on RT data does not tell the whole picture. For instance, Agranov and Ortoleva (2017) find that there are no statistical differences between the RT distribution of stochastic and non-stochastic choices in difficult choice problems; this may suggest that without employing the DD framework, RT data may turn out to be less informative. Hence, in our analysis we combine these two concepts to study the impact of time pressure on the consistency and efficiency of food choices.

3 Materials and Methods

We use data from Oud et al. (2016) to answer our research questions. Forty-nine subjects participated in the study and received CHF 30 (1 CHF is around 1 USD). In the first part of the study, subjects were endowed with CHF 2.50 and presented with 100 different snack foods and were asked to report their Willingness-to-Pay (WTP) for each snack using the Becker-DeGroot-Marshak (BDM) mechanism (Becker et al., 1964). In every trial, subjects were shown a colored photo of each food product, and they were asked to submit a bid for the item from CHF 0 to CHF 2.50, in CHF 0.25 increments. In the second part, a within-subject design framework was employed, and subjects were presented with five blocks of choice tasks, that included randomly paired snacks from the first part; each block lasted 150 seconds. Each block contained 100 choice problems, with two different snacks per problem. Subjects were asked to choose one of the snacks. In this study, we focus only on choices with non-zero WTP differences. After 150 seconds, if a subject still had incomplete choice tasks, the computer made a decision and randomly picked one of the snacks, so it was in the best interest of subjects to make fast and accurate decisions. In all cases, the first block was the control block (C), and subjects were informed that two blocks out of the following four had a time constraint. We denote time restricted blocks with Treatment (T) and non-time constrained blocks with Non-Treatment (NT). NT blocks were identical to the C block and the only difference was that NT blocks contained different choice tasks. In T blocks, after a pre-determined time (the mean RT of 30% of the slowest decisions), a subject was shown a "*Choose Now*" message on the computer screen, and if she/he didn't conclude the task within 0.5 seconds after the message appeared on the screen, the computer automatically and randomly selected one of the products on the subject's behalf, and the next choice task started. Subjects were randomly assigned to one of the following two block sequences: C-NT-T-NT-T or C-T-NT-T-NT. In total, subjects went through six decision blocks: one block from the first part and five blocks from the second part. After completing the experiment, one of the decision tasks from the two parts was randomly drawn, and subjects were rewarded based on their choices. If the first block was chosen, a subject received the food, provided that the randomly drawn market price was equal to or less than the subject's WTP; otherwise, she/he kept the CHF 2.50 endowment. For the remaining five blocks, subjects received their preferred product if the randomly selected choice task was from those blocks.

In this article, we focus only on human-made decisions and regroup choice tasks into three categories: *no time pressure, time pressure and post time pressure.* The choice tasks from NT (if they come before the first T block) and C blocks have been analyzed under *no time pressure*, since these tasks had the same experimental conditions, i.e., without time limitations. We classify tasks from T blocks under *time pressure* and tasks of NT blocks (which came after T blocks) under *post time pressure.* The choice tasks in the *no time pressure* allow for analysis of the behavior of subjects under general time limitations and without a task-specific intervention. This resembles general time limitations of daily life, such as 24 hours in a day, which is mostly not salient for a specific task. Feelings of urgency are notable and can affect the behavior when a DM faces task-specific time constraints, such as a project deadline (Ariely and Wertenbroch, 2002). On the other hand, choices in the *time pressure*, help us to understand the effect of choice-specific deadlines. Furthermore, *post time pressure* tasks are suitable to capture any learning effects from the treatment conditions.

4 Methodology

4.1 *The Drift Diffusion (DD) Model*

In this section, we briefly describe the DD estimation procedures. When a DM faces a choice problem between option x and option y, at time t, she/he observes evidence (signals) x_t and y_t, that are randomly drawn from two distributions with mean u_x and u_y respectively (Krajbich et al., 2014). The DD model assumes that subjects gradually collect food snack information before making their final choices. Hence, according to the DD model, this information accumulation process progresses continuously and behaves like the "random walk" model. We follow Navarro and Fuss (2009) and assume that $V(t)$ represents the accumulated information at t about the binary decision alternatives (a similar setup is found in Krajbich et al. (2014)):

$$V(t) = V(t-1) + \delta(x_t - y_t) \tag{1}$$

where δ is the drift rate and it indicates how $V(t)$ evolves through time. Notice that, the accumulated information evolves via the stochastic differential equation $\frac{d}{dt}V(t) \sim Normal(v, \sigma^2)$, which is another mathematical formulation for the drift rate δ in equation (1). We also assume that the drift rate is constant within a choice task (Krajbich and Smith, 2015). Figure 1 sketches a general graphical representation of the DD model.

[*Figure* 1 *about here*]

Let's assume that the initial level of information at $t = 0$ is $0 < V(0) < \alpha$. Then the decision is made when either $V(t) \leq 0$ (the DM chooses y) or $V(t) \geq \alpha$ (the DM chooses x) at $t \neq 0$. Here α is the *boundary separation* parameter that can be interpreted as the informational distance between alternatives. If α gets larger, it will increase the decision time, since the DM will need more information to reach one of the two boundaries. Note that α can also be interpreted as a confidence level for the DM to conclude a choice decision. It should be noted that we assume α and δ change across trials (Ratcliff, 1978; Ratcliff and McKoon, 2008; Krajbich and Smith, 2015).

