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PRESENT-BIAS, PROCRASTINATION AND DEADLINES IN A FIELD EXPERIMENT

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ABSTRACT

We study procrastination in the context of a field experiment involving students who must exert costly effort to complete certain tasks by a fixed deadline. Descriptively, we document a strong demand for commitment, in the form of self-imposed deadlines, which appear to be associated with students' self-reported psychological characteristics and cost of time. We structurally estimate students' present-bias and cost of time by fitting the experimental data to a stylized stopping time choice model. We find that present-bias is relatively widespread but that having multiple repeated tasks appears to activate effective internal self-control mechanisms. Finally, we also document an important form of partial naïveté on the part of students in anticipating their ability to self-control when setting deadlines.

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1 Introduction

Procrastination is generally defined in the psychological literature as the the practice of putting off impending tasks to a later time even when such practice results in "counterproductive and needless delay" (see e.g., Schraw, Wadkins, and Olafson, 2007). The qualification that delay be counterproductive and needless is important. Delay may represent an optimal strategy in an environment in which the cost of effort evolves over time, when waiting for the best moment to complete a task. Procrastination is then typically construed in psychology and economics as the result of a present-bias in preferences, on account of which agents delay doing unpleasant tasks that they themselves wish they would do sooner (O'Donoghue and Rabin, 1999a).

In this paper we experimentally study procrastination in students' academic work – a context procrastination appears widespread in. Solomon and Rothblum (1984) find that at least 46% of college students consider themselves serious procrastinators; Steel (2007) finds that between 80% and 95% of college students regularly procrastinate when performing academic tasks.[1] Indeed several recent field experiments on procrastination have focused on students' homework activity (e.g., Ariely and Wertenbroch (2002), Burger, Charness, and Lynham (2011)). We design and conduct a framed field experiment in which students must exert costly effort to perform a certain number of tasks by a fixed deadline for a monetary payment after completion of each task. Each student in the experiment chooses when to complete the task, if ever, in his/her own private residence over the course of his/her normal daily activities. Each student trades off the requirement of the experimental tasks with the various demands on his/her time, in terms of academic work, leisure, and employment activities, which we conceptualize as an effort cost associated to each task.

In a dynamic choice context like the one we study, students with a present-bias might adopt various internal (psychological) and/or external self-control mechanisms to avoid procrastinating on the task(s). Internal mechanisms include mental deadlines, cues, and anticipatory planning. External mechanisms include binding self-imposed deadlines and voluntary exposure to social pressure. We shall study explicitly the role of binding deadlines in affecting procrastination. Furthermore, by comparing students' behavior when faced with a single task versus multiple repeated tasks, we are able to indirectly observe the operation of internal self-control mechanisms. Multiple repeated tasks have, in fact, been shown to induce self-regulatory behavior; see e.g., Baumeister, Heatherton, and Tice (1994), Kuhl and Beckmann (1985) and Gollwitzer and Bargh (1996) for extensive surveys. On the other hand students might be partially naïve with respect to their ability to exert internal self-control — perhaps over-estimating or under-estimating their ability to do so. By allowing students to self-impose possibly restrictive deadlines before undertaking the dynamic choice experiment, we are able to gauge their naïveté in this respect.

Our experiment provides us with several interesting findings. First, we document a robust demand for commitment. When given the opportunity, a substantial fraction of students self-impose binding deadlines. However, descriptively, the presence of deadlines does not appear to increase task completion rates. This is in contrast with the findings of Ariely and Wertenbroch (2002), but is consistent with those of Burger, Charness, and Lynham

[1] Novarese and Giovinazzo (2013) also studies university administration data concluding that lack of student promptness in enrollment is negatively correlated with academic achievement, a finding which could be interpreted as due to procrastination.

(2011). In our Endogenous deadlines treatments, in which subjects are given the opportunity to self-impose binding deadlines, we do not see any significant differences in the number of tasks completed between those who do and those who do not. Amongst those students who successfully complete a task, the average time (from the final deadline) is never significantly different between those students who do and do not self-impose a deadline.

To better understand this and other aspects of students' behavior in our experiment, we identify and estimate their deep preference parameters, notably, their present-bias and other possible behavioral aspects of their decision making. Each student's behavior will, in general, depend on his/her discounting preferences, e.g., how patient he/she is and whether he/she is subject to a present-bias. Since delay might be an optimal response to the evolution of effort costs, we shall have to separately identify students' preference parameters from the properties of the costs they face. To this end we fit a stylized model of a decision maker's choice regarding when to complete a task in an environment in which effort is costly and evolves according to a finite state Markov process; that is, an optimal stopping time problem. We analyze and characterize the solution to this problem depending on whether the agent's preferences are either exponential or quasi-hyperbolic ($\beta-\delta$, as first studied by Laibson (1994, 1997); O'Donoghue and Rabin (1999a,b) and by Phelps and Pollak (1968) with regards to inter-generational altruism), which display present-bias and time-inconsistency.

Our empirical strategy allows for (i) a reliable identification and an explicit quantitative measure for present-bias, which depends on the subjects' decision to self-impose deadlines as well as their behavioral choice regarding when to complete the task; (ii) a flexible approach to account for the differential operation of internal self-control mechanisms, by allowing for our estimates of present-bias to be different in single task versus multiple repeated tasks treatments; (iii) a quantitative measure of the relative roles of costs and present-bias in explaining delay in task completion. Finally, our empirical strategy also allows us to test whether (iv) students display partial naïveté in anticipating their ability to exercise self-control.

We find strong evidence for widespread present-bias: the posterior probability distribution over present-bias identifies about 30% of likely quasi-hyperbolic subjects (with a posterior probability $> 60\%$). In the single task treatments quasi-hyperbolic students display a high present bias, as measured by $1-\beta$: 77%; furthermore they perceive a higher and more volatile cost of time, possibly indicating a correlation between present-bias and a distorted perception of such cost.

Contrary to what we observe in the single task treatments, in the multiple-task treatments present-bias is estimated equal to 0. Indeed, in the multiple-task treatments there is virtually no difference in the distribution for completion times between exponential and quasi-hyperbolic students. This implies that repeated similar tasks activate internal self-control through various framing effects. This is consistent with independent evidence on the determinants of self-regulation mechanisms. Possible mechanisms include inducing the "budgeting" of these tasks into more prominent "mental accounts" for time (Thaler, 1980, 1990), and/or the formulation of more explicit and precise simple plans and implementation intentions (Gollwitzer, 1999). We interpret this result as suggesting that present-bias, while present and large, appears not to significantly affect behavior in the context of repeated similar tasks.

Finally, we find that, in the multiple tasks treatment, subjects are partially naïve in the sense that they underestimate their ability to self control. Indeed, they display a robust demand for commitment by setting binding deadlines for themselves, even though they are able to fully exercise self-control (Present bias, $1 - \beta$, is estimated to be 0 for all students in these treatments). While we cannot empirically assess whether students overestimate or underestimate their ability to self-control in single task treatment, we find evidence that the ability to set deadlines ends up reducing, on average, the completion rates of partially naïve students, which would not happen for sophisticated students who set deadlines optimally.[2]

The data we obtain from our experiment are actually substantially richer than just the timing of completions. Specifically, we also observe the timing of attempts to complete the task by students and whether the attempt is ultimately successful. This is important in our understanding of the students' behavior in the experiment. In principle, several interesting characteristics of the behavior of subjects such as forecast inaccuracy and over-confidence might induce them to disregard the possibility of not completing the task after having attempted it. In this case, present-bias might interact with these characteristics in explaining task completion in our experiment and our estimates for present-bias would account for other behavioral components. To gain more insight regarding the interaction between, for example, forecast inaccuracy, over-confidence, and present-bias, we re-estimate the model with attempts data in place of completion data. We find that focusing on completions over-estimates the extent of present-bias. By accounting for attempts data and hence, indirectly, for other behavioral components like forecast inaccuracy and over-confidence, estimated present-biased is greatly reduced, from 77% to 38%. This result is consistent, in the context of our experiment, with self-reported beliefs about how likely subjects were to complete the task(s), which we collect prior to the beginning of the experiment. These beliefs clearly show that subjects do not accurately forecast their future behavior in terms of task completion — specifically, they are over-confident.[3]

2 Related Literature

The theoretical literature on present-bias and time-inconsistency dates back at least to Strotz (1956), while Phelps and Pollak (1968), Laibson (1994, 1997) and O'Donoghue and Rabin (1999a) formalized the model of $\beta - \delta$ quasi-hyperbolic discounting, which forms the basis for our theoretical and empirical framework. A rich experimental literature in psychology and economics has first motivated and then supported this theoretical framework, providing evidence for present-bias.[4] Similar behavioral regularities have been documented as well in

[2] In Section 5.2 we discuss further evidence which we interpret as indication of the fact that partially naïve subjects do not set deadlines optimally, potentially inducing negative welfare effects.

[3] More generally, the interaction between imperfect foresight and present-bias in time preferences is formally studied by Gabaix and Laibson (2017).

[4] First, by eliciting students' intertemporal preferences, many of the early papers find evidence of declining discount rates; see e.g., (Thaler (1991), Loewenstein and Thaler (1989), Loewenstein and Prelec (1992), Kirby and Herrnstein (1995) and Benzion, Rapoport, and Yagil (1989)); and Herrnstein (1961); de Villiers and Herrnstein (1976); Ainslie and Herrnstein (1981) for early evidence in the experimental psychology. Also, many studies document preference reversals which are inconsistent with exponential discounting; see Ainslie (1992, 2001), Loewenstein and Prelec (1992) and Frederick, Loewenstein, and O'Donoghue (2002) for surveys of this literature and Rachlin and Laibson (1997) for a collection of early essays on the topic. More recently, in a lab experiment conducted in class, Halevy (2012) is able to identify separately time-consistency and time-invariance, finding 52% of time-inconsistent agents, more then half of which also displaying time-invariance.

field experiments with monetary payments,[5] though the evidence is more mixed.[6] However, eliciting preferences over non-monetary choices eliminates some relevant confounding factors and strong evidence for present-bias is typically reinstated.[7]

However, the evidence for present-bias in laboratory and field experiments eliciting discount rates cannot directly be interpreted as evidence for procrastination, which is rather a property of behavior in dynamic choice environments than of preferences.[8] On the other hand, observing agents who, when given the option, adopt external commitment devices such as binding self-imposed deadlines, can be interpreted as evidence that the agents themselves perceive procrastination as a obstacle to the implementation of their preferred dynamic choice plan.[9] Ample evidence in this respect is obtained both in the lab and in the field. With regards to lab experiments, Trope and Fishbach (2000) experimentally study two commitment mechanisms: the ability to make a fixed payment conditional on task completion and the ability to impose a penalty for failing to complete a task. In both cases, they find that many students willingly choose such commitments. Casari (2009) finds that among the students who exhibit reversals in monetary choices, 60% prefer to commit to a lower amount today rather than making a choice at a later period. In an experiment about effort choice allocations, Augenblick, Niederle, and Sprenger (2015) find that present-biased students are more likely to demand commitment than others. Houser, Schunk, Winter, and Xiao (2010) study commitment behavior under repeated temptations to surf the Internet and find that more than 20% of students are willing to remove their Internet access at the first opportunity they get. As for field evidence, most of it regards voluntary exposure to social pressure. Examples include regular attendance to meeting groups such as Alcoholics Anonymous or Weight Watchers and commitment markets whereby agents enter into a contract with a disinterested third party, specifying the goal to be achieved, the time in which it is to be achieved and the financial penalties for failure.[10]

In lab studies using monetary payments, Casari (2009) finds that about 65% of students exhibit some form of choice reversal while Benhabib, Bisin, and Schotter (2010) find strong evidence of present-bias in the form of a fixed cost. Finally, a recent series of studies strengthen these results by complementing the choice data with data regarding the neurological processes underlying intertemporal choices in lab experiments; see e.g., McClure, Laibson, Loewenstein, and Cohen (2004); Kable and Glimcher (2007).

[5] See Ashraf, Karlan, and Yin (2006), Bauer, Chytilová, and Morduch (2012), Meier and Sprenger (2010) and Tanaka, Camerer, and Nguyen (2010); and by Dean and Sautmann (2013) with consumption and savings data.

[6] Andreoni and Sprenger (2012a,b); Giné, Goldberg, Silverman, and Yang (2013); Harrison and Lau (2005); Harrison, Lau, and Williams (2002); Andersen, Harrison, Lau, and Rutström (2011, 2008); Dohmen, Falk, and Sunde (2012) can be interpreted to show that, when carefully controlling for risk, transaction costs and payment reliability, present-bias in monetary choices tends to disappear in the aggregate.

[7] See Casari and Dragone (2012) or Augenblick, Niederle, and Sprenger (2015) in the context of effort choice, or Brown, Chua, and Camerer (2009) for brief intertemporal choices of juices or soda. See DellaVigna (2009) for a survey.

[8] A large theoretical literature in psychology and economics studies the form and the effectiveness of self-control mechanisms. For a theoretical point of view, see e.g., Ainslie (1992, 2001); Laibson (1994). More recent work includes Benabou and Tirole (2004); Benhabib and Bisin (2005) and Hsiaw (2013).

[9] Theoretical studies of the effects of external commitment devices in dynamic choice environments include O'Donoghue and Rabin (1999b), who characterize general external mechanisms to induce second-best optimal behavior in agents who procrastinate due to present-bias preferences, Sáez-Martí and Sjögren (2008), who study how binding deadlines affect the timing of effort when agents get distracted, and Battaglini, Benabou, and Tirole (2005) for a theoretical analysis of commitment through peer groups.

[10] See e.g., `http://www.stickk.com` and Bryan, Karlan, and Nelson (2010) for more examples and discussion. Mahajan and Tarozzi (2011) conduct a field study exploiting investment choices in bednets providing protection

Direct evidence of procrastination is typically obtained in the literature by comparing the behavior of agents in the same dynamic choice environment with or without the option of external commitment devices. For example, Giné, Karlan, and Zinman (2010) study a voluntary commitment product designed to help smokers to quit. Smokers are given the opportunity to deposit money in a bank account. After 6 months they are given a test for nicotine. Those who pass the test receive their money back, while those who fail see their money donated to charity. Giné, Karlan, and Zinman (2010) find that smokers in the commitment group are more likely to pass the test for nicotine after 12 months than those who are not given the chance to commit. A few studies have also shown (c.f., Thaler and Benartzi (2004); Ashraf, Karlan, and Yin (2006) and Duflo, Kremer, and Robinson (2011)) that products with certain commitment features lead to higher savings. For example, Thaler and Benartzi (2004) propose a mechanism whereby employees commit to allocating some percentage of future salary increases to their retirement savings. They show both that a large number of people join the program and that savings increase by a considerable amount after 40 months of participation. In the context of self-control at work, Kaur, Kremer, and Mullainathan (2010) find that workers are willing to choose dominated contracts as a commitment device to increase their productivity.[11]

Evidence for partial naïveté in dynamic choice contexts has been suggested by DellaVigna and Malmendier (2006) in their study of gym memberships and attendance. More recently Augenblick and Rabin (Forthcoming), studying subjects who choose how much of an unpleasant task to complete immediately for various payment schemes, find strong evidence for present bias, but also that subjects only anticipate 10-24% of their present bias. Fang and Wang (2015) provide a method for estimating dynamic discrete choice models and also find evidence for partial naïveté in women's decisions to undergo mammograms. More closely related to us is the field study by John (2017) who provides evidence that partially naïve subjects are more likely to choose weak commitment devices which lead to eventual default. In our case, subjects are partially naïve about their ability to internally self-control, which leads them to self-impose binding deadlines in the multiple task treatment, to their detriment.