The parameter β is the *initial bias,* meaning if the DM has pre-decisional preferences, then β will capture them. $\beta = 0.5$ corresponds to the non-bias case, but if it changes upwards (downwards) it reflects a positive (negative) bias to the corresponding alternative. The parameter τ is *non-decision time* which is needed for the DM to react to external stimulus. Large values of τ suggest that the DM spends more time to encode product stimuli. Finally, as mentioned before, δ is a *drift rate* and represents the slope of the information accumulation process as described in equation (1).[3]

4.2 *Drift Diffusion Estimation*

We compute the density of actual RT $d(t, choiceconsistent = 0 \mid \alpha, \beta, \tau, \delta)$ (i.e. when the DM chooses y) for each subject using the following formula:

$$\frac{1}{\alpha^2} exp\left[-\alpha\beta\delta - \frac{1}{2}\delta^2(t-\tau)\right] f\left(\frac{t-\tau}{\alpha^2} \mid \beta\right) \tag{2}$$

where t is the observed time. A similar formula for the upper boundary, i.e. $d(t, choiceconsistent = 1 \mid \alpha, \beta, \tau, \delta)$ can be obtained using the following reformulation:

[3] see Wabersich and Vandekerckhove (2014) for a detailed discussion.

$$d(t, choiceconsistent = 1 \mid \alpha, \beta, \tau, \delta) = d(t, choiceconsistent = 0 \mid \alpha, 1 - \beta, \tau, -\delta) \quad (3)$$

We fit $d(t, choiceconsistent = 1 \mid \alpha, \beta, \tau, \delta)$ density function with the data for each subject separately and the parameters are estimated using the best fit which better approximates the response time distribution for each subject. We also set β to 0.5 as we do not expect that subjects had a pre-decisional bias. We use the Rwiener package to estimate the model parameters for each subject under each experimental condition (Wabersich and Vandekerckhove, 2014).[4] Then, we pool the estimated parameters to compute the average values for each experimental condition. We also calculate 95% confidence intervals using the non-parametric bootstrap method.

4.3 *Mixed Effects Logit Estimation*

We estimate a *mixed effects logit* model for each experimental condition to analyze the role of the WTP difference and possible learning effects in choosing the consistent alternative. Our dependent variable *choiceconsistent* is a binary measure and takes the value of 1 if in the choice task the DM chooses the alternative with a larger self-identified WTP, and 0 otherwise. *trialn* and *absdiff* are independent variables and represent the presentation order of choice pairs and WTP differences between the choice options, respectively. The inclusion of *trialn* helps us to control for any learning effects as subjects proceed along the experimental tasks. We also control for block effects by including block dummies into our regressions. Furthermore, we also estimate another mixed effects logit model using $\hat{\alpha}$ and $\hat{\alpha}^2$ from the estimated DD model in order to assess the efficiency of information usage by subjects across experimental conditions. Furthermore, the existence of multiple observations per subject over time suggests that there can exist a non-linear relationship between covariates and

[4]We compiled estimation results in latex tables with the Stargazer package (Hlavac, 2014).

individual level unobservables. Thus we employ the mixed effects logit model with the following specification (Hosmer Jr et al., 2013):

$$log\left[\frac{Pr(Y_{ij}=1)}{Pr(Y_{ij}=0)}\right] = \beta_{0i} + \beta_k X_{ij} \tag{4}$$

where $\beta_{0i} = \beta_0 + \xi_i$. i and j subscripts denote individuals and observations respectively. X_{ij} is a matrix of independent variables. β_0 is population level intercept and ξ_i captures individual level random effect.

5 Estimation Results

We start our analysis by scrutinizing the overall performance of subjects across the experimental conditions. Table 1 shows that 89.75%, 88.81% and 91.01% of food choices were *time-consistent* in the *no time pressure*, *time pressure* and *post time pressure* conditions, respectively. The proportion of consistent choices slightly varies across experimental conditions. Nevertheless, we observe that on average at least 89% of food choices are consistent across experimental conditions. A one-sided Wilcoxon–Mann–Whitney test shows that there is no statistically significant difference when we compare the average number of *time-consistent* choices from *no time pressure* to *time pressure* ($Z = -0.89$, $p = 0.19$) and *no time pressure* to *post time pressure* ($Z = -0.90$, $p = 0.19$).[5] However, the test indicates that the percentage of time-consistent choices increased in the *post time pressure condition* compared to *time pressure* ($Z = -1.75$, $p = 0.04$). Furthermore, the average RT was 1.17s, 0.73s, and 0.84s in the *no time pressure*, *time pressure* and *post time pressure* conditions, respectively. Thus, subjects spent less time on food choices under time pressure compared to the *no time pressure* condition ($Z = -7.31$, $p < 0.01$), but they increased the average RT in the *post time pressure condition* ($Z = -2.88$, $p < 0.01$). The food choice and RT performance show that under time pressure, on average subjects spent less time on choice tasks but it did not

[5] We clustered the average number of *time-consistent* choices at the individual level and then conducted the statistical tests.

significantly decrease the number of *time-consistent* food choices.

[$Table\ 1\ about\ here$]

Figure 2 depicts the average RT for consistent and inconsistent choices across experimental conditions. In all cases, subjects spent significantly more time when their choices were *time-inconsistent.* This finding is in line with previous studies that show "decision errors" can be slower (Ditterich, 2006; Churchland et al., 2008; Achtziger and Alós-Ferrer, 2013). The plain reading of the results shows that time was not a crucial factor in improving the number of *time-consistent* choices. However, this conclusion might be problematic since RT is endogenous and is highly related to other individual characteristics. Thus we conducted an additional analysis to uncover the role of RT in *time-consistent* choices. Table 2 shows the results of instrumental variable logit regressions for the pooled sample and the experimental conditions separately. Since RT is endogenous, we used absdiff (the absolute WTP difference between alternatives) as an instrumental variable (IV). The IV variable (absdiff) is completely random (i.e., choice pairs were constructed randomly) and changes across choice problems. Using the Montiel-Pflueger robust weak instrument test ($F - stat = 237.07, p < 0.01$) we reject the null hypothesis that absdiff is a weak instrument (Olea and Pflueger, 2013). Instrumental variable logit regression results show that RT is negatively correlated with *time-consistent* choices in the pooled sample, as well as in subsamples. This result is in line with the literature, suggesting that as subjects spend more time for choice tasks, they become more prone to make inconsistent decisions (Krajbich and Smith, 2015; Busemeyer and Townsend, 1993). For instance, Armel and Rangel (2008) find that an increase in RT from 0.5 to 3.5 seconds consequently increases subjects' WTP for junk food around 43 cents. In our setting, we cannot differentiate RT for *time-consistent* and *time-inconsistent* alternatives in the same choice problem, since our RT measure is the total response time that a subject spent for a choice task. However, several studies confirm that as subjects spend more time looking at inferior alternatives, they are more likely to end up choosing those alternatives (Cavanagh et al., 2014; Krajbich and Smith, 2015).

[*Figure 2 about here*]

[*Table 2 about here*]

Up to this point, our results indicate that although subjects under time pressure spend less time to make their choices, the average number of *time-consistent* decisions do not change. Also, spending more time on the choice problem does not guarantee *time-consistent* decisions. Recall that on average subjects spend more time on *time-inconsistent* outcomes. It seems that subjects adjust their behavior when facing time constraints and other factors were also effective in the decision process. Thus, we turn to the DD estimations results to understand the background process of food decision-making. Table 3 reports the estimated parameters of the DD model for each experimental condition. The coefficient of α (*boundary separation* parameter) is 2.30, 1.50 and 1.86 for *no time pressure*, *time pressure,* and *post time pressure* conditions, respectively. Recall that α indicates the amount of information subjects needed to make their choices. α is endogenous and the change in its values across experimental conditions reflects how subjects adjusted their behavior under time pressure. Parameter estimates are significantly different when we compare the *no time pressure* to the *time pressure* condition. The results provide evidence that under the time constraint, on average subjects considered less information to finalize their decisions. The parameterτ shows the time subjects spent to process product stimuli and it is 0.53, 0.42 and 0.45 for the *no time pressure*, *time pressure,* and *post time pressure* conditions, respectively. τ's value for the *time pressure* and *post time pressure* conditions are significantly different from the *no time pressure*, implying that subjects spent less time encoding products' stimuli under time pressure. This indicates that subjects spent less time acquiring and preparing product-related information before the start of the decision process. Furthermore, we observe a spill-over effect from the *time pressure* condition, as subjects demonstrated less pre-decisional information encoding time in the *post time pressure* compared to *no time pressure* condition. δ is the slope of the information accumulation process, and its values are 1.35, 2.04 and 1.82 in the *no time pressure*, *time pressure* and *post time pressure* conditions, respectively. This result means that information accumulation speed under time pressure is significantly higher compared to the *no time pressure* condition. Overall, the results of DD estimates show that subjects tend to achieve fast decisions under time constraints as they accumulated significantly less information (α), incurred less pre-decisional encoding time (τ) and had more information accumulation speed (δ) to complete the food choice tasks.