Like us, a few recent papers study procrastination in the context of students' academic work. Results are somewhat mixed. In the experiments conducted by Ariely and Wertenbroch (2002) students have to complete a series of tasks before a final deadline. Students are either given exogenous and evenly spaced intermediate deadlines, are free to choose their own intermediate deadlines or, in one study, no intermediate deadlines. Their main results are that many students self-impose binding deadlines and that their performance increases under evenly spaced deadlines (whether self-imposed or exogenously set) compared to the case of no deadlines. However, it is interesting to note that in Ariely and Wertenbroch's

against malaria, Schwartz, Mochon, Wyper, Maroba, Patel, and Ariely (2014); Schwartz, Riis, Elbel, and Ariely (2012) study commitment on health food consumption and calories intake .

[11]See Bryan, Karlan, and Nelson (2010) for a comprehensive survey of both the theoretical and experimental literature on commitment and self-control. While in this paper we focus on present-bias and quasi-hyperbolic discounting as a possible cause for procrastination, it is the case that other types of preferences may lead to procrastination and demand for commitment. Examples include the models of temptation and self-control by Gul and Pesendorfer (2001, 2004), dual-self models such as Benhabib and Bisin (2005) and Fudenberg and Levine (2006), optimal expectations and over-confidence models such as Brunnermeier, Papakonstantinou, and Parker (2008). In the concluding section we discuss how our results can be interpreted as suggestive evidence in favor of models of optimal expectations and over-confidence along the lines of Brunnermeier, Papakonstantinou, and Parker (2008).

(2002) Study 1, the gains in performance are not significant when restricted to the treatment tasks. Instead, it is the final grades (which includes the treatment tasks, a final paper, and other components) where we see performance being significantly higher in the Endogenous deadlines treatment. In their Study 2, the effects are more clearcut in terms of performance, but students end-up disliking the task more when they are subject to deadlines, leaving some doubts about whether the effect of deadlines is effectively on procrastination. In a recent paper, Burger, Charness, and Lynham (2011) conduct an experiment in which students are faced with a time allocation problem over a task of significant duration (studying 75 hours over a 5-week period) under different constraints in the form of binding sub-deadlines (e.g., 15 hours in the first week). The main result of the paper is that deadlines do not lead to more students successfully completing the task.

While we follow Ariely and Wertenbroch (2002), Burger, Charness, and Lynham (2011) and the previous literature on procrastination cited above in many respects, notably in the general approach of exploiting the demand for commitment to identify present-bias and possibly procrastination, we diverge from them in several important elements of the experimental design, as well as in the methodology we adopt to analyze the data.

First of all, because students in our experiment are rewarded through a fixed, known, homogeneous monetary payment at a pre-specified delay from completion, our experiment controls for student motivation in performing tasks. This is in contrast e.g., to Ariely and Wertenbroch's Study 1 in which students are rewarded for (less measurable) academic performance. Secondly, the tasks in our experiment are the same for all students (alphabetize either one or up to three lists of "words") and do not require any special skill which could be heterogenously distributed across the student pool; this is in contrast to the writing task of Ariely and Wertenbroch's Study 1 as well as to the proof-reading task of their Study 2, in which heterogeneous ability could arguably affect the results.[12] Most importantly, we impose an upper bound on the time to complete the task after initiating it, so that students are essentially required to complete each task in one sitting. Without such a restriction, as in Ariely and Wertenbroch (2002), there is no clear link between the time effort is exerted and the time the reward is obtained: students could smooth effort over time and could even trade off effort and time, all of which makes it difficult to interpret the results of the experiments as evidence for/against procrastination due to present-bias. Furthermore, the time restriction to complete the task we impose allows us to collect data on failed attempts, which can be exploited to better understand the determinants of students' behavior. Another distinctive feature of our design is that self-imposed deadlines are necessarily hard deadlines, while the deadlines in the Ariely and Wertenbroch (2002) experiments are "soft" in the sense that only a per period penalty is imposed for completion after the deadline. While soft deadlines occur perhaps more naturally outside of the realm of these experiments, their theoretical implications are harder to obtain and hence it is harder to interpret any effects of such deadlines in terms of the underlying characteristics of the preferences of students which might motivate their demand for commitment and their behavior.

Most importantly, our formulation of what constitutes a task and of the dynamic choice

[12] In fact, in our experiment, the "words" to be alphabetized were not meaningful words, but rather (partially random) character strings which are less likely to provide an advantage to native English speakers. An initial pilot study suggested great variation in students' approaches (and consequently required time) to completing the task. Therefore, to further level the playing field, in the instructions we suggested a particular method for completing the tasks. According to a post-experiment survey, most students followed the suggested method.

problem faced by the experimental students allows us to map directly the experimental data to the underlying theoretical structure, where the dynamic choice problem the agents solve is an optimal stopping time problem. Therefore, our analysis is not limited to a descriptive study of procrastination and of the mostly qualitative effects of deadlines on such behavior, but rather it allows us to estimate deep preference parameter from students' behavior as well as some contextual parameters (e.g., effort costs). The experimental design adopted by Burger, Charness, and Lynham (2011) is more similar to ours in the sense that student behavior, time spent in the study room, is also unaffected by possibly heterogenous skills and is clearly measurable; also, the monetary reward mechanism is clearly specified and so is the delay with respect to completion at which it is obtained. However, the dynamic choice problem students are faced with in Burger, Charness, and Lynham (2011) is quite complex as a student's choice at any time optimally depends on the time he/she has previously spent in the study room in the course of the experiment, effectively a state variable. As a consequence, a structural analysis of the experimental data, to be able to estimate preference and other contextual parameters, is not viable with their experimental design.

3 Experimental Design

We conduct two distinct sets of experiments. In the first students have one week to complete a single task. We distinguish two treatments corresponding to two different intermediate (before the natural end-of-experiment) deadline scenarios: No deadline and Endogenous (*i.e.,* self-imposed) deadlines. We call these the 1T(ask) treatments. In the second set of experiments, students have two weeks to complete three tasks, with three different treatments corresponding to different intermediate deadline scenarios: No deadlines, Exogenous deadlines and Endogenous deadlines. We call these the 3T(ask) treatments.

In the 1T treatments, subjects are paid \$20 if they successfully complete the task, while in the 3T treatments, subjects are paid \$15 for each task successfully completed by the relevant deadline. In what follows we describe the experimental procedures we use for the 3T treatments. Identical procedures are used for the 1T treatments.

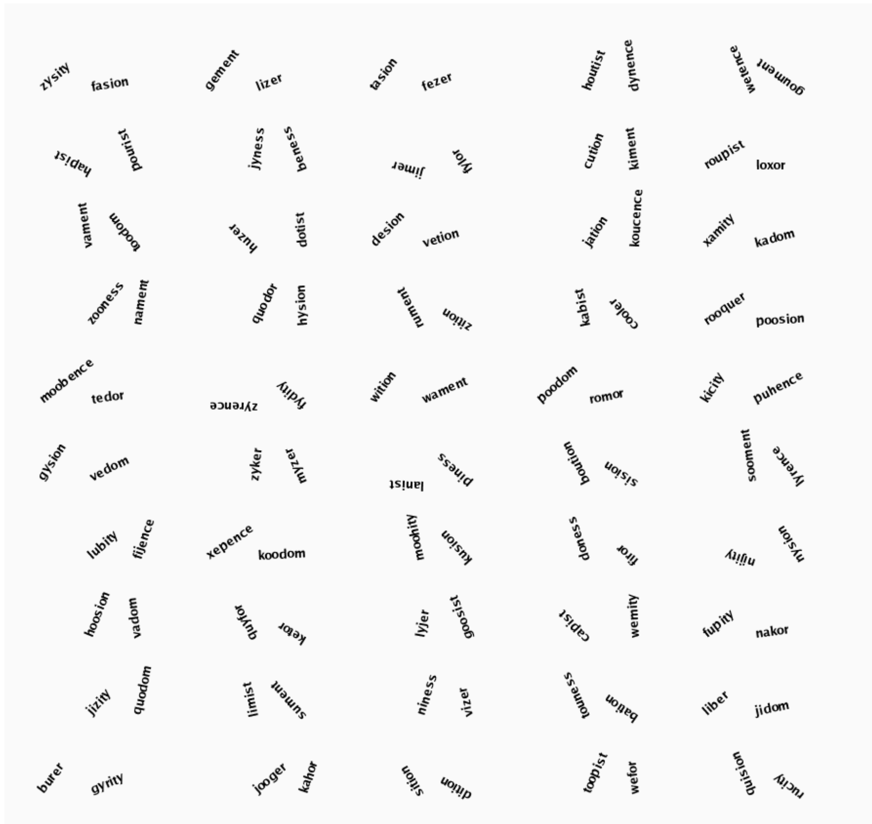
3.1 Phase 1: The Lab-based Component

Each session begins with a lab-based component in which students read the instructions for their treatment and are given a user name and password in order to gain access to the web-based experimental software. The instructions outline the nature of the tasks, explain the software and also tell students the nature of any deadlines that they face.

After reading the instructions, students log on to the experimental software and are reminded of their deadlines for each task. For students in the No deadlines treatment, all tasks have a deadline set at the end of the experiment; i.e., two weeks after coming into the lab. For students in the Exogenous deadlines treatment, each of the three tasks has a different deadline; deadlines are evenly spaced, with the deadline for task 3 being at the end of the experiment. Students in the Endogenous deadlines treatment are able to choose an intermediate deadline for each of the three tasks. The latest deadline that students could set is the end of the experiment.

After observing or choosing their deadlines, in the lab, students answer a series of survey questions. The survey asks about their (work, academic and social) schedules for the two-

Figure 1: A Sample Task



week duration of the experiment. It also asks students to report their subjective expectation (in probability form) of completing 0, 1, 2 or all 3 tasks. Finally, the survey asks a number of questions designed to gauge students' perceptions about several of their own psychological characteristics, like reliability, punctuality, organization, *etc.* Appendix B contains a sample of the experimental instructions and the survey questions used.

This component of the experiment is conducted at the Center for Experimental Social Science (C.E.S.S.) at New York University and lasted between 30 and 45 minutes. At the end of this phase, students are given a $10 participation fee.

3.2 Phase 2: The Experiment

Upon completing the first component of the experiment, students leave the C.E.S.S. lab and are free to work on the tasks at any time they wish. To do so, students log on to a website using their user name and password. Upon logging in, they are issued a list of words for the current task and are asked to list them in alphabetical order. In order to simulate as best as possible a stopping time problem, once a list of words is given, students have to alphabetize the list within the lesser of 2 hours and the time until the task deadline. Failing to do so implies that a new list of words is issued if time remains; if no time remains before that task's deadline, students are automatically taken to the next task. Additionally, each time students refresh the browser or log into the software, a new list of words is issued.

If a student submits an incorrectly alphabetized list, the software sends a message alerting her of the existence of at least one mistake in the submitted list, without any indication about the position of the mistake(s). If a student submits a correctly alphabetized list, she is immediately taken to the next task, which she can work on if she so chooses.

Each task that is successfully completed by the relevant deadline generates a payment of \$15, via petty cash vouchers mailed to students.[13] In particular, all tasks that are completed by 1:00PM on a given day are processed for payment that same day. Tasks completed after 1:00PM or on weekends are processed the next weekday.

3.3 Phase 3: Post-experiment Survey

Upon completion of the third task, or after the end of the experiment, students are asked to complete a post-experiment survey. The purpose of this is to gain information on any unanticipated shocks that they may have faced during the field component of the experiment.

3.4 Different Sessions

In Table 1 we summarize the details of our experimental sessions. In the 3T treatments, Sessions 1 and 2 were conducted during the Spring semester of 2010, while Session 3 took place during the Spring semester of 2011. Sessions 2 and 3 were aimed at adding variation in the data. In particular, Session 2 was scheduled so that it ended on the final day of classes for the semester. We conjectured that students would be busier or under greater pressure at the end of the semester where they also had final exams and projects to complete. Session 3 made the task more difficult to complete by increasing the number of words to alphabetize from 150 to 200. The 1T treatments were conducted during the Spring semester of 2011 and involved 150 words.

Table 1: Summary of the Various Treatments and Sessions

Treatment	Session	Intermediate deadlines	Timing	Words	Tasks	N
1T-None	1	None	Mid-semester	150	1	46
1T-Endog	1	Endogenous	Mid-semester	150	1	35
3T-None	1	None	Mid-semester	150	3	23
3T-None	2	None	End-semester	150	3	24
3T-None	3	None	Mid-semester	200	3	14
3T-Exog	1	Exogenous	Mid-semester	150	3	21
3T-Exog	2	Exogenous	End-semester	150	3	24
3T-Exog	3	Exogenous	Mid-semester	200	3	24
3T-Endog	1	Endogenous	Mid-semester	150	3	21
3T-Endog	2	Endogenous	End-semester	150	3	24
3T-Endog	3	Endogenous	Mid-semester	200	3	22

[13] In Phase 1, students pre-address envelopes and fill in their petty-cash vouchers. This is done to both increase the credibility and saliency of payments, and to make the processing of payments easier for us.

4 Model

We now introduce the basic model we adopt to represent the decision problems students face in our experiment.

Sequence of Events. We can divide the decision problem into two distinct stages. First, there is an *ex-ante stage*, denoted by $t = -1$, and an *active decision stage* which consists of an ordered set of discrete time periods, $t = 0, ..., T$, during which subjects may choose to complete the task(s) assigned. The active decision stage is, formally, a stopping time problem, in which each student must exert costly effort to perform a certain number of tasks by the fixed deadline for a monetary payment after completion of each task. The ex-ante stage is when agents choose (possibly intermediate binding) deadlines for each of the tasks they have the option to complete starting at $t = 0$.

Present Bias. We consider two types of agents: (i) those with exponential time preferences and (ii) those who are present-biased. For the present-biased agents, we posit that they may possess some internal psychological mechanism that allows them to exert self-control, but we also allow that they may be partially naïve about their ability to internally self-control. That is, agents might misperceive how effective their self-control mechanism will be in the stopping-time problem. Consistent with the psychology literature (Baumeister, Heatherton, and Tice, 1994; Kuhl and Beckmann, 1985; Gollwitzer and Bargh, 1996), this mechanism may depend on the frame of the decision problem, specifically, 1T v. 3T.

We adopt the $\beta - \delta$ quasi-hyperbolic framework to model present-biased time preferences. Specifically, let time preference be denoted by $0 < \delta < 1$ and present bias by $0 < \beta_0 \leq 1$. We consider $\beta_0 < 1$ to be an underlying parameter that distinguishes between exponential ($\beta_0 = 1$) and present-biased agents ($\beta_0 < 1$). However, behavior in the active decision stage for present-biased agents is governed by $\beta_\tau \in [\beta_0, 1]$, $\tau \in \{1T, 3T\}$ which incorporates the agents internal self-control mechanism when she faces a single task (1T) or multiple repeated tasks (3T).

When solving the stopping time problem, we assume quasi-hyperbolic agents are sophisticated in that they are aware of their future incentive to procrastinate; that is, they know β_τ. On the other hand, at the ex-ante stage, quasi-hyperbolic agents do not necessarily correctly anticipate their ability to exert internal self-control; that is, they may *misperceive* β_τ. Let $\hat{\beta}_\tau$ denote a present-biased agent's perception about their own present-bias in the ex ante stage. We say that present-biased agents are *partially naïve* if $\hat{\beta}_\tau \neq \beta_\tau$. On the other hand, exponential agents do not misperceive their time preferences. That is, for an exponential agent, $\hat{\beta}_\tau = \beta_\tau = 1$.

Effort Cost. We conceptualize each agent's trade-off between the requirements of the experimental tasks and the various alternative demands to his/her time with a stochastic effort costs associated to each task.

Formally, each student faces a cost $c(t)$ of completing the task at time t. We assume that costs evolve according to a Markov process. In particular, let $\mathcal{C} = \{c_1, c_2, \ldots c_N\}$ denote the set of possible costs (with $0 = c_1 < c_2 < \ldots < c_N$). Let $P(c' \mid c)$ denote a Markov transition matrix so that if the cost in time t is $c \in \mathcal{C}$, then with probability $P(c' \mid c)$ the cost will be

$c' \in \mathcal{C}$ at time $t+1$. We assume that for all c_i, $i = 1, ..., n-1$, $P(\cdot \mid c_{i+1})$, seen as a probability distribution over $\mathcal{C}$, first-order stochastically dominates $P(\cdot \mid c_i)$. In our empirical analysis, we will impose more structure on this process.