[$Table\ 3\ about\ here$]

However, under time pressure subjects focus on more crucial information about decision alternatives. Table 1 shows that subjects did not have significantly less *time-consistent* choices and it may suggest that subjects only considered important information (from their perspectives) for making their decisions. Unfortunately, data limitations do not allow us to identify what kind of information (the color and/or size of packages, the type of snacks and etc.) was salient under time pressure. Future studies may explore this dimension using technological advances, such as eye-tracking. Nevertheless, we can hypothesize that perhaps under time pressure subjects managed to consider less, but more vital information about the choice alternatives. An additional mixed effects analysis was conducted to test this hypothesis. We ran a mixed effects logit regression where we regress *choiceconsistent* on $\hat{\alpha}$ and $\hat{\alpha}^2$. The inclusion of $\hat{\alpha}^2$ enables to capture the diminishing return of information in the decision process. After fitting this model for each experimental condition, the estimated coefficients were used to predict the probability of *time-consistent* choices. Figure 3 shows fitted probability graphs for each experimental condition, where the relationship between $\hat{\alpha}$ (information threshold) and the probability of making a time-consistent choice is depicted for each experimental condition. Wilcoxon–Mann–Whitney test results ($Z = -12.88$, $p < 0.01$)

confirm that the distribution of predicted probabilities for *no time pressure* is smaller compared to the *time pressure* condition. Furthermore, the mean of the distribution of predicted probabilities for the *post time pressure* condition is greater compared to the *no time pressure* condition. This result indicates that for the same amount of information *($\hat{\alpha}$)* subjects were more likely to make *time-consistent* choices under time pressure compared to the *no time pressure* condition. Figure 3 suggests that subjects may focus on more crucial information under the time limitation condition. Thus, subjects were more efficient in utilizing limited product information under time pressure compared to *no time pressure* condition. In fact, a growing literature that focuses on time pressure and selective attention to the cues of choice alternatives report congruent findings. For instance, Rieskamp and Hoffrage (2008) find that subjects spend on average 2%-5% more time on important cues of choice alternatives under *high time pressure* condition compared to *low time pressure* condition. Although we cannot identify the type of food product information that was more salient under time pressure, our analysis suggests that subjects managed to be more efficient with collected information when facing time restrictions. This finding also may explain why they did not make less *time-consistent* choices in the *time pressure* condition.

[*Figure 3 about here*]

Table 4 shows that absdiff (the absolute difference in WTP) is positively correlated with *time-consistent* choices and the coefficient estimates are significant across all experimental conditions. These results confirm that as the WTP difference between alternatives become larger, subjects are more likely to choose *time-consistent* choices. Moreover, trialn represents the presentation order of each choice problem, and statistically, its effect is not different from zero. Controlling trialn and block dummies ensures that our results are not contaminated by learning effects in the experimental tasks.

[*Table 4 about here*]

6 Conclusion

Time limitations are one of the most critical external factors influencing consumer behavior. The majority of economic studies scrutinize decision time with the help of outcome-based models. We show that the economics literature may also substantially benefit from process-based models. Process-based models not only help to explain choice outcomes, but they also provide valuable insights about specific mechanisms of economic choices (Spiliopoulos and Ortmann, 2014). These insights are useful in predicting choice outcomes, as well as in understanding how decision makers adapt to various changes in the decision environment (Spiliopoulos and Ortmann, 2014). For instance, from a policy perspective, process-based models are helpful to understand food choice behavior and to design appropriate nudges to promote healthy-eating behavior. The existing literature has mainly focused on formal procedural models (Spiliopoulos and Ortmann, 2014; Kahneman, 2011; Brocas and Carrillo, 2014; Levine and Fudenberg, 2006), but this direction of research is prone to inverse inference and identification problems (Krajbich et al., 2015; Spiliopoulos and Ortmann, 2014). Our work fills this gap with a well-established sequential-sampling model, which has a long history in the psychology literature and has also received attention in recent economic studies (Milosavljevic et al., 2010; Fudenberg et al., 2017; Clithero, 2018; Ke et al., 2016; Fudenberg et al., 2017; Echenique and Saito, 2017; Caplin, 2016).

Our primary focus is time pressure and its impact on food choices. Increased choice overload in grocery stores, overwhelming complexity of food labels, and a reduction in the amount of the time spent in food-related shopping transactions motivate our research. Because of these three trends, policy-making initiatives are converging on developing necessary tools to facilitate welfare increasing food choices. Previous studies focused on WTP measures as proxies of welfare consequences of the changes in food demand (Lusk and Anderson, 2004; Gao and Schroeder, 2009). Thus, we use self-identified incentivized WTP values to assess the impact of time constraints on the consistency of food decisions.

Our study documents that the cognitive process behind food decisions is subject to changes under time pressure. Specifically, our Drift Diffusion estimates show that subjects achieve fast decisions under time constraints by increasing the speed of evidence accumulation process. Moreover, we show that under time pressure subjects accumulate significantly less product information compared to the *no time pressure* condition. They also spend less time encoding pre-decisional product stimuli. However, faster decisions do not reduce the number of *time-consistent* food choices. Our *post hoc* analysis suggests that subjects manage to use acquired product-related information more efficiently under time pressure. Specifically, with the same information threshold subjects are more likely to make *time-consistent* choices under time constraints compared to the *no time pressure* condition. Thus, we conclude that subjects adapt their behavior to time constraints and become more efficient in using food information.