Proceeding backwards, we first consider the stopping time problem and then the optimal deadline problem. For ease of exposition, we relegate most details and proofs are relegated to Appendix A.

4.1 Optimal Stopping Time Problem

We first consider the model in which a single task must be completed and then extend it to the multiple tasks case.

4.1.1 Single Task

Consider an agent with a given deadline $1 \leq D \leq T$; that is, he/she has a task to complete before D. The agent must exert a single unit of effort to complete the task. If he/she completes the task at any time $t \leq D$, then in period $t+1$, he/she will receive a payment of $V > 0$.

As of time 0, the payoff of a decision maker completing the task at time t at cost c is $\beta_{1T}\delta^t(\delta V - c)$. However, at time t the payoff is $\beta_{1T}\delta V - c$. The agent's choice problem is therefore time-consistent if and only if he/she is exponential, with $\beta_{1T} = 1$.

We can construct the agent's value function proceeding backwards. At time D he/she will complete the task if and only if $\beta_{1T}\delta V \geq c$. His/her value function will therefore be:

$$W(c, D; D, \beta_{1T}) = \max\{\beta_{1T}\delta V - c, 0\}.$$

We assume that the agent is sophisticated in that she is aware that her future incentive to procrastinate. As a consequence, at time $D-1$, the undiscounted value that he/she *perceives* she will obtain in time D if she delays completing the task is

$$w(c, D; D, \beta_{1T}) = \begin{cases} \delta V - c, & \text{if } c \leq \beta_{1T}\delta V \\ 0, & \text{otherwise} \end{cases}.$$

The agent will then complete the task at time $T-1$ if and only if $\beta_{1T}\delta V - c \geq \beta_{1T}\delta \sum_{c' \in \mathcal{C}} P(c' \mid c)w(c, T; D, \beta_{1T})$; and the value function at $T-1$ is

$$W(c, D-1; D, \beta_{1T}) = \max\{\beta_{1T}\delta V - c, \beta_{1T}\delta \sum_{c' \in \mathcal{C}} P(c' \mid c)w(c, D; D, \beta_{1T})\}.$$

Proceeding iteratively (see Appendix A for details) we obtain:

$$\begin{aligned} W(c, t; D, \beta_{1T}) &= \max\{\beta_{1T}\delta V - c, \beta_{1T}\delta \sum_{c' \in \mathcal{C}} P(c' \mid c)w(c, t+1; D, \beta_{1T})\}, \\ w(c, t; D, \beta_{1T}) &= \begin{cases} \delta V - c, & \text{if } \begin{array}{l} \beta_{1T}\delta V - c \geq \\ \beta_{1T}\delta \sum_{c' \in \mathcal{C}} P(c' \mid c)w(c, t+1; D, \beta_{1T}) \end{array} \\ \delta \sum_{c' \in \mathcal{C}} P(c' \mid c)w(c, t+1; D, \beta_{1T}) & \text{otherwise} \end{cases}. \end{aligned}$$

In the exponential case, with $\beta_{1T} = 1$, the value function simplifies to:

$$W(c,t;D,1) = \max\{\delta V - c, \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W(c,t+1;D,1)\}.$$

Each agent's optimal behavior can then be characterized in the following proposition:

PROPOSITION 1 *Assume $c_k > \delta V$, for some $k \leq N$. Then*

(i) The value function, $W(c,t;D,\beta_{1T})$, is decreasing in c and t, and is increasing in D;

(ii) for all time periods t, there exist a threshold $\bar{c}(t;D,\beta_{1T})$ such that the decision maker's optimal decision rule is to complete the task if and only if $c(t) \leq \bar{c}(t;D,\beta_{1T})$, where $c(t)$ denotes the realization of the cost at t;

(iii) the threshold $\bar{c}(t;D,\beta_{1T})$ is decreasing in $\beta_{1T} \leq 1$; also, if $\beta_{1T} = 1$, it is increasing in t and decreasing in D.

The optimal behavior of students in the stopping time problem is to employ a threshold rule. This is the case for both exponential and quasi-hyperbolic students. However, the threshold for quasi-hyperbolic agents will generally be lower. Indeed, time-inconsistency of preferences introduces an incentive to procrastinate since, from the $t = 0$ perspective, the benefit/cost ratio of completing the task at time $t' > 0$ is $\frac{\delta V}{c}$, while at time $t' > 0$, when the decision is actually taken, the benefit/cost ratio of completing the task is $\frac{\beta_{1T}\delta V}{c} < \frac{\delta V}{c}$. Note also that while a quasi-hyperbolic decision maker will employ a threshold rule, there is no guarantee that the threshold will be monotone in either t or D.[14]

4.1.2 Multiple Tasks

We now turn to the case in which the decision maker must complete multiple tasks. In accordance with the experiment, we present the model for the case of three tasks. Assume that the deadline for task i is D_i, with $D_1 \leq D_2 \leq D_3 \leq T$. Each task completed by the appropriate deadline pays V with one period of delay. As in the experiment, we assume that the tasks must be done sequentially. Therefore, the decision maker cannot start task $i+1$ until either task i has been completed or the deadline, D_i, to complete task i has passed.

In order to allow for the possibility that it may get easier to complete an additional task immediately after completing one task (learning by doing) or more difficult (fatigue), we will assume that the cost of task completion jumps by J index values upon completing a task. Let $c''(c)$ denote the new cost that the decision maker faces after having completed a task at cost c. We assume that for all $i \in \{1,\ldots,N\}$, $c''(c_i) = c_{\max\{1,\min\{i+J,N\}\}}$. Observe that if $J < 0$, then there is learning by doing, while if $J > 0$, fatigue sets in.

The problem of solving for the optimal decision rule with three tasks is now substantially more difficult. By completing task 1 at time t, the decision maker not only receives the

[14] We have omitted any discussion of naïve quasi-hyperbolic discounters. These are decision makers who have a present-bias, but are unaware of it. Such decision makers will also employ a threshold rule, and that the threshold will be lower than for sophisticated quasi-hyperbolic discounters. It turns out, however, that the thresholds for sophisticated and naïve are generally very close in the relevant range of parameters making it difficult to separately identify these students based on the distribution of task completions. For this and other reasons discussed in detail in Section 5.3, our empirical analysis, below, will focus only on exponential and sophisticated quasi-hyperbolic discounters.

direct payment of V but also receives an option to complete task 2 (starting from time t). Moreover, the tasks are linked more explicitly by the possibility for fatigue or learning by doing. All of this will affect behavior. Indeed, notice that we cannot immediately conclude that an exponential decision maker will complete task $i \in \{1, 2\}$ at deadline D_i if and only if $\beta_{3T}\delta V - c \geq 0$. If a decision maker gets fatigued, then costs will increase, which could substantially reduce the probability of completing task $i+1$. Therefore, even if $\beta_{3T}\delta V - c > 0$, a decision maker may prefer not to complete task i. Similarly, if there is strong learning by doing, the decision maker may actually prefer to complete task i even if $\beta_{3T}\delta V - c < 0$. More details can be found in Appendix A.

4.2 Optimal Deadlines.

Consider now the optimal choice of deadlines at the ex-ante stage. As we noted, we assume that exponential agents rationally anticipate that they do not display any present-bias:

$$\text{if } \beta_0 = 1, \text{ then } \hat{\beta}_\tau = \beta_\tau = 1, \ \tau = 1T, 3T. \tag{Exp}$$

However, present-biased agents may misperceive their present bias at the ex-ante stage:

$$\text{if } \beta_0 < 1, \text{ then } \hat{\beta}_\tau \neq \beta_\tau, \ \tau = 1T, 3T. \tag{Quasi-Hyp}$$

We do not postulate ex-ante whether the mis-perception bias is positive or negative.

For simplicity, consider the single task case.[15] Let $\mathbb{E}(\cdot)$ denote the unconditional (from the ex-ante stage, $t = -1$) expectation operator with respect to the cost process c. The optimal deadline choice problem of the agent is:

$$\max_{D \leq T} \mathbb{E}\left(W(c, 0; D, \hat{\beta}_{1T}\right).$$

A decision maker with exponential discounting always prefers not to self-impose any deadline since doing so only destroys the option value of waiting for a lower cost, while providing no commitment benefit.

Proposition 2 *An exponential agent, with $\beta_0 = \hat{\beta}_{1T} = \beta_{1T} = 1$, optimally chooses $D = T$.*

However, the same cannot be said for a present-biased decision maker. Because she knows that she may be tempted to delay in the future, she may prefer to commit to an earlier deadline. We are not able to solve in closed form for the conditions on the parameters under which an quasi-hyperbolic discounter would self-impose a deadline. We can however show the following.

Proposition 3 *A quasi-hyperbolic agent, with $\beta_\tau \leq 1$, $\tau = 1T, 3T$ optimally chooses $D = T$ if he/she perceives no present-bias, $\hat{\beta}_\tau = 1$. He/she possibly chooses $D < T$ only when perceiving some present-bias, $\hat{\beta}_\tau < 1$.*

If the agent is sophisticated at the ex-ante stage (i.e., $\hat{\beta}_\tau = \beta_\tau < 1$), then any deadline $D < T$ induces the decision maker to complete the task on average earlier than without the deadline. On the other hand, if the agent is partially naïve *(i.e., $\hat{\beta}_\tau < 1$ and $\hat{\beta}_\tau \neq \beta_\tau$), then a deadline $D < T$ can induce him/her to complete the task either earlier or later on average than it would be optimal for β_τ.*

[15] Results extend straightforwardly to the multiple tasks case.

Relying on numerical results, in Appendix A, we document that a lower present bias (a higher $\hat{\beta}_{1T}$), a higher discount rate δ, a lower volatility of the cost process (which we parameterize by σ), a lower upper bound on costs C_N, all make self-imposed deadlines relatively less-desirable for a quasi-hyperbolic discounter; see Figure A.1.

5 Empirical Analysis

In this section we analyze our experimental data structurally; that is, we estimate the model of subject behavior that we introduced in the previous section. The ex-ante stage in the model corresponds to Phase 1 of the experiment in which subjects came to the lab to be introduced to the task(s) and, possibly, to choose their own deadlines or have them exogenously imposed by the experimenter. The active decision stage corresponds instead to the experimental task students complete on their own time outside of the experimental lab.. Different treatments in the lab correspond to restricted versions of the model; e.g., the No deadlines/Exogenous deadlines treatments have a moot ex-ante stage, and the 1T treatments have just a single task.

Proceeding backward, we first study the stopping time problem, given deadlines, if any. We then study the optimal deadline problem.

5.1 Present-Bias and Costs in the Stopping-Time Problem

The theoretical analysis of the previous sections shows that, independently of their discounting preferences, agents should adopt a threshold rule whereby they complete the task at any given moment if their cost is below a threshold. We also have shown that, other things equal, present-biased agents have a threshold which is strictly below that of exponential agents. Therefore, other things equal, present-biased students should complete the task stochastically later than exponential subjects. Combined with a classification procedure of subjects as either exponential or quasi-hyperbolic, we use these insights to identify the possible behavioral aspects of their decision making and the effort costs associated to the completion of the tasks. Our empirical strategy allows for (i) a reliable identification strategy for present-bias, which depends on the subjects' decision to self-impose deadlines as well as their behavioral choice regarding when to complete the task; (ii) a quantitative measure of the relative roles of costs and present-bias in explaining delay in task completion; and (iii) an explicit quantitative measure of present-bias. Finally, our empirical strategy also allows us to test whether (iv) differential treatments such as single versus repeated tasks impact students' ability to exercise some form of self-control, as well as (v) whether students display partial naïveté in anticipating their ability to exercise self-control.

More in detail, the parameters of the stopping time model include the preference parameters and the cost parameters. Identification requires appropriate restrictions regarding how heterogeneous across subjects the parameters are allowed to be. We exploit a parsimonious specification which allows for both present-biased and exponential subjects and for some heterogeneity in terms of the cost of time subjects face.

We allow subjects to differ in whether they display present-bias or not, but we restrict all present-biased agents to be identical. To capture different psychological self-control mechanisms, present-bias is allowed to depend on whether subjects face a single task or multiple tasks. More specifically, we restrict δ and the vector $\boldsymbol{\beta} = (\beta_{1T}, \beta_{3T})$ to be the same across subjects.

We interpret the cost process in our environment as determined by both factual (e.g., how busy the subject is) as well as psychological (e.g., how she values and experiences available time) characteristics, the latter of which might be correlated with time preferences. More specifically, when estimating the single task model we allow for the cost process to depend on whether the subject is present-biased or not and estimate $(c_N^k, \sigma^k)_{k\in\{e,h\}}$, where e, h index respectively, exponential and quasi-hyperbolic subjects. When we estimate the multiple task model, however, the computational burden is too severe and we restrict the parameters of the cost process, c_N, σ, J to be the same across subjects.[16]

The general approach we take is maximum simulated likelihood. Given the underlying structural model and for each parameter value, (i) we simulate behavior for a large number of hypothetical subjects and (ii) we then compute the probability distribution of completion times. From this, we calculate the likelihood function of the parameters given the experimental data on the actual completion times by our subjects, which we finally maximize to produce our parameter estimates. In what follows we provide more specific details.

5.1.1 Identification of Exponential and Present-Biased Subjects

Since we allow a subset of the parameters to be indexed by subject type, $k \in \{e, h\}$, estimating our structural model requires identifying each subject as either exponential or quasi-hyperbolic. As we already noted, according to theory, only present-biased subjects would self-impose a deadline. Our identification strategy seeks to exploit this.[17] We pursue a general and flexible approach to identification and seek to estimate the probability that a subject is present-biased. Consider the single task model. We estimate two logit models – one for each of the 1T and 3T Endogenous deadlines treatments – on the decision to self-impose a deadline, where the Phase 1 survey responses are the explanatory variables. Using the parameter estimates from each model, we can compute, for a subject in *any treatment*, the predicted probability that the subject would self-impose a deadline (and hence be present-biased).[18] Let p_j^{3T} denote the predicted probability that subject j would set a deadline according to the logit model based on survey responses from the 3T treatment. Let p_j^{1T} denote the predicted probability that subject j would set a deadline according to a similar logit model based on survey responses for the 1T treatment. Let $\mu_j = \nu p_j^{3T} + (1-\nu)p_j^{1T}$ denote the prior probability that subject j is present-biased; where $\nu \in [0, 1]$ is a parameter to be estimated, which measures how much the identification based on 3T is also valid for the 1T treatment.

Since setting a deadline should also be indicative of present-bias, for subjects in the 1T Endogenous deadlines treatment, we update this prior depending on whether or not they set

[16] Note we avoid the index indicating treatment (1T v. 3T) in the cost parameters, as they are distinguished by the index k which only appears in 1T.

[17] To be sure it is possible that subjects' deadline choices are driven by considerations other than demand for commitment and, hence, outside the model.

[18] We estimate these logit models both using all survey questions and, more parsimoniously, by only including the most relevant variables for the decision to self-impose a deadline. This should guard against the possibility of over-fitting the model and making for worse out of sample predictions, which is our primary interest. Qualitatively, the results are not sensitive to whether the full or parsimonious model is used.

a deadline. Specifically, the posterior probability of being present-biased is:

$$\mu'_j = \begin{cases} \alpha\mu_j / (\alpha\mu_j + (1-\alpha)(1-\mu_j)), & \text{if set deadline} \\ (1-\alpha)\mu_j / ((1-\alpha)\mu_j + \alpha(1-\mu_j)), & \text{if did not set deadline but had option to} \\ \mu_j, & \text{if no option to set deadline} \end{cases}$$

where $\alpha \in [0.5, 1]$ measures the strength of the signal that setting a deadline implies the subject is present-biased.

In conclusion, let $\theta_{1T} = \left\{\beta_{1T}, \delta, (c_N^k, \sigma^k)_{k\in\{e,h\}}\right\}$ be the fundamental set of model parameters to be estimated from the data in the 1T treatment. The likelihood of a subject j who completes the task at time $t^j \in \{1, \ldots, T\} \cup \{\infty\}$, where $\{\infty\}$ denotes that the task was not finished, is given by:

$$L_j(t^j; \theta_{1T}, \nu, \alpha) = \mu'_j L_j^h(t^j; \theta_{1T}) + (1 - \mu'_j) L^e(t^j; \theta_{1T}),$$

where $L_j^k(t^j; \theta_{1T})$ is the simulated probability that a type $k \in \{e, h\}$ completes the task at time t^j. Notice that the fundamental model parameters are augmented by ν and α, the parameters which link the probability of present-bias to each subject's individual psychological characteristics from the survey questions.

The overall likelihood is then

$$L(\theta_{1T}, \nu, \alpha|\text{data}) = \prod_{i=1}^{N} L_i(t^i; \theta_{1T}, \nu, \alpha);$$

and the parameter estimates $(\hat{\theta_{1T}}, \hat{\nu}, \hat{\alpha})$ minimize $-\log(L(\theta_{1T}, \nu, \alpha|\text{data}))$.

Turn now to the 3T treatment. Estimating the structural model in this case – where subjects face different deadlines – is computationally demanding. Therefore, we must necessarily simplify our approach. First, we estimate the structural model using only completions data from the No deadlines and the Exogenous deadlines treatments (though we continue to rely on data from the Endogenous deadlines treatment to identify which subjects are present-biased). As a consequence, for any subject j, $\mu'_j = \mu_j$ and the parameter α does not appear in the estimation. Second, we fix $\nu = 1$; that is, we assume that only the determinants of the decision to self-impose deadlines in 3T are exploited in identifying subjects with present bias. While the assumption is restrictive, it is motivated by the fact the observation – see Table 3 – that deadlines appear to be more strict and more in line with a demand for commitment in 3T than in 1T.[19] Lastly, with regard to present-bias, we will consider a subject to be present-biased if $\mu_j > 1/2$. Our final simplification is that assume that exponential and present-biased subjects have the same cost process; that is, $(c_N^k, \sigma^k) = (c_N, \sigma)$, for $k \in \{e, h\}$.

In conclusion, given the parameters $\theta_{3T} = (\beta_{3T}, \delta, c_N, \sigma, J)$ we can numerically calculate the threshold $\bar{c}_l^k(t)$ such that a subject of type $k \in \{e, h\}$ will complete task l at time t if and only if $c(t) \leq \bar{c}_l^k(t)$. We then simulate the stopping time problem for a large number of simulated decision makers for each pair in {Exogenous, No Deadlines} $\times \{e, h\}$ and find the time at which they complete the task.[20] This gives us 12 distributions of completion

[19] The assumption is ex-post validated by the fact that parameter ν is estimated to be 1 in 1T, as we will document in the next section.

[20] Specifically, in the 3T treatment, we simulated 40,000 hypothetical students – 10,000 for each of the pairs in {Exogenous, No Deadlines} $\times \{e, h\}$.

times - one for each triple {Exogenous, No Deadlines} $\times$ $\{e, h\}$ $\times$ {Task 1, Task 2, Task 3} - each of which has support $\{1, 2, \ldots, T\} \cup \{\infty\}$. Denote these distributions by $L_{dkl}(t; \theta_{3T}) = L_{\text{deadline, type, task}}(t; \theta_{3T})$. Given these distributions, as well as the completion times of subjects and their classification as quasi-hyperbolic or exponential, we can then construct the likelihood function. Let t^j_{dkl} denote subject j's completion time of task l when he/she is in deadline treatment d and classified as type k. The likelihood function for treatment is then:

$$L(\theta_{3T}|\text{data}) = \prod_{j=1}^{N} \prod_{l=1}^{3} L_{d_j k_j l}(t^j_{d_j k_j l}; \theta_{3T}),$$

where $d_j \in$ {No Deadlines, Exogneous} is the deadline treatment of subject j and $k_j \in$ {Exponential, Quasi-Hyperbolic} is the classified type of subject j. We then search for the parameter vector, $\theta_{3T} = (\beta_{3T}, \delta, c_N, \sigma, J)$ which minimizes $-\log(L(\theta_{3T}|\text{data}))$.[21]

5.1.2 Main Results

The estimation results are provided in Table 2, where panel (a) contains the results for 1T and panel (b) contains the results for 3T. Except for the α and ν parameters in panel (a), the

Table 2: Estimation Results

(a) One Task Treatment

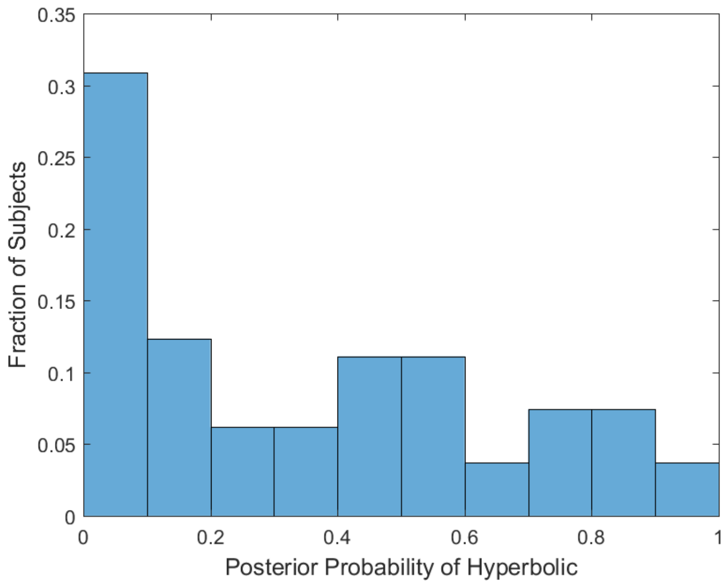
Present-Bias - β_{1T}	0.23	(0.018)
Upper Bound on Cost (Exp) - c^e_N	42.1	(0.088)
Cost Volatility (Exp) - σ^e	1.549	(0.118)
Upper Bound on Cost (Hyp) - c^h_N	64.1	(0.499)
Cost Volatility (Hyp) - σ^h	60.0	(0.768)
Updating Parameter - α	0.50	(0.327)
Weight on 3T Logit Identification - ν	1.00	(0.347)
LL	-140.7	

(b) Three Task Treatment

Parameter	Estimate	
Present-Bias - β_{3T}	1.00	(0.009)
Upper Bound on Cost - C_N	40.8	(0.108)
Cost Volatility - σ	5.595	(0.078)
Cost Jump on Completion - J	0.682	(0.111)
LL	-722.69	

[21] As a practical matter, we divide each day into 2 time periods of 12 hours each. All tasks that were completed in that window are counted as being completed in that period. This greatly reduces the computational complexity of the problem by reducing the number of possible completion times. We assume that $P(c' \mid c)$ is uniform on $[\max\{0, c - \sigma\}, \min\{c_N, c + \sigma\}]$ and we break up the interval of possible costs $[0, c_N]$ into 300 evenly spaced values, giving us a 300×300 Markov transition matrix. Finally, we fix δ at a given value, since initial trials suggested this parameter had a negligible effect on behavior.

Figure 2: Posterior Probability of Being Quasi-Hyperbolic in 1T



estimates seem to be fairly precisely estimated.[22] The posterior probability distribution over present-bias that we estimate for subjects in the single task treatment is shown in Figure 2.

We discuss the main results of our empirical analysis in the following.

Present Bias. First, our analysis documents a *strong evidence for present-bias in the single task treatment*: we estimate $\beta_{1T} = 0.23$. Present-bias is also relatively widespread in our sample: the posterior probability distribution over present-bias identifies about 30% of likely quasi-hyperbolic subjects (posterior probability $> 60\%$). Nonetheless, 45% of subjects are likely exponential (posterior probability of present-bias $< 20\%$).

We also find that the cost of time process differs for exponential and quasi-hyperbolic subjects. In particular, *subjects with present-bias perceive a higher and much more volatile costs of time in the single task treatment.* The maximal dollar value of the time to perform the task, c_N, is \$64.1 for quasi-hyperbolic and \$42.1 for exponential subjects; while the volatility of costs is \$60 as opposed to \$1.5. One interpretation for this is that there is a large and important psychological component of costs and that there may be a correlation between present-bias and a possibly distorted perception of the cost of time.[23]

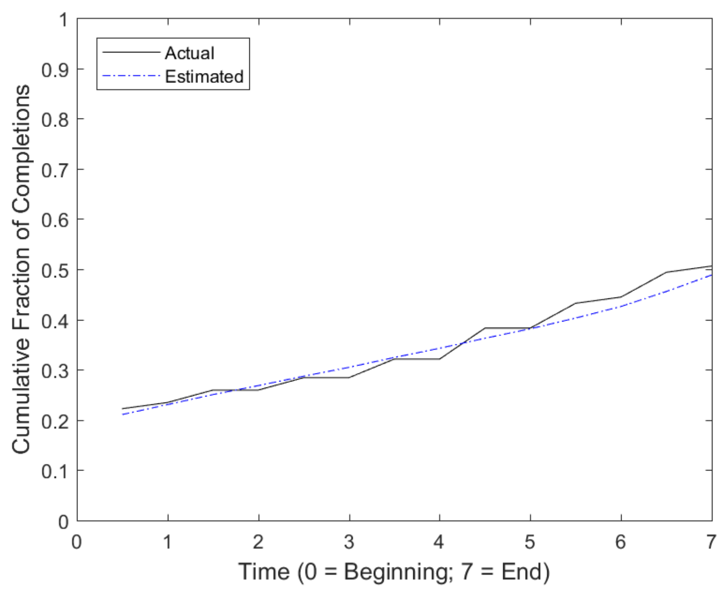
Most importantly our analysis documents an important fundamental difference between the single task and multiple tasks treatments in our subjects' ability to exercise internal self-

[22] However, it is interesting to note that, given the estimates $\alpha = 0.5$ and $\nu = 1$, the identification of present-bias relies entirely on the determinants of deadline choice in the 3T treatment ($\nu = 1$) and that setting a deadline does not increase the prior probability of present bias ($\alpha = 1$). This implies that it is mostly in 3T that deadlines represent demand for commitment.

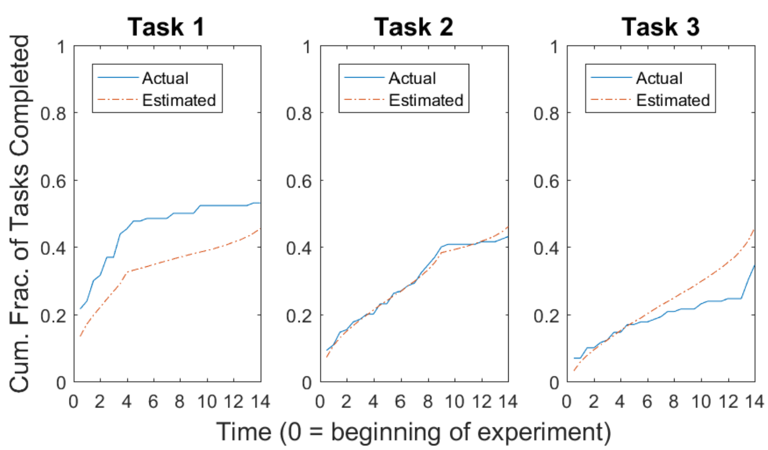
[23] This interpretation is consistent with Gabaix and Laibson (2017), who argue that present-bias may actually be confused with forecasting errors of future events, as long as forecasting errors are plausibly connected to a distorted perception of the cost of time; see also Retz Lucci (2013) for a discussion of the possible relationship between time preference and time perception.

Figure 3: Simulated Task Completions

(a) One Task Treatment



(b) Three Task Treatment



control. Specifically, while we estimate a strong present-bias in 1T with $\beta_{1T} = .23$, we find *no evidence of present-bias in multiple tasks*: $\beta_{3T} = 1$. These estimates are consistent with the interpretation that present-bias essentially disappears in the multiple task case; that is, when faced with multiple tasks subjects are successful at exercising various forms of psychological self-control, perhaps because the repetition of the tasks induces them to formulate a plan regarding when to complete them (see Gollwitzer and Bargh, 1996; Gollwitzer, 1999). Interestingly, present-biased subjects in the multiple tasks treatment also appear to control any mis-perception they might have regarding their cost of time: the estimated upper bound of the cost of time in 3T is \$40.80, comparable to that found in the 1T treatment for exponential subjects; and the volatility (\$5.6) is also relatively close to the one estimated for exponential subjects in the single task case.

Finally, our estimate of the cost of time process in the multiple tasks treatment imply *fatigue in completing tasks*; that is, the cost of completing the next task immediately after the current task increases. Indeed, we consistently observe that some students appear to spread them out over the course of the experiment.[24]

5.1.3 Model Fit

Figure 3 gives a visual sense of the model fit comparing the actual distributions of task completions with the predicted distributions given our parameter estimates. Figure 3(a), which is for the 1T treatment, shows that our model is almost perfect at matching completions up to day 5, after which the model under-estimates the observed completion rate. After that, our model predicts a slower rate of completions and a modest deadline effect for days 6 and 7. In contrast, the data show a somewhat faster rate of completion over the final 3 days and no deadline effect to speak of.

In the 3T treatments, which is depicted in Figure 3(b), our empirical model generally predicts the correct shape, but it underestimates task 1 completions and overestimates task 3. The model predicts a smoother completion rate for task 3 and a modest deadline effect, while the subjects show a flattening completion rate after day 5 and a strong final deadline effect. Still, with effectively only three parameters (given $\beta = 1$), it is remarkable that the model captures the qualitative features of the data so well. Indeed, for Task 2, the fit is nearly perfect.

5.2 Optimal Deadline Choice

Our empirical model identifies present-biased subjects' β in the active decision stage. Ideally, we would like to also estimate their perceived present-bias parameter, $\hat{\beta}$, which would allow us to quantify their misperceptions about present-bias and their ability to self-control. Unfortunately, the deadline data are too noisy to accomplish this goal with great confidence. The observed heterogeneity across deadlines, even after conditioning on the choice of binding deadlines, suggests a prominent role of unobserved characteristics in the explanation of optimal deadline choice.[25]

[24] However, other students bunch their task completions, but this is also consistent with fatigue provided that the initial cost is low enough.

[25] For example, one natural modeling choice would be to posit a positing stochastic perceived present-bias parameter, $\hat{\beta}_\tau$, $\tau = 1T$, $3T$, with each subject's parameter being drawn from some distribution.

As a consequence, rather than attempting to provide point estimates of $\hat{\beta}_\tau$, $\tau = 1T$, $3T$, our analysis of the deadline data from the experiment aims to test whether (i) students we identify as present-biased expect to be able to fully exercise self-control or not; that is, whether $\hat{\beta}_\tau = 1$; and whether (ii) these students are *partially naïve* at the ex-ante state; that is, whether their expectations regarding their ability to self-control are indeed correct: $\hat{\beta}_\tau = \beta_\tau$.