Since due to time constraints subjects reduce their information thresholds to conclude food choices, our results suggest that consumers cannot attend complex food information to the full extent under time pressure. The policy implication of this finding is that less complicated and crucial product information can be an effective way to modify food choices. For example, Balcombe et al. (2015) find that exposing consumers to food information in the form of complex nutritional facts does not increase healthy food choices. They also show that consumers prefer having less and customized food information, instead of having a large amount of generic information (Balcombe et al., 2015). Furthermore, Khachatryan et al. (2018) show that impulsive buyers exhibit fewer fixations on product signs and more fixations on displays. Therefore, focusing on the important product information can decrease impulsive purchases. Moreover, McFadden (2018) finds that consumer attitude to Genetically Modified (GM) products has an impact on the attention to food labels. Thus exposing consumers to less, but more crucial food information and encouraging them to evaluate choice alternatives carefully can improve welfare increasing choices (Van Loo et al., 2018). Furthermore, we also present evidence that *time-inconsistent* food decisions took longer compared *time-consistent* choices. Future studies may scrutinize the relationship between attention and *time-inconsistent* food choices using the *fixation time* for each choice alternative. This venue of research may also yield effective nudges to direct the attention of consumers to more critical food information (such as calorie and saturated fat) and may lead to healthier food choices. One potential challenge is that not every consumer cares about the same information. However, in this regard, a good starting point is to provide simplified information targeting high-risk individuals or vulnerable populations for chronic diseases, such as diabetes, obesity, cardiovascular and neurodegenerative diseases.

References

Achtziger, A. and C. Alós-Ferrer (2013). Fast or rational? a response-times study of bayesian updating. *Management Science 60*(4), 923–938.

Agranov, M. and P. Ortoleva (2017). Stochastic choice and preferences for randomization. *Journal of Political Economy 125*(1), 40–68.

Alós-Ferrer, C. (2018). A dual-process diffusion model. *Journal of Behavioral Decision Making 31*(2), 203–218.

Ariely, D. and K. Wertenbroch (2002). Procrastination, deadlines, and performance: Self-control by precommitment. *Psychological science 13*(3), 219–224.

Armel, K. C. and A. Rangel (2008). The impact of computation time and experience on decision values. *The American Economic Review 98*(2), 163–168.

Balcombe, K., I. Fraser, B. Lowe, and D. Souza Monteiro (2015). Information customization and food choice. *American Journal of Agricultural Economics 98*(1), 54–73.

Barberini, C. L., S. E. Morrison, A. Saez, B. Lau, and C. D. Salzman (2012). Complexity and competition in appetitive and aversive neural circuits. *Frontiers in neuroscience 6*, 170.

Becker, G. M., M. H. DeGroot, and J. Marschak (1964). Measuring utility by a single-response sequential method. *Systems Research and Behavioral Science 9*(3), 226–232.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013). Salience and consumer choice. *Journal of Political Economy 121*(5), 803–843.

Brocas, I. and J. D. Carrillo (2014). Dual-process theories of decision-making: A selective survey. *Journal of economic psychology 41*, 45–54.

Busemeyer, J. R. and J. T. Townsend (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological review 100*(3), 432.

Camerer, C. F. (1998). Prospect theory in the wild: Evidence from the field.

Caplin, A. (2016). Measuring and modeling attention. *Annual Review of Economics 8*, 379–403.

Caplin, A. and D. Martin (2016). The dual-process drift diffusion model: Evidence from response times. *Economic Inquiry 54*(2), 1274–1282.

Cavanagh, J. F., T. V. Wiecki, A. Kochar, and M. J. Frank (2014). Eye tracking and pupillometry are indicators of dissociable latent decision processes. *Journal of Experimental Psychology: General 143*(4), 1476.

Churchland, A. K., R. Kiani, and M. N. Shadlen (2008). Decision-making with multiple alternatives. *Nature neuroscience 11*(6), 693.

Clithero, J. A. (2018). Improving out-of-sample predictions using response times and a model of the decision process. *Journal of Economic Behavior & Organization 148*, 344–375.

Conte, A., M. Scarsini, and O. Sürücü (2016). The impact of time limitation: Insights from a queueing experiment. *Judgment and Decision Making 11*(3).

Ditterich, J. (2006). Stochastic models of decisions about motion direction: behavior and physiology. *Neural networks 19*(8), 981–1012.

Echenique, F. and K. Saito (2017). Response time and utility. *Journal of Economic Behavior & Organization 139*, 49–59.

Enax, L., Y. Hu, P. Trautner, and B. Weber (2015). Nutrition labels influence value computation of food products in the ventromedial prefrontal cortex. *Obesity 23*(4), 786–792.

Enax, L., I. Krajbich, and B. Weber (2016). Salient nutrition labels increase the integration of health attributes in food decision-making. *Judgment and Decision Making 11*(5), 460.

Enax, L., B. Weber, M. Ahlers, U. Kaiser, K. Diethelm, D. Holtkamp, U. Faupel, H. H. Holzmüller, and M. Kersting (2015). Food packaging cues influence taste perception and increase effort provision for a recommended snack product in children. *Frontiers in psychology 6*, 882.