The theoretical analysis, in Proposition 2 and 3 implies that only subjects with $\hat{\beta}_\tau < 1$ would self-impose deadlines in treatment $\tau = 1T$, $3T$. Therefore, evidence that subjects perceive themselves to be present-biased would manifest as a significant fraction of subjects choosing to self-impose a strictly more binding deadline than we, the experimenters, imposed. Table 3 shows that the fraction of students who choose to self-impose deadlines is generally 30% or higher across all the experimental treatments we run. Indeed, proportions tests of the frequency of self-imposing a deadline against a null hypothesis that the true proportion is 0.01 are easily rejected for both the 1T and 3T treatments, and indeed, for each individual task in 3T ($p \ll 0.01$).[26] Table 3 also shows stark differences between the 1T and 3T treatments. In particular, in the 1T treatment with Endogenous deadlines 31.4% of students self-impose a binding deadline, while in the equivalent (i.e., mid-semester, 150 words) 3T treatment we observe a more robust demand for commitment, with over 60% of students self-imposing a binding deadline on task 1. We conclude that

$$\hat{\beta}_\tau < 1, \quad \text{for both } \tau = 1T,\ 3T;$$

that is, *present-biased students expect not to be able to fully self-control in both single and multiple tasks treatments.*

This result, that subjects perceive themselves to lack self-control ($\hat{\beta}_\tau < 1$), is especially striking for the 3T treatment. Recall that our structural model estimated $\beta_{3T} = 1$, suggesting that in the active decision stage, present-biased subjects are able to fully self-control. Therefore, we obtain::

$$\hat{\beta}_{3T} < \beta_{3T} = 1.$$

Interpreting the subjects' choice to self-impose deadlines as a demand for commitment, this result indicates that, when facing multiple tasks, subjects display a robust demand for commitment, even though they are able to fully exercise self-control. In other words, *subjects are partially naïve in the sense that they underestimate their ability to self control in the multiple task treatment.*

Proposition 3, in turn, implies that *partially naïve* agents might self-impose deadlines which negatively affect their completion rates. This is consistent with our experimental data as documented in Table 4. Indeed, students in the Endogenous deadlines treatment have the lowest task completion rate, significantly lower than the completion rate in the No deadlines treatment ($p = 0.043$). Also, in 3T, the task completion rate is highest in the No Deadlines treatment.

We also see that subjects' behavior displays a strong deadline effect in 3T, as apparent in Figure 4(b): large spikes in task completions in the time immediately before the deadline. The deadline effect is particularly clear in the Exogenous deadlines treatment, but can also

[26]The proportions test cannot test against a zero null hypothesis. Therefore, we tested against a "true" proportion of 0.01.

Table 3: Self-Imposed deadlines

(a) 1T Treatments

Mid-semester, 150 Words	Task 1	Task 2	Task 3
Days Before (Conditional)	1.6	—	—
% Setting deadlines	31.4	—	—

(b) 3T Treatments

	Task 1	Task 2	Task 3
Mid-semester, 150 Words			
Days Before (Conditional)	7.7	5.6	5.1
% Setting deadlines	61.9	57.1	42.9
End-semester, 150 Words			
Days Before (Conditional)	4.5	2.5	2.3
% Setting deadlines	33.3	33.3	20.8
Mid-semester, 200 Words			
Days Before (Conditional)	5.4	4.2	3.8
% Setting deadlines	50.0	50.0	40.9

be seen in Task 3 of the Endogenous deadlines treatment. In contrast, in the No deadlines treatment, any deadline effects are muted, if present at all. We interpret this as an indication of the fact that partially naïve subjects do not set deadlines optimally, potentially inducing negative welfare effects.

On the other hand, in the 1T treatment, combining the optimal deadline and the structural estimates of our model of behavior in the active decision stage, we conclude that:

$$\hat{\beta}_{1T}, \beta_{1T} < 1.$$

Therefore, we cannot directly identify whether $\hat{\beta}_{1T}$ is greater, equal, or smaller than $\beta_{1T} < 1$; that is, while we document *partial naïveté* in the 1T treatment, we cannot empirically assess whether students overestimate or underestimate their ability to self-control. However, by exploiting the implications of Proposition 3, we can test whether deadlines are effective in inducing completion in 1T. If they are, it is an indication that $\hat{\beta}_{1T} = \beta_{1T}$.

Although Table 4 shows that subjects in the 1T Endogenous deadlines treatment have a higher completion rate than subjects in the 1T No deadlines treatment, the difference is not statistically significant ($p = 0.306$). Moreover, focusing on the Endogenous deadlines treatment and comparing those who did and did not self-impose a deadline, we also find that there is no significant difference in behavior ($p = 0.834$). Therefore, it would seem that due to random factors, unrelated to whether a subject self-imposed a deadline or not, the completion rate is slightly higher (but not significantly so) in the Endogenous deadlines treatment.

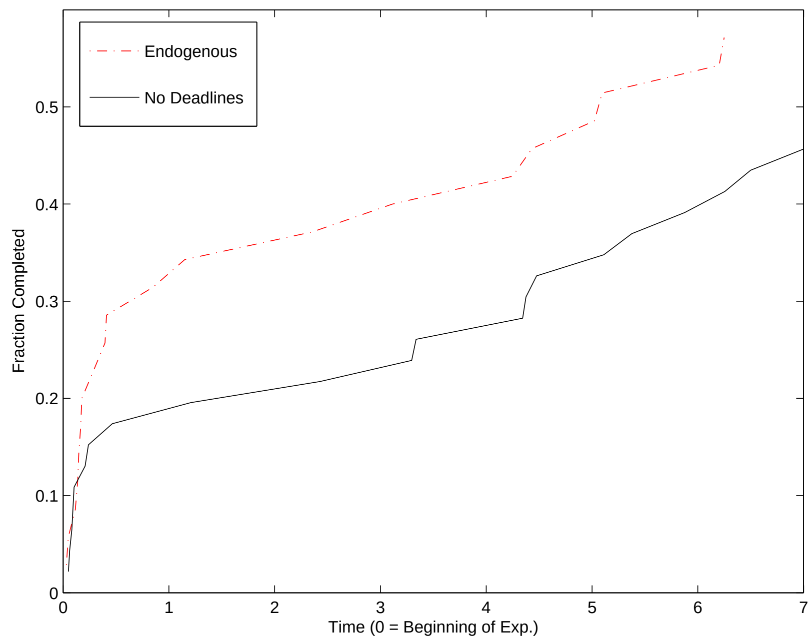
Table 4: Descriptive Summary of the Completion Statistics

	Fraction of Tasks Completed		
	Endogenous	Exogenous	No deadlines
1T Treatments	57.1%	—	45.6%
3T Treatments	36.8%	40.6%	47.0%

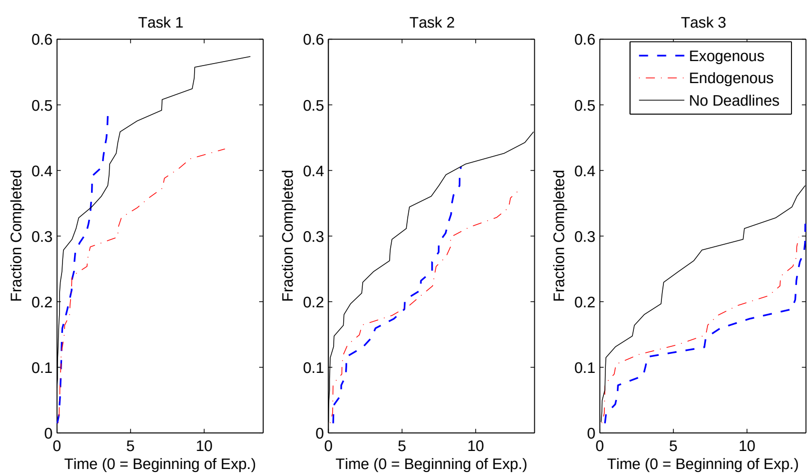
Highlighted cells indicate a statistically significant difference at the 5% level or better between the two treatments (two-sided test).

Figure 4: Cumulative Distribution of Task Completions

(a) 1T Treatments



(b) 3T Treatments



5.3 Other Behavioral Phenomena

Our structural model is driven by a single behavioral component, present bias. In this section we try to uncover additional patterns in the data that may speak about these aspects.

Over-Confidence, Forecast Errors, and Perseverance. As we mentioned in Section 3.2, if a student submits an incorrectly alphabetized list, the software sends a message alerting him/her of the existence of at least one mistake in the submitted list. He/she can then submit successive new lists until the task is correctly completed, or give up. Our data contains therefore evidence of any attempts to complete the task, even if unsuccessful. Indeed, in 1T treatments we have 104 attempts made by 67 of the 81 subjects; of these attempts only 41 are successful. Therefore, some subjects have one or more attempts before either successfully completing the task or giving up in failure. A similar pattern holds in our 3T treatments.

In our pre-experiment survey, in addition to the cost and psychological factors that we elicited, we also asked subjects to report their beliefs about how likely they were to complete the task(s). Comparing stated beliefs with actual completion rates, as we do in Table 5, provides an interesting contrast and suggests that subjects are over-confident about their likelihood of completing the tasks. While beliefs about completing all tasks range from 83% to almost 91%, actual completion rates are never higher than 57%. However, stated beliefs are much more closely aligned with the fraction of tasks attempted.

Table 5: Self-Reported Beliefs of Completing Tasks (Pooling Over Sessions)

(a) 1T Treatments

	Endogenous	Exogenous	No deadlines
Beliefs: Finish Task	85.97%	—	90.70%
Frac. of Tasks Attempted	77.1%	—	87.0%
Frac. of Tasks Completed	57.1%	—	45.6%

(b) 3T Treatments

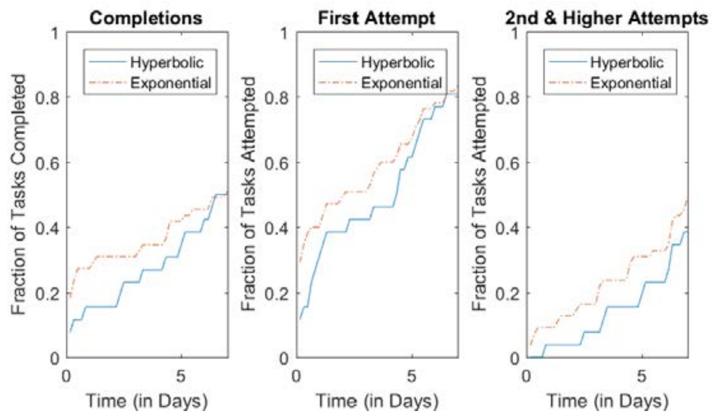
	Endogenous	Exogenous	No deadlines
Beliefs: Finish 3 Tasks	86.52%	83.25%	90.48%
Frac. of Tasks Attempted	53.2%	57.5%	61.2%
Frac. of Tasks Completed	36.8%	40.6%	47.0%

Highlighted cells indicate a statistically significant difference at the 10% level or better between the two treatments (two-sided test).

Moreover, if we look at the 95 students who complete zero tasks in the 3T treatments (which could be suggestive of procrastination), we see that 72 (75.8%) log into the experimental software at least once and 67 (69.8%) have at least one submission failure. Thus, although their lack of success at completing a task suggests procrastination, a look at their attempts suggests a partially alternative explanation: at least some subjects find the task more difficult than they initially expected and simply give up.[27] Thus the dynamics of failed

[27] As can be seen in the instructions, we tried to give subjects "reasonable" expectations of task difficulty by suggesting a particular method for completing the task. We also provided a time estimate, stating "If you are careful with this method, then it should be possible to complete each task in 1 hour or less." In fact, most

Figure 5: The Cumulative Fraction of Tasks Completed & Attempted (1T Treatments)



attempts can be important in our understanding of students' behavior in the experiment. At a minimum, it suggests that procrastination is not the only factor that explains our completion data; instead, over-confidence (or forecast inaccuracy) is an important part of the story.

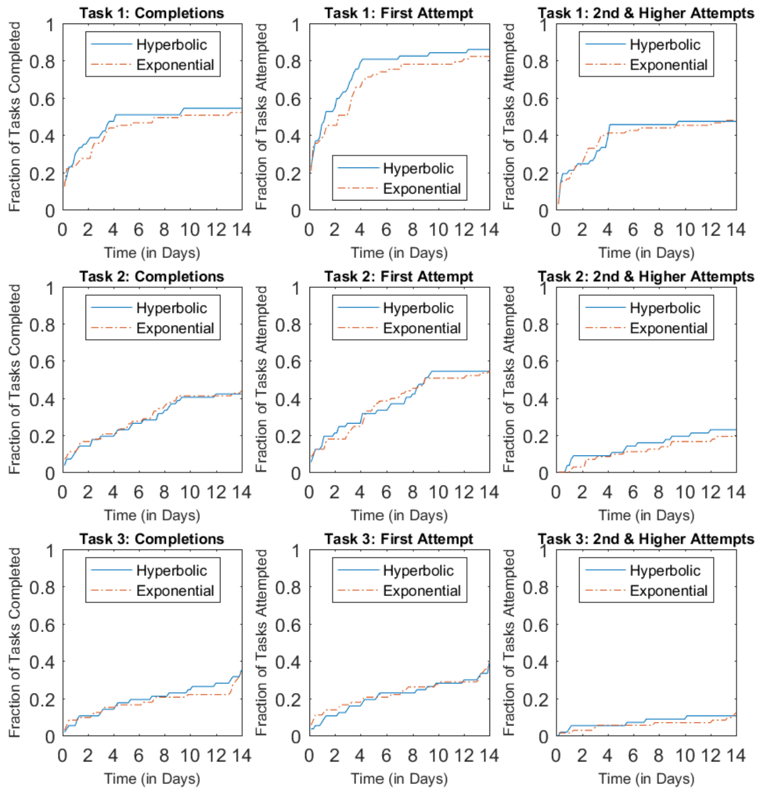
In principal, over-confidence and present-bias might interact in some way. In fact, our results suggest that they may instead be relatively distinct phenomena, in the sense that over-confidence affects both exponential and quasi-hyperbolic subjects. For the 1T treatments, Figure 5 plots the observed distributions of task completions, first attempts as well as second and higher attempts for both quasi-hyperbolic and exponential discounters according to our logit classification of subject types. Just as was the case for completions (the first panel), quasi-hyperbolic discounters delay their attempts relative to exponential discounters, though for completions and first attempts these differences disappear by the final deadline. Only for second and higher attempts do quasi-hyperbolic subjects have a modestly lower rate by the end of the experiment.

For the 3T treatments, Figure 6 plots, for each of the three tasks, the observed distributions of task completions, first attempts as well as second and higher attempts for both quasi-hyperbolic and exponential discounters. Just as with completions, the differences between exponential and quasi-hyperbolic discounters for attempts are very small, with quasi-hyperbolic discounters delaying somewhat less. Thus for both the 1T and 3T treatments, the distributions of attempts for quasi-hyperbolic and exponential subjects have the same qualitative features as the distributions of completions.

To see more evidence that failed attempts are at least partially distinct from present-bias, note that both exponential and quasi-hyperbolic subjects have approximately equal success rates: Of those subjects who have at least one attempt, 36.96% of exponential and 38.1% of quasi-hyperbolic discounters succeed on first attempt. Of those who are unsuccessful on their first attempt, 62.1% of exponential and 61.5% of quasi-hyperbolic discounters do not make any further attempts. Finally, conditional on at least one failed attempt, exponential discounters have an average of 1.93 attempts and quasi-hyperbolic discounters an average of 1.77 attempts. None of these differences are statistically significant.

tasks were completed in substantially less time. However, by attempting to complete the task too quickly, the chance of making a mistake, which was difficult to subsequently find, was increased.

Figure 6: The Cumulative Fraction of Tasks Completed & Attempted (3T Treatments)



To gauge more precisely at the interaction between over-confidence and present-bias, we re-estimated the single task model with attempts data in place of completion data.[28,29] This allows us to obtain an accurate picture of the subjects' cost process and present-bias under the assumption that over-confidence induces them to disregard the possibility of not completing the task after having attempted it. Indeed, for an over-confident subject, an attempt to complete the task at time t (even if not ultimately successful), reveals that the cost crossed his/her stopping time threshold.[30] The results for this exercise are reported in Table 6, while Figure 7 shows compares the actual and estimated distributions of attempts.

The most important result is that present-bias is now substantially smaller: our estimate of β_{1T} goes from 0.23 for completions data to 0.68. for attempts data. We also see that

[28]Since we do not observe present-bias in the 3T treatment, and since Figure 6 suggests that attempts follow a similar pattern as completions for exponential and quasi-hyperbolic agents, we do not expect any interesting interactions between over-confidence and present-bias in the 3T treatments.

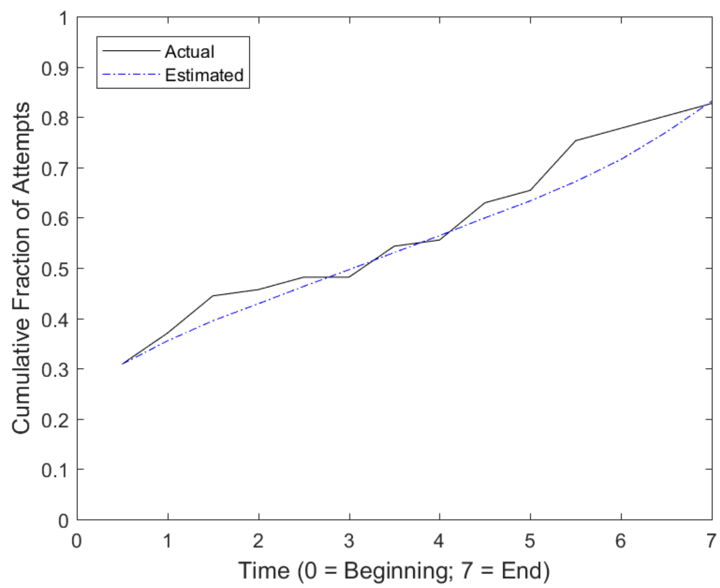
[29]In order to capture the empirical observation that roughly 30% of subjects made a nearly immediate attempt to complete the task, we allowed for initial costs to be scaled downward by a factor. To avoid confusion and facilitate comparison with the estimates using completions data, the scaling parameter is omitted from Table 6.

[30]In a previous draft we extend the model to allow subjects to update their perception of the cost of time after an unsuccessful attempt at the task and even to quit. Results are not qualitatively different.

Table 6: Structural Model of First Attempt (1T Treatment)

Present-Bias - β_{1T}	0.62	(0.017)
Upper Bound on Cost (Exp) - c_N^e	31.7	(0.125)
Cost Volatility (Exp) - σ^e	2.226	(0.154)
Upper Bound on Cost (Hyp) - c_N^h	47.1	(0.578)
Cost Volatility (Hyp) - σ^h	38.6	(0.625)
Updating Parameter (α)	0.59	(0.269)
Weight on 3T Logit Identification	0.97	(0.314)
LL	-187.37	

Figure 7: Model Fit for One Task Treatment Using Attempts Data

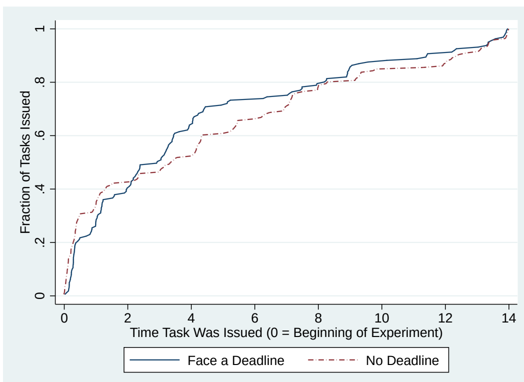


costs have a lower, more reasonable, upper bound and are relatively less volatile for quasi-hyperbolic subjects. Thus we conclude that *focusing on completions over-estimates the extent of present-bias; by accounting for over-confidence, through the use of attempts data, estimated present-biased is greatly reduced.*

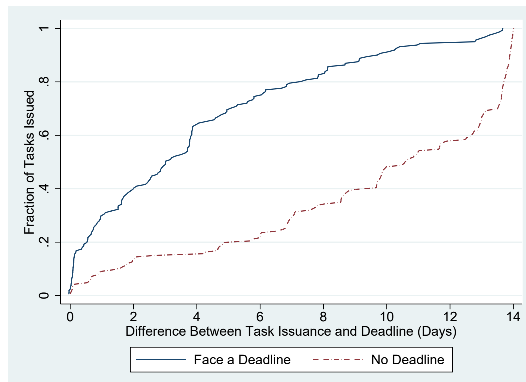
We note here that the potential negative welfare effects of deadlines for *partially naïve* agents we uncover in our empirical analysis are in our experimental data amplified by the fact that not all attempted task completions are eventually successful. The likelihood of ultimately completing a task is increasing the further from the deadline the task is attempted. Thus, binding intermediate deadlines impede task completion. Consider Figure 8. Panel (a) shows that subjects who face a deadline start working on the task – in absolute terms – earlier than subjects who do not face a deadline (Kolmogorov-Smirnov test, $p = 0.069$). However, as panel (b) clearly shows, these subjects begin working on tasks *much* closer to their deadline than subjects who do not face binding intermediate deadlines. Finally, Figure 8(c) shows that subjects who begin working on a task closer to the deadline are much less likely to ultimately complete the task. Specifically, subjects who begin a few hours before the deadline have a less-than 50% chance of completing the task, while subjects who begin a week or or more before the deadline have a 70% chance or higher of completing the task. We draw the same conclusion as in Figure 8(c) with a random effects logit regression. The estimated coefficient on time remaining is positive and significant ($p = 0.002$). For every additional day before the deadline that one starts a task, the probability of completing the task increases by approximately 2.6%.

Figure 8: The Time of Task Issuance (3T Treatments)

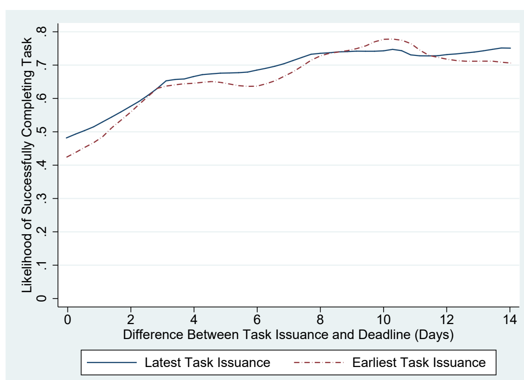
(a) Time At Which Task Was Issued



(b) Time From deadline At Which Task Was Issued



(c) Likelihood of Completing Task Given Time Issued From Deadline



Naïveté in the stopping-time problem. The behavioral literature on present-bias distinguishes between two classes of quasi-hyperbolic discounters: sophisticated and naïve, depending on whether or not they are aware of their present-bias. In our theoretical and empirical analysis we allow for *partial naïveté* at the ex-ante stage, but do not in the stopping-time problem, effectively classifying all quasi-hyperbolic discounters as sophisticated. We now provide a discussion of this issue.

First, our procedure to identify quasi-hyperbolic discounters is really designed to identify sophisticated quasi-hyperbolic discounters. This is because it is based on the self-reported characteristics of those who self-impose binding deadlines. A naïve quasi-hyperbolic discounter – who is unaware of her present-bias – would never self-impose binding deadlines. In Table C.1 we provide summary statistics on our survey questions, differentiating between those who did and did not self-impose deadlines in the 3T Endogenous deadlines treatment. As can be seen, the most significant difference between students who do and do not self-impose deadlines is how they answer the conscientiousness question. Specifically, those who *do* self-impose deadlines report themselves to be *less* conscientious. This is supportive of the notion that it is the sophisticated students who are willing to impose a deadline on themselves. Thus we feel that the group we label as quasi-hyperbolic can confidently be assumed to be composed of sophisticated quasi-hyperbolic students.

It is possible that some naïve quasi-hyperbolic discounters remain hidden in the group of students we classify as exponential discounters. It might be argued that this explains why we find no difference between exponential and quasi-hyperbolic subjects in the 3T treatment. The combination of naïve quasi-hyperbolic and exponential subjects might lead to behavior which is indistinguishable from sophisticated quasi-hyperbolic subjects. However, if this were the case, we would expect the same to happen in 1T as well. Yet, as we have shown, quasi-hyperbolic subjects delay more than exponential subjects in the one task treatments. Thus, our results are in partial accordance with Mahajan and Tarozzi (2011) who shows that even if naïve quasi-hyperbolic subjects make up a substantial portion of the total population of quasi-hyperbolic subjects, they display a much smaller present bias.

In an attempt to dig more deeply regarding the identification of naïve quasi-hyperbolic discounters, we can exploit a series of questions we asked in the pre-experimental survey. These questions were previously used by Americks, Caplin, Leahy, and Tyler (2007) to gauge this same issue. Specifically, students are asked to consider being given 10 restaurant vouchers that were valid for two years at *any* restaurant and are then asked the following hypotheticals:

q14 From your current perspective how many vouchers would you like to use in year 1?

q16 If you were to give in to your temptation, how many vouchers do you think you would use in year 1?

q17 Based on your most accurate forecast of how you think you would actually behave, how many vouchers would you use in year 1?

Following Americks, Caplin, Leahy, and Tyler (2007), $SCP = q17 - q14$ can be adopted as a measure of self-control problems, and in particular $SCP > 0$ can be interpreted as evidence of present-bias. However, since these questions refer to a specific context of self-control (spending on restaurants), a subject could be unaware of their general self-control problems/present-bias (i.e., they could be naïve) while still eliciting $SCP > 0$. We can then identify naïve quasi-hyperbolic students as those who, according to our logit analysis are not sophisticated (i.e., we say $SOPH = 0$) but have $SCP > 0$.[31] This is the case for about 20.8% of students in the 3T treatments. On average, these students finish 1.195 tasks, while the non-naïve finish 1.25 tasks. The difference is not significant. Once more this analysis is consistent with the interpretation that, even if naives are present, they display a small

[31] In support of this analysis, it turns out that there is a significantly negative relationship between the predicted probability of setting a deadline and SCP. That is, as SCP increases, we are less likely to label that subject as sophisticated. Moreover, we cannot reject that the correlation between SCP and one's self-reported level of conscientiousness (which was a key factor in the decision to self-impose a deadline) is 0 ($p = 0.45$).

present-bias as in Mahajan and Tarozzi (2011).

Lack of Attention. Given that the 3T treatments take place over a two-week period, it is possible that students who fail to complete some tasks simply forget about the experiment. To test this, at the end of Spring 2011, we ran a fourth session with three treatments. In all three treatments, students are able to set their own deadlines and each task consists of 200 words. The first treatment is a baseline where no reminders are possible. In the second treatment, students can request, at no cost, to receive a reminder. In the third treatment, students can request to receive a reminder at a cost of $3 (deducted from the participation fee). Reminders are sent via email daily at approximately 9:00AM and they inform the student of his/her deadlines and also provide the URL to the experimental software. We draw two conclusions from the data we obtain in these sessions.[32] First, no student is willing to pay $3 out of his/her participation fee in order to receive a daily reminder. Moreover, even when reminders are free, 25% of the students choose to not receive them. Second, the presence of reminders makes people more likely to self-impose a deadline. Specifically, in the absence of reminders, 6 out of 16 subjects self-imposed a deadline on at least one task, which is comparable to the 9 out of 24 who did the same in the previously reported end of semester session. In contrast, when subjects had the option to receive reminders 31 out of 39 subjects chose to self-impose a deadline on at least one task. A proportions test easily rejects equality of proportions ($p < 0.01$).[33] If subjects used deadlines as *de facto* reminders, then giving subjects to ability to receive reminders should lead to *fewer* self-imposed deadlines. Instead, we saw the opposite. This confirms our prior interpretation that binding self-imposed deadlines are a manifestation of students' demand for commitment.

6 Conclusions

In this paper we study procrastination in the context of a field experiment. We find that students display a substantial demand for commitment in the form of self-imposed deadlines. Deadlines however do not appear to increase task completion rates. Present-bias, and hence procrastination, appear to constitute an important determinant of students' behavior in the experiment. Importantly, however, the effects of present-bias appear to be completely undone by internal self-control when subjects engage in repeated similar tasks. Furthermore, we document that the behavior of students when setting deadlines reveals that, while they tend to be sophisticated in that they generally anticipate being present-biased, they are partially naïve in that they do not correctly anticipate their ability to internally self-control. More specifically, in the multiple repeated tasks treatment students under-estimate their ability to self-control. Finally, our data suggests that present-bias and other behavioral characteristics, like e.g., forecast inaccuracy and over-confidence might significantly interact in inducing delay and lowering completion rates. This interaction generates behavior which may look like procrastination, consistently with recent theoretical work by Gabaix and Laibson (2017).

[32] We only discuss the lab data, the set-up of reminders and deadlines, not the behavioral data because a glitch in the software corrupted the the latter.

[33] See Cadena, Schoar, Cristea, and Delgado-Medrano (2011) for somewhat different results on the relationship between reminders and procrastination.

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Appendix A The Model

Assume[34] that students face a cost $c(t)$ of completing the task at time t. Costs evolve according to a Markov process. In particular, let $\mathcal{C} = \{c_1, c_2, \ldots c_N\}$ denote the set of possible costs (with $0 = c_1 < c_2 < \ldots < c_N$). Let $P(c' \mid c)$ denote a Markov transition matrix so that if the cost in time t is c, then with probability $P(c' \mid c)$ the cost will be c' in time $t+1$, $c, c' \in \mathcal{C}$. Let σ denote some measure of variance for costs. We maintain the assumption that for all c_i, $i = 1, ..., n-1$, $P(. \mid c_{i+1})$, seen as a probability distribution over $\mathcal{C}$, first order stochastically dominates $P(. \mid c_i)$.

A.1 Single Task

A decision maker has a task to complete before some ultimate deadline, D. Time is discrete and the decision maker must exert a single unit of effort to complete the task. Formally, the decision maker is solving a stopping time problem. If she completes that task at any time $t \leq D$, then in period $t+1$, she will receive a payment of $V > 0$.

It is convenient to distinguish the case in which the decision maker displays exponential discounting, $\beta_{1T} = 1$, from the case in which she displays quasi-hyperbolic discounting, $\beta_{1T} < 1$. In this Appendix we consider the two cases in turn. Proposition 1 in the text is then presented and proved in its two components, Propostion A.1 and A.2, in this appendix.

A.1.1 Exponential Discounting

Let $\delta < 1$ denote the (exponential) discount rate. Consider first the case in which the decision maker is exponential, that is, she displays no present-bias: $\beta_{1T} = 1$. Then, as of time 0, the payoff of a decision maker completing the task in time t at cost c is $\delta^t (\delta V - c)$. We will assume that there is some index k, such that $c_k > \delta V$.

We can solve for the optimal policy via backward induction. At the time of the deadline D, we know that the decision maker will complete the task if and only if $\delta V \geq c$. The value function $W(c, t; D, \beta_{1T})$, evaluated at $t = D$, given an arbitrary cost $c \in \mathcal{C}$, and with $\beta_{1T} = 1$, can we written as:

$$W(c, D; D, 1) = \max\{\delta V - c, 0\}.$$

At time $D-1$, given again an arbitrary cost $c \in \mathcal{C}$ the decision maker's rule is to complete the task if and only if

$$\delta V - c \geq \sum_{c' \in \mathcal{C}} \delta P(c' \mid c) W(c', D; D, 1),$$

Hence, the value function is given by:

$$W(c, D-1; D, 1) = \max\{\delta V - c, \sum_{c' \in \mathcal{C}} \delta P(c' \mid c) W(c', D; D, 1)\}.$$

This process can be continued for any arbitrary time period, $t < D$, so that:

$$W(c, t; D, 1) = \max\{\delta V - c, \sum_{c' \in \mathcal{C}} \delta P(c' \mid c) W(c', t+1; D, 1)\}.$$

[34] At the cost of some overlap with the text, we keep this appendix self-contained to make it easier for a reader interested in more than a superficial account of the model.

Proposition A. 1 *Assume $c_k > \delta V$, for some $k \leq N$. Then,*

(i) $W(c, t; D, 1)$ *is decreasing in c and t, and is increasing in D;*

(ii) for all time periods t, there exist a threshold $\bar{c}(t; D, 1)$ such that the decision maker's optimal decision rule is to complete the task if and only if $c(t) \leq \bar{c}(t; D, 1)$, where $c(t)$ denotes the realization of the cost at t; and

(iii) the threshold $\bar{c}(t; D, 1)$ is increasing in t and decreasing in D.