FDA (2014). Food labeling; nutrition labeling of standard menu items in restaurants and similar retail food establishments. final rule. *Federal register 79*(230), 71155.

Fehr, E. and A. Rangel (2011). Neuroeconomic foundations of economic choice–recent advances. *Journal of Economic Perspectives 25*(4), 3–30.

Fudenberg, D., P. Strack, and T. Strzalecki (2017). Stochastic choice and optimal sequential sampling.

Fudenberg, D., P. Strack, T. Strzalecki, et al. (2017). Speed, accuracy, and the optimal timing of choices. *Available at SSRN*.

Gabaix, X., D. Laibson, G. Moloche, and S. Weinberg (2006). Costly information acquisition: Experimental analysis of a boundedly rational model. *The American Economic Review*, 1043–1068.

Gao, Z. and T. C. Schroeder (2009). Effects of label information on consumer willingness-to-pay for food attributes. *American Journal of Agricultural Economics 91*(3), 795–809.

Grebitus, C. and J. Roosen (2018). Influence of non-attendance on choices with varying complexity. *European Journal of Marketing*.

Grunert, K. G. and J. M. Wills (2007). A review of european research on consumer response to nutrition information on food labels. *Journal of public health 15*(5), 385–399.

Hawkes, C., T. G. Smith, J. Jewell, J. Wardle, R. A. Hammond, S. Friel, A. M. Thow, and J. Kain (2015). Smart food policies for obesity prevention. *The Lancet 385*(9985), 2410–2421.

Hlavac, M. (2014). Stargazer: Latex code and ascii text for well-formatted regression and summary statistics tables [r package version 5.1].

Hosmer Jr, D. W., S. Lemeshow, and R. X. Sturdivant (2013). *Applied logistic regression*, Volume 398. John Wiley & Sons.

Jabs, J. and C. M. Devine (2006). Time scarcity and food choices: an overview. *Appetite 47*(2), 196–204.

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.

Karmarkar, U. R. and H. Plassmann (2017). Consumer neuroscience: Past, present, and future. *Organizational Research Methods*, 1094428117730598.

Ke, T. T., Z.-J. M. Shen, and J. M. Villas-Boas (2016). Search for information on multiple products. *Management Science 62*(12), 3576–3603.

Khachatryan, H., A. Rihn, B. Behe, C. Hall, B. Campbell, J. Dennis, and C. Yue (2018). Visual attention, buying impulsiveness, and consumer behavior. *Marketing Letters 29*(1), 23–35.

Kocher, M. G. and M. Sutter (2006). Time is money time pressure, incentives, and the quality of decision-making. *Journal of Economic Behavior & Organization 61*(3), 375–392.

Kőszegi, B. and A. Szeidl (2012). A model of focusing in economic choice. *The Quarterly journal of economics 128*(1), 53–104.

Krajbich, I., B. Bartling, T. Hare, and E. Fehr (2015). Rethinking fast and slow based on a critique of reaction-time reverse inference. *Nature communications 6*, 7455.

Krajbich, I., D. Lu, C. Camerer, and A. Rangel (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in psychology 3*.

Krajbich, I., B. Oud, and E. Fehr (2014). Benefits of neuroeconomic modeling: new policy interventions and predictors of preference. *The American Economic Review 104*(5), 501–506.

Krajbich, I. and S. M. Smith (2015). Modeling eye movements and response times in consumer choice. *Journal of agricultural & food industrial organization 13*(1), 55–72.

Levine, D. and D. Fudenberg (2006). A dual-self model of impulse control. *American Economic Review 96*(5), 1449–1476.

Lusk, J. L. and J. D. Anderson (2004). Effects of country-of-origin labeling on meat producers and consumers. *Journal of Agricultural and Resource Economics*, 185–205.

Masatlioglu, Y., D. Nakajima, and E. Y. Ozbay (2016). Revealed attention. In *Behavioral Economics of Preferences, Choices, and Happiness*, pp. 495–522. Springer.

McFadden, B. (2018). How will mandatory labeling of genetically modified food nudge consumer decision-making? *Journal of Behavioral and Experimental Economics*.

Messer, K. D., M. Costanigro, and H. M. Kaiser (2017). Labeling food processes: The good, the bad and the ugly. *Applied Economic Perspectives and Policy 39*(3), 407–427.

Milosavljevic, M., J. Malmaud, A. Huth, C. Koch, and A. Rangel (2010). The drift diffusion model can account for the accuracy and reaction time of value-based choices under high and low time pressure. *Judgment and Decision Making 5*(6), 437–449.

Navarro, D. J. and I. G. Fuss (2009). Fast and accurate calculations for first-passage times in wiener diffusion models. *Journal of Mathematical Psychology 53*(4), 222–230.

Olea, J. L. M. and C. Pflueger (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics 31*(3), 358–369.

Oud, B., I. Krajbich, K. Miller, J. H. Cheong, M. Botvinick, and E. Fehr (2016). Irrational time allocation in decision-making. In *Proc. R. Soc. B*, Volume 283, pp. 20151439. The Royal Society.