Proof of Proposition A.1. We begin by proving that the value function is decreasing in t. The proof is by induction. First, note that

$$W(c, D-1; D, 1) = \max\{\delta V - c, \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W(c', D; D, 1)\} \geq \max\{\delta V - c, 0\} = W(c, D; D, 1).$$

Next, suppose that for all $t \in \{\bar{t}, \ldots, T-1\}$, $W(c, t; D, 1) \geq W(c, t+1; D, 1)$. It is then easy to see that:

$$W(c, \bar{t}-1; D, 1) = \max\{\delta V - c, \delta \textstyle\sum_{c' \in \mathcal{C}} P(c' \mid c) W(c', \bar{t}; D, 1)\} \geq$$

$$\geq \max\{\delta V - c, \delta \textstyle\sum_{c' \in \mathcal{C}} P(c' \mid c) W(c', \bar{t}+1; D, 1)\} = W(c, \bar{t}; D, 1).$$

This follows by the induction hypothesis and because the max operator preserves the inequality. This completes the proof. The proof that $W(c, t; D, 1)$ is decreasing in c and increasing in D is similar and, therefore, omitted.

To prove part (ii), observe that by the definition of first-order stochastic dominance, we know that for any increasing function, $u(c)$,

$$\sum_{j=1}^{n} P(c_j \mid c_{i+1}) u(c_j) \geq \sum_{j=1}^{n} P(c_j \mid c_i) u(c_j)$$

We begin at time $T-1$ and proceed backwards. Since $W(c, D; D, 1)$ is decreasing in c, $-W(c, D; D, 1)$ is increasing. Therefore, we can conclude that:

$$-\sum_{j=1}^{n} P(c_j \mid c_{i+1}) W(c_j, D; D, 1) \geq -\sum_{j=1}^{n} P(c_j \mid c_i) W(c_j, D; D, 1),$$

or

$$\sum_{j=1}^{n} P(c_j \mid c_{i+1}) W(c_j, D; D, 1) \leq \sum_{j=1}^{n} P(c_j \mid c_i) W(c_j, D; D, 1).$$

We must now show that there exists a cost, $\bar{c}_{T-1}$ such that

$$\delta V - c - \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W(c', D; D, 1) \geq 0$$

is satisfied if and only if $c < \bar{c}_{T-1}$.

Note that the inequality is strictly positive at $c = c_1 = 0$ and the inequality is strictly negative for $c = c_N > \delta V$. Therefore, to show that there is a unique threshold, it is enough to show that the left-hand side is decreasing in c. This follows because $\delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W(c', D; D, 1)$ is decreasing in c with slope bounded below by $-\delta > -1$. Thus, the decision maker employs a threshold rule at time $D - 1$.

The exact same arguments can be used to show that the decision maker will employ a threshold rule at any time t. This completes the proof of part (ii).

Finally, to prove part (iii), we show that $\bar{c}(t; D, 1)$ is increasing in t. The argument is adapted straighforwardly to show that $\bar{c}(t; D, 1)$ is also decreasing in D. Suppose that there exists $t_1 < t_2$ such that the thresholds are: $\bar{c}(t_1; D, 1) > \bar{c}(t_2; D, 1)$. Choose $c \in (\bar{c}(t_2; D, 1), \bar{c}(t_1; D, 1)]$. Then, we know that $W(c, t_1; D, 1) = \bar{V} - c$. Moreover, since $c > \bar{c}(t_2; D, 1)$, we also know that $W(c, t_2; D, 1) > \delta V - c$. Putting this together, it implies that $W(c, t_1; D, 1) = \delta V - c < W(c, t_2; D, 1)$, a contradiction to the fact (proven in part (i)) that the value function is *decreasing* in t. ■

A.1.2 Quasi-Hyperbolic Discounting

Let $\beta_{1T} = \beta < 1$ denote present-bias, while $\delta < 1$ still denote the (exponential) discount rate. Then, as of time 0, the payoff of a decision maker completing the task in time t at cost c is $\beta\delta^t(\delta V - c)$; as of time t, however, the payoff is $\beta\delta V - c$. We assume that the decision maker is sophisticated in that she is aware that her future incentive to procrastinate. As in the case of an exponential decision maker, a sophisticated quasi-hyperbolic decision maker will employ a threshold rule.

At the time of the deadline D the decision maker will complete the task if and only if $\beta\delta V \geq c$, making her value function:

$$W(c, D; D, \beta) = \max\{\beta\delta V - c, 0\}.$$

Next move to time $D - 1$. Define

$$w(c, D; D, \beta) = \begin{cases} \delta V - c, & \text{if } c \leq \beta\delta V \\ 0, & \text{otherwise} \end{cases}$$

to be the undiscounted value that she *perceives* she will obtain in time D if she delays completing the task.[35] She will complete the task at time $D - 1$ if and only if:

$$\beta\delta V - c \geq \beta\delta \sum_{c' \in \mathcal{C}} P(c' \mid c) w(c', D; D, \beta).$$

Note that since $c_1 = 0$ is a possible cost realization, there are always costs such that the decision maker would find it optimal to complete the task. This, combined with similar arguments as above allow us to conclude that the sophisticated decision maker will also employ a threshold rule. Therefore, the value function of the decision maker is:

$$W(c, D-1; D, \beta) = \max\{\beta V - c, \beta\delta \sum_{c' \in \mathcal{C}} P(c' \mid c) w(c', D; D, \beta)\}$$

and the *perceived* value is:

$$w(c, D-1; D, \beta) = \begin{cases} \delta V - c, & \text{if } \beta\delta V - c \geq \beta\delta \sum_{c' \in \mathcal{C}} P(c' \mid c) w(c', D; D, \beta) \\ \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) w(c', D; D, \beta), & \text{otherwise} \end{cases}.$$

[35] Observe that she applies the correct policy function, but the β term disappears.

We can apply the same iterative logic to conclude that:

$$W(c, t; D, \beta) = \max\{\beta\delta V - c, \beta\delta \sum_{c' \in \mathcal{C}} P(c' \mid c) w(c', t+1; D, \beta)\}.$$

Proposition A. 2 *Then,*

(i) $W(c, t; D, \beta)$ *is decreasing in* c *and* t*; and increasing in* D*.*

(ii) for all time periods t*, there exist a threshold* $\bar{c}(t; D, \beta)$ *such that the decision maker's optimal decision rule is to complete the task if and only if* $c(t) \leq \bar{c}(t; D, \beta)$*, where* $c(t)$ *denotes the realization of the cost at* t*.*

(iii) the threshold $\bar{c}(t; D, \beta)$ *is decreasing in* β*.*

The proof of the proposition follows the lines of the preceding one, Proposition A.1, regarding exponential discounters, and is therefore omitted. Note that while a quasi-hyperbolic decision maker will employ a threshold rule, there is no guarantee that it will be monotone in t and D.[36]

A.1.3 The Optimality of Deadlines

The optimal deadline choice problem of the agent is:

$$\max_{D \leq T} \mathbb{E}\left(W(c, 0; D, \hat{\beta}_{1T})\right).$$

Proposition 2 and 3 in the text are straighforward implications of Proposition A.1 and A.2. Since we are not able to solve in closed form for the conditions on the parameters under which a quasi-hyperbolic discounter would self-impose a deadline, we show some numerical results.

In each of the four panels of Figure A.1, we allow one of the model's parameters to vary while holding the other parameters constant. In all cases, $\beta < 1$. On the horizontal axis is the time (in days) one has until the deadline, while the vertical axis is the *ex ante* expected value of the option to complete the task. This figure captures the two main forces at work. On the one hand, there is the commitment value of a tight deadline which induces the decision maker to complete the task immediately. This can be seen by observing that the expected value is initially decreasing at very short deadlines. While a tight deadline has commitment value, it comes at the cost of destroying a lot of *option value* of being able to wait for a lower

[36] We have omitted any discussion of naïve quasi-hyperbolic discounters. These are decision makers who have a present bias, but are unaware of it and believe, incorrectly, that they will behave as an exponential discounter would in the future. Using the same techniques, it is possible to show that the value function of the naïve decision maker is given by:

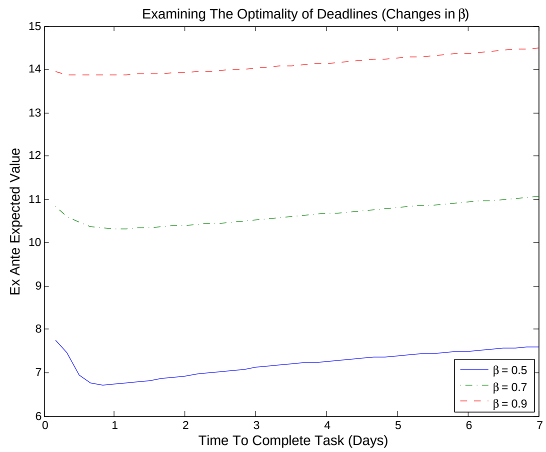
$$N(c, t; D, \beta) = \max\{\beta\delta V - c, \beta\delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W(c, t+1; D, 1)\},$$

where $w(c, t+1; D, 1)$ denotes the value function of the exponential decision maker with cost c at time $t+1$.

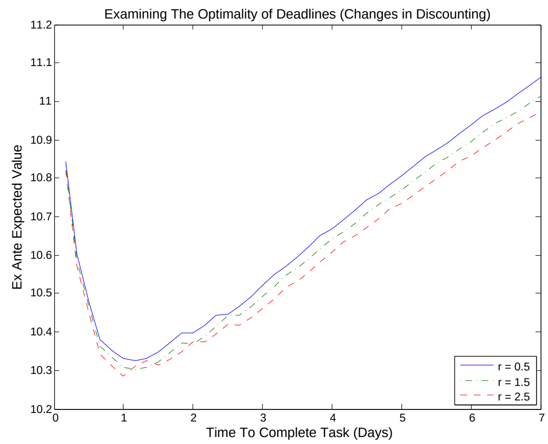
One can show that such decision makers will also employ a threshold rule, and that the threshold will be lower than for sophisticated quasi-hyperbolic discounters. That is, naïve decision makers are most prone to procrastination.

Figure A.1: The Optimality of Deadlines With (Sophisticated) Quasi-Hyperbolic Time Preferences

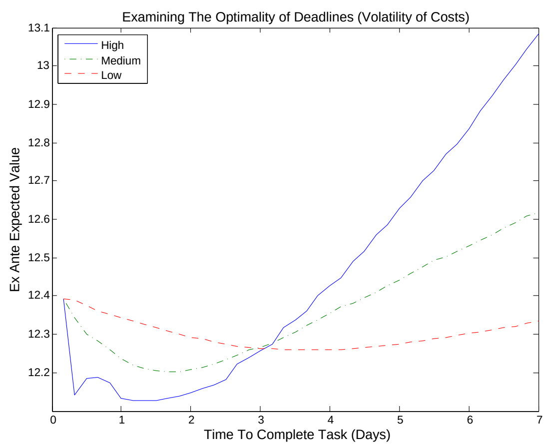
(a) Changes in β



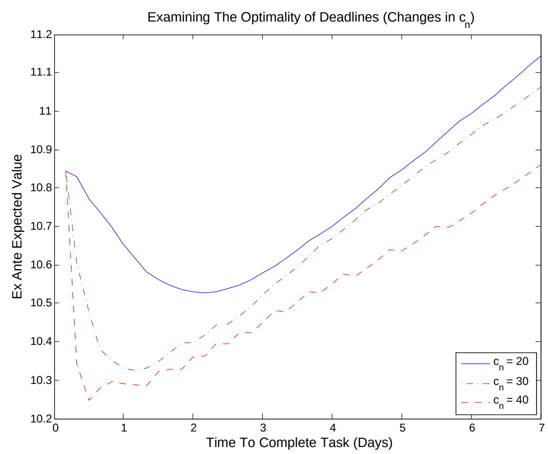
(b) Changes in r



(c) Changes in Volatility



(d) Changes in c_n



cost. Eventually, as the time available to complete the task grows, this option value becomes more important and the expected value begins to increase.[37] The figure shows that a low present-bias (a higher β), a high patience (a lower interest rate r), a low volatility of the cost process, a low maximal cost all make self-imposed deadlines relatively less-desirable for an quasi-hyperbolic discounter.

[37] Although we do not provide figures, intermediate deadlines may be optimal. This is likely to be the case when the set of possible initial costs is fairly coarse. In this case, an intermediate deadline may be able to induce some of the low-cost types to complete the task immediately (which gives the decision maker a discrete benefit), while also preserving option value for higher cost types who cannot be induced to complete the task immediately.

A.2 Multiple Tasks

We now turn to the case in which the decision maker must complete multiple tasks. In fact, in accordance with the experiment, we present the model for the case of three tasks. Assume that the deadline for task i is D_i, with $D_1 \leq D_2 \leq D_3$. Each task completed by the appropriate deadline pays V with one period of delay. As in the experiment, we assume that the tasks must be done sequentially. Therefore, the decision maker cannot start task 2 until either task 1 has been completed or the deadline, T_1, to complete task 1 has passed; similarly for task 3.

In order to allow for the possibility of either learning by doing or fatigue, we will assume that the cost of task completion jumps by J index values upon completing a task. Let $c''(c)$ denote the new cost that the decision maker faces after having completed a task at cost c. We assume that for all $i \in \{1, \ldots, N\}$, $c''(c_i) = c_{\max\{1,\min\{i+J,N\}\}}$. Observe that if $J < 0$, then there is learning by doing, while if $J > 0$, fatigue sets in.

The problem of solving for the optimal decision rule with three tasks is now substantially more difficult. By completing task 1 at time t, the decision maker not only receives the direct payment of V but also receives an option to complete task 2 (starting from time t). Moreover, the tasks are linked more explicitly by the possibility for fatigue or learning by doing. All of this will affect behavior.

Consider first the case of agents with exponential discounting. For the final task, task 3, the problem is formally equivalent to the single task model presented in the previous subsection. Therefore, we may write the value function as $W_3(c, t; D_3, 1)$, where t indexes the current time period and D_3 is the deadline for that task. We will say that $W_3(c, t; D_3), 1 = 0$ for all $t > D_3$. Now consider task 2 and start at the time of the associated deadline D_2. The decision maker will complete the task if and only if:

$$\delta V - c + W_3(c''(c), D_2; D_3, 1) \geq \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W_3(c', D_2 + 1; D_3, 1),$$

That is, she will complete the task if and only if the immediate value of completing task 2 plus the additional value of being able to start task 3 (at cost c'_i) is greater than the value of not completing task 2 and waiting until next period to consider completing task 3.

Notice that we cannot immediately conclude that an exponential decision maker will complete task $i \in \{1, 2\}$ at deadline D_i if and only if $\delta V - c \geq 0$. If a decision maker gets fatigued, then costs will increase, which could substantially reduce the probability of completing task $i + 1$. Therefore, even if $\delta V - c > 0$, a decision maker may prefer not to complete task 2. Similarly, if there is strong learning by doing, the decision maker may actually prefer to complete task 2 even if $\delta V - c < 0$. A similar reasoning holds for quasi-hyperbolic decision makers.

In general, we can write the value functions as:

$$W_3(c, t; D_3, 1) = \max\{\delta V - c, \sum_{c' \in \mathcal{C}} \delta P(c' \mid c) W_3(c', t + 1; D_3, 1)\}$$

$$W_2(c, t; D_2, 1) = \begin{cases} \delta V - c + W_3(c''(c), t; D_3, 1), & \text{if } \left[\begin{array}{l} \delta V - c + W_3(c''(c), t; D_3, 1) \geq \\ \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W_2(c', t + 1; D_2, 1) \end{array} \right. \\ \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W_2(c', t + 1; D_2, 1) & \text{otherwise} \end{cases}$$

$$W_1(c,t;D_1) = \begin{cases} \delta V - c + W_2(c''(c),t;D_2,1), & \text{if } \left[\begin{array}{l} \delta V - c + W_2(c''(c),t;D_2,1) \geq \\ \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W_1(c', t+1; D_1, 1) \end{array} \right. \\ \delta \sum_{c' \in \mathcal{C}} P(c' \mid c) W_1(c', t+1; D_1, 1), & \text{otherwise} \end{cases}$$

Just as was noted above, the threshold for completion of task 1 at time D_1 will not necessarily be $c \leq \delta V$. It may be higher (resp. lower) if there is learning by doing (resp. fatigue).

As there are no additional insights to be gained, we omit here in the text the details of the sophisticated decision maker's problem when faced with three tasks. In order to characterise the optimal decision rule, we follow the same backward induction procedure, making sure that the decision maker correctly anticipates the policy rule that her future selves use, but evaluated with quasi-hyperbolic time preferences.

Just like in the case of a single task, when there are three tasks, only a quasi-hyperbolic discounter is willing to self-impose a deadline: self-imposing a deadline may reduce the decision maker's tendency to procrastinate, and may even induce him/her to complete (at least) one task immediately.

Appendix B Instructions & Pre-Experiment Survey Questions

B.1 Sample Experimental Instructions

This is an experiment in the economics of decision-making. Your earnings will depend on your decisions. Details of how you will make decisions and earn money will be provided below.

This experiment will take place over the course of the next several days and will end no later than **1:00PM two weeks from today**. That it, the experiment ends no later than **1:00PM, 7 April 2010**.

The Tasks

You will be given **three** tasks to be completed over the internet. While the tasks are not specifically related to each other, they can only be completed sequentially (that is, you may only work on one task at a time).

For each task, you will be given a list of **150 words** which have been arranged randomly and you will be asked to enter them on a computer terminal in **alphabetical order**. An example is shown in Figure B.1.

For each task properly completed, by the appropriate time, you will be paid **$15**. Details of how you will be paid will be given later.

The Interface

- This experiment will take place over the internet. Any time that you wish to work on a task, simply go to the following website:

  `http://www.cess.nyu.edu/web_experiments/ny`

- Upon arriving at the website, you will be prompted for your user ID and password. Shortly, you will be provided with a user ID and password. Please keep the sheet of paper on which your user ID and password are written as this is your only means of gaining access to the experimental software.

- Once you have logged into the system, you may now work on a task.

- As can be seen in Figure B.1, the list of words is given in the center of the screen and words are entered alphabetically at the left and right. The earliest word alphabetically, should be entered in the cell labeled **1**.

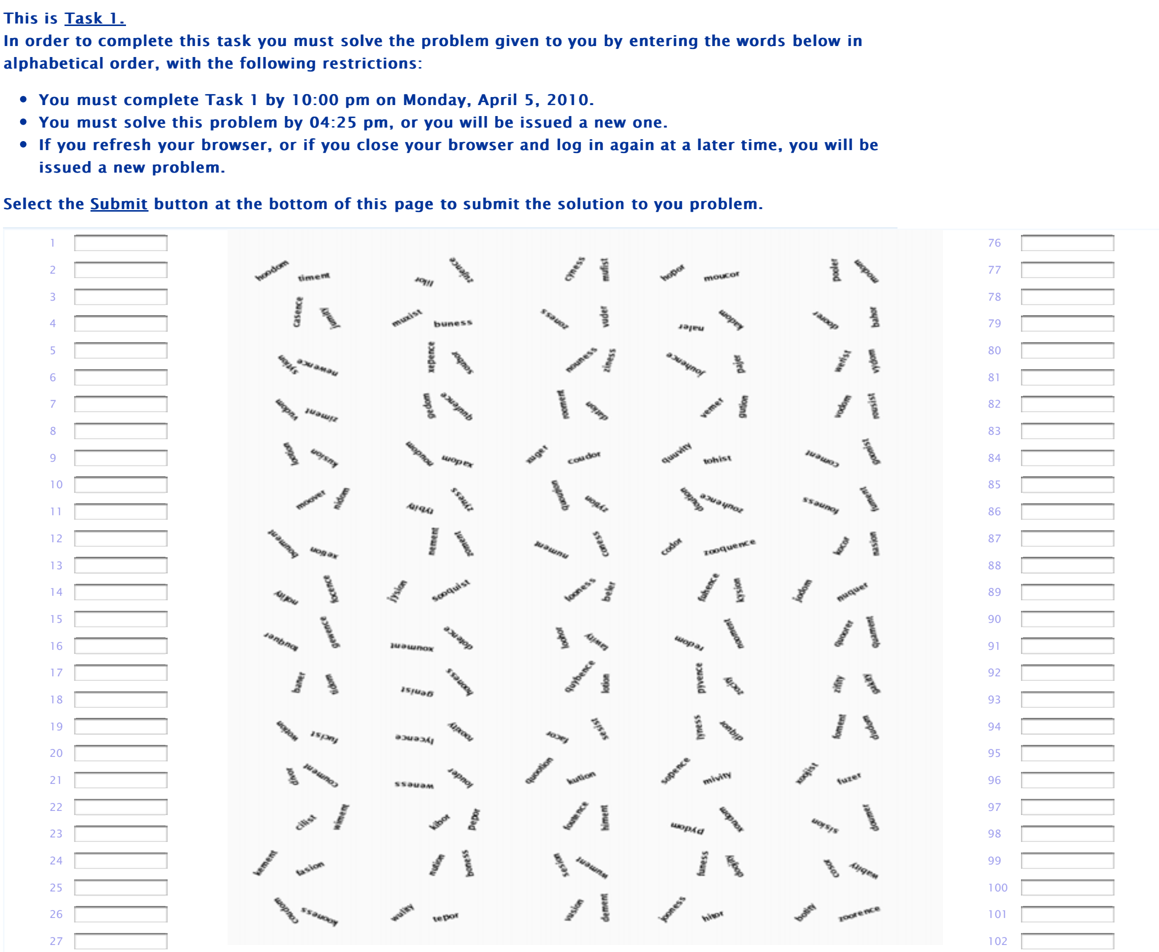
- When you have completed a task (*i.e.,* when you have arranged all words in the proper order), press the submit button, which is at the bottom of the screen.

- If you have done it correctly, then you will be taken to a new screen where, if you choose, you may work on the next (if any) task.

- If there are mistakes, you will be told:

  The list you submitted contains one or more errors.

Figure B.1: Experimental Interface For Tasks



and remain on the screen for the current task. Observe that you will not be told the nature of the mistakes, simply that the task has not been properly completed.

- Once you have been issued a list of words to alphabetize for a particular task, then you must complete it within **2 hours** (or before the deadline for that task, whichever is earlier). If you do not complete the task within this time, you will be given a new list of words.

- Note that if you press the refresh button or close the web browser and return later, you will be given a new list of words.

Completing the Tasks

Of course, there are many different ways that one might wish to approach this task. One way that we have found to work reasonably well is to print the screen containing the words, enter the words into a spreadsheet application such as Excel (Microsoft), Numbers (Apple) or Calc (Open Office), use the sort command and then enter the words in the appropriate order through the experimental interface. If you are careful with this method, then it should be possible to complete each task in 1 hour or less.

Deadlines

As indicated above, the experiment will end no later than **1:00PM, 7 April 2010**. That is, all tasks not correctly completed before this time will be considered incomplete and no payments will be made incomplete tasks. However, if you wish, you may set a separate deadline for each of the tasks. If you do so, the deadline must be **no earlier** than 1:00PM today and no later than **1:00PM, 7 April 2010**. Also, the deadline for Task 2 must be the same or after the deadline for Task 1, and similarly for Task 3.

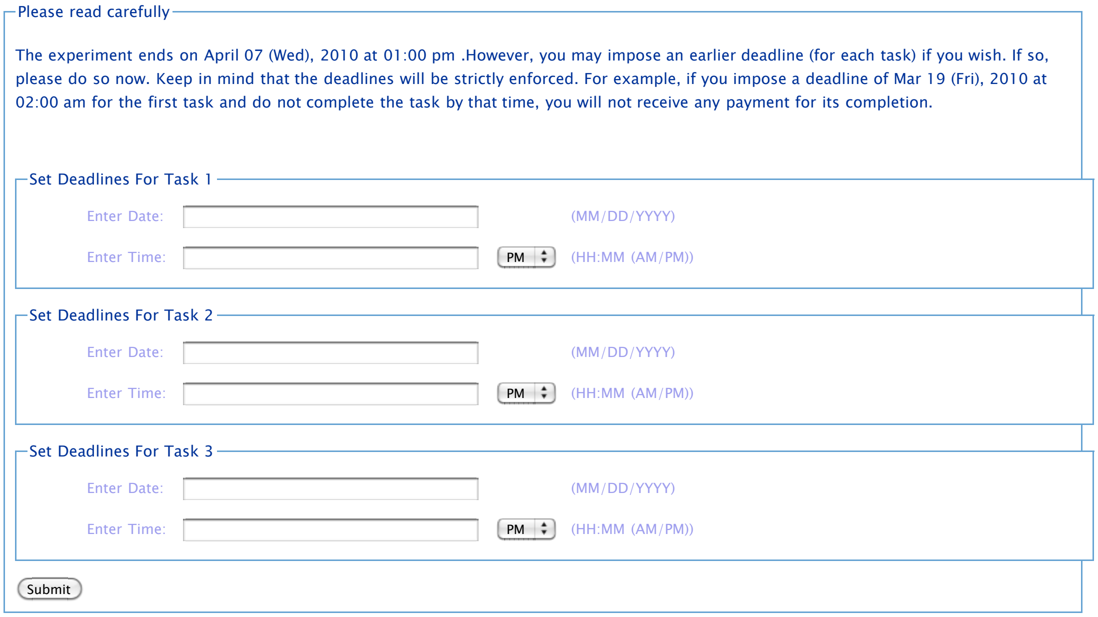
It is important to note that the deadlines will be strictly enforced. For example, if you impose a deadline of 8:26PM tomorrow for the first task and do not complete it by that time, you will not receive any payment for this task. However, if you miss a deadline for one task, you will be permitted to move immediately to the subsequent task. That is, if you miss the deadline for Task 1, you may proceed immediately to Task 2 provided that there is still time remaining in the experiment and its deadline has also not passed.

At the appropriate time, once you have logged in to the experimental software, you will enter your deadlines for each of the tasks. The interface for this is displayed in Figure B.2.

Payment

For each task that you have properly completed by the appropriate deadline, you will be paid **$15**. When you have completed a task, the experimental software will immediately notify one of the experimenters that a task has been completed. For all tasks which have been completed by **1:00PM** on any given day, the experimenter will write a check and place it in the mail by the end of the day. Payments for any tasks completed **after** the 1:00PM cutoff will be processed and mailed the next day.

Figure B.2: Experimental Interface For Choosing deadlines


Please read carefully

The experiment ends on April 07 (Wed), 2010 at 01:00 pm .However, you may impose an earlier deadline (for each task) if you wish. If so, please do so now. Keep in mind that the deadlines will be strictly enforced. For example, if you impose a deadline of Mar 19 (Fri), 2010 at 02:00 am for the first task and do not complete the task by that time, you will not receive any payment for its completion.

Set Deadlines For Task 1

Enter Date: (MM/DD/YYYY)

Enter Time: PM (HH:MM (AM/PM))

Set Deadlines For Task 2

Enter Date: (MM/DD/YYYY)

Enter Time: PM (HH:MM (AM/PM))

Set Deadlines For Task 3

Enter Date: (MM/DD/YYYY)

Enter Time: PM (HH:MM (AM/PM))

Submit

Questions

If there are any questions, please ask them now. If not, we will now provide a demonstration of the experimental software and also provide you with your user ID and password.

B.2 Survey Questions

1. How many courses are you taking?
2. What is your major?
3. What is your GPA?
4. Over the course of the next two weeks, how many of each of the following to you have:
   (a) minor assignments?
   (b) major assignments or term papers?
   (c) exams?
5. In response to the question above, please list the due dates for each assignment and the date of any exams you have in the next two weeks.
6. Are you presently employed?
7. How many social, academic or sports clubs do you belong to?
8. Over the course of the next two weeks, how much time (in hours) do you expect to allocate to:

(a) your course work?
(b) your job?
(c) social obligations or recreational activities?
(d) family obligations?

9. In response to Question 8(a), please provide details of your work schedule over the next two weeks.

10. In response to Question 8(b), please provide the dates for which you plan to participate in social or recreational activities.

11. In response to Question 8(c), please provide the dates for which you have planned family obligations.

12. On a scale from 1 to 5 with 1 being “hardly at all” and 5 being “very much so”, please answer the following questions:

    (a) How conscientious are you?
    (b) How often are you late turning in assignments?
    (c) How often are you on time for appointments?

13. On a scale from 1 to 5 with 1 being “strongly disagree” and 5 being “strongly agree”, rate how closely you identify with the following statements:

    (a) Unexpected things which require my time and attention always seem to occur.
    (b) Sometimes I am not as dependable or reliable as I should be.
    (c) I follow a schedule.
    (d) I never seem to be able to get organised.
    (e) I always pay attention to details.

    Suppose that you win 10 certificates, each of which can be used (once) to receive a dream restaurant night. On each such night, you and a companion will get the best table and an unlimited budget for food and drink at a restaurant of your choosing. There will be no cost to you: all payments including gratuities come as part of the prize. The certificates are available for immediate use, starting tonight, and there is an absolute guarantee that they will be honored by any restaurant you select if they are used within a two year window. However if they are not used up within this two year period, any that remain are valueless.

    The questions below concern how many of the certificates you would ideally like to use in each year, how tempted you would be to depart from this ideal, and what you expect you would do in practice:

14. From your current perspective, how many of the ten certificates would you ideally like to use in year 1?

15. Continue with the scenario of Question 14. Some people might be tempted to depart from their ideal allocation in Question 14. Which of the following best describes you:

(a) I would have no temptation in either direction.

(b) I would be somewhat/strongly tempted to use more certificates in the first year than would be ideal.

(c) I would be strongly/somewhat tempted to keep more certificates for use in the second year than would be ideal.

16. Continue with the scenario of Question 14. If you were to give in to your temptation, how many certificates do you think you would use in year 1 as opposed to year 2?

17. Continue with the scenario of Question 14. Based on your most accurate forecast of how you think you would actually behave, how many of the nights would you end up using in year 1?

18. On a scale from 0 to 100, how likely do you think each of the following events are?

    (a) I will complete no tasks.

    (b) I will complete at least one task.

    (c) I will complete at least two tasks.

    (d) I will complete all three tasks.

Appendix C Supplemental Analysis

While in the main body, we mainly focused on a structural analysis of behavior, in this appendix, we provide a brief discussion of some additional descriptive results.

Demand For Commitment

We first discuss in more detail the demand for commitment. As can be seen from Table 3 in the main text, the fraction of students who choose to self-impose deadlines is generally 30% or higher across all the experimental treatments we run, though there are interesting differences across treatments. First, in the 1T treatment with Endogenous deadlines 31.4% of students (11 in total) self-impose a binding deadline, while in the equivalent (i.e., mid-semester, 150 words) 3T treatment we observe a more robust demand for commitment, with over 60% of students self-imposing a binding deadline on task 1.[38] Second, in the 3T treatment, variation in the frequency of setting a deadline appears related to the implicit cost in terms of missed options to complete the task. Postulating that deadlines are less costly the easier the task (150 vs 200 words) and in the mid-semester setting (as opposed to the end), Table 3 shows that subjects' demand for commitment declines in its implicit cost.[39] Third, deadlines become less strict as their implicit cost increases: increasing the number of words from 150 to 200 or shifting the timing of the experiment from mid-semester to end-semester. In fact, we can say that deadlines are significantly less strict in the end of semester implementation than in the mid-semester, 150 words implementation (conditional on setting a binding deadline: $p = 0.075$; unconditional on setting a binding deadline: $p = 0.015$).

Having looked at the incidence and strictness of self-imposed deadlines, we are now interested in the factors that influence the decision to self-impose a deadline. Table C.1, which compares subjects' responses to the various cost of time and psychological characteristics depending on whether or not they self-imposed a deadline (for the 3T Endogenous deadlines treatment), shows that both psychological and cost factors influence the decision to self-impose a deadline. In particular, subjects who self-impose deadlines tend to face a higher cost of their time at the margin