Padoa-Schioppa, C. (2011). Neurobiology of economic choice: a good-based model. *Annual review of neuroscience 34*, 333–359.

Park, C. W., E. S. Iyer, and D. C. Smith (1989). The effects of situational factors on in-store grocery shopping behavior: The role of store environment and time available for shopping. *Journal of consumer research 15*(4), 422–433.

Payne, J. W., J. R. Bettman, and E. J. Johnson (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition 14*(3), 534.

Payne, J. W., J. R. Bettman, and E. J. Johnson (1993). *The adaptive decision maker*. Cambridge University Press.

Petrosky-Nadeau, N., E. Wasmer, and S. Zeng (2016). Shopping time. *Economics Letters 143*, 52–60.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological review 85*(2), 59.

Ratcliff, R. and G. McKoon (2008). The diffusion decision model: theory and data for two-choice decision tasks. *Neural computation 20*(4), 873–922.

Ratcliff, R. and P. L. Smith (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological review 111*(2), 333.

Reutskaja, E., R. Nagel, C. F. Camerer, and A. Rangel (2011). Search dynamics in consumer choice under time pressure: An eye-tracking study. *The American Economic Review 101*(2), 900–926.

Rieskamp, J. and U. Hoffrage (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta psychologica 127*(2), 258–276.

Rubenstein, A. (2013). Response time and decision making: An experimental study. *Judgment and Decision Making 8*(5), 540.

Rubinstein, A. (2016). A typology of players: Between instinctive and contemplative. *The Quarterly Journal of Economics 131*(2), 859–890.

Ruhlman, M. (2017). *Grocery: The Buying and Selling of Food in America.* Abrams Press.

Sokol-Hessner, P., C. Hutcherson, T. Hare, and A. Rangel (2012). Decision value computation in dlpfc and vmpfc adjusts to the available decision time. *European Journal of Neuroscience 35*(7), 1065–1074.

Spiliopoulos, L. and A. Ortmann (2014). The bcd of response time analysis in experimental economics. *Experimental Economics*, 1–51.

Sundararajan, R. R., M. A. Palma, and M. Pourahmadi (2017). Reducing brain signal noise in the prediction of economic choices: A case study in neuroeconomics. *Frontiers in Neuroscience 11*, 704.

Suri, R. and K. B. Monroe (2003). The effects of time constraints on consumers' judgments of prices and products. *Journal of consumer research 30*(1), 92–104.

Van Loo, E. J., C. Grebitus, R. M. Nayga, W. Verbeke, and J. Roosen (2018). On the measurement of consumer preferences and food choice behavior: The relation between visual attention and choices. *Applied Economic Perspectives and Policy*.

Wabersich, D. and J. Vandekerckhove (2014). The rwiener package: an r package providing distribution functions for the wiener diffusion model. *R Journal 6*(1).

Woodford, M. (2014). Stochastic choice: An optimizing neuroeconomic model. *American Economic Review 104*(5), 495–500.

Zur, H. B. and S. J. Breznitz (1981). The effect of time pressure on risky choice behavior. *Acta Psychologica 47*(2), 89–104.

Figure 1: Illustration of the DD model

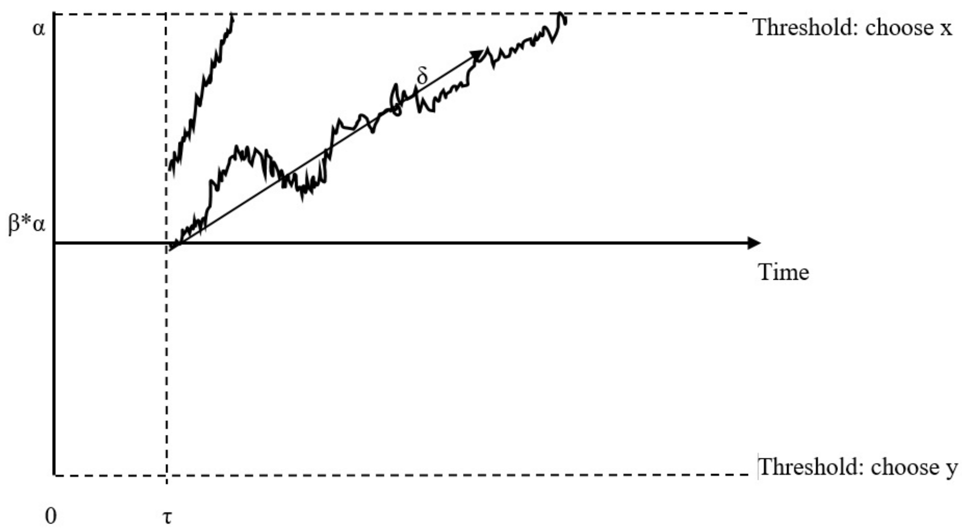

Figure 2: Response time (in seconds) performance across consistent and inconsistent choices

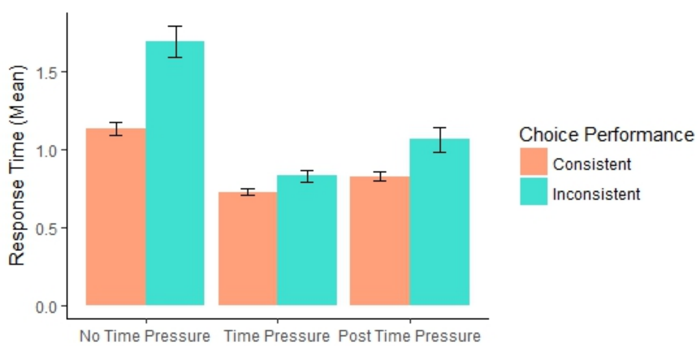

Figure 3: Fitted probabilities of time consistent choices across experimental conditions

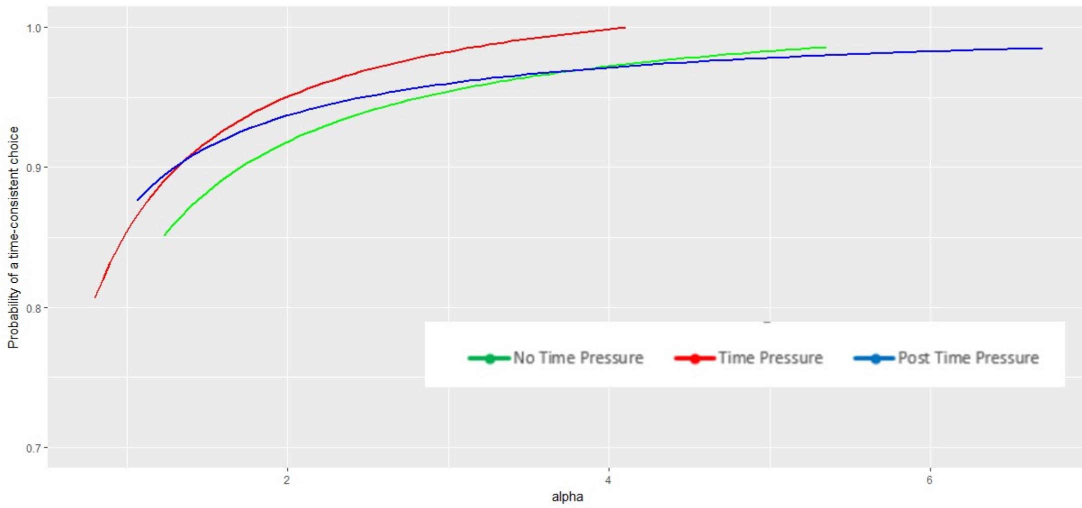

Table 1: Performance of subjets across conditions

	N	Mean RT (in seconds)	Percentage of Time-Consistent Choices
No Time Pressure	2240	1.17(1.09, 1.27)	89.75(85.24, 92.25)
Time Pressure	3777	0.73(0.70, 0.77)	88.81(84.21, 91.33)
Post Time Pressure	2507	0.84(0.79, 0.90)	91.01(86.70, 93.30)

Note: Non-parametric bootstrap 95 percent confidence intervals are shown in brackets

Table 2: The effect of RT on consistent choices: IV Logit Regression Results

	Pooled Sample	No Time Pressure	Time Pressure	Post Time Pressure
rt	-9.355***	-6.801***	-18.591***	-7.600***
	(0.679)	(0.731)	(1.756)	(1.295)
Constant	10.525***	10.412***	15.841***	8.730***
	(0.585)	(0.829)	(1.286)	(1.079)
N	8524	2240	3777	2507

The dependent variable is choiceconsistent.

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Estimated DD Model Parameters

	(alpha)	(tau)	(delta)
No Time Pressure	2.30	0.53	1.35
	$(2.10, 2.62)$	$(0.49, 0.57)$	$(1.11, 1.59)$
Time Pressure	1.50	0.42	2.04
	$(1.38, 1.76)$	$(0.38, 0.44)$	$(1.74, 2.29)$
Post Time Pressure	1.86	0.45	1.82
	$(1.66, 2.25)$	$(0.42, 0.48)$	$(1.54, 2.14)$

Note: Non-parametric bootstrap 95 percent confidence intervals are shown in brackets

Table 4: Testing Learning Across Conditions: Mixed Effects Logit Regression Results

	Dependent variable:		
	choiceconsistent		
	No Time Pressure	Time Pressure	Post Time Pressure
absdiff	2.087***	1.995***	1.418***
	(0.148)	(0.106)	(0.127)
log(trialn)	0.008	−0.122	0.017
	(0.119)	(0.102)	(0.109)
Dummies for Blocks	Yes	Yes	Yes
Constant	0.061	−0.074	0.491
	(0.356)	(0.393)	(0.415)
Observations	2,240	3,777	2,507
Log Likelihood	-526.696	-1,009.164	-667.081
Akaike Inf. Crit.	1,063.392	2,032.329	1,346.161
Bayesian Inf. Crit.	1,091.964	2,075.986	1,381.122
Note:			*p<0.1; **p<0.05; ***p<0.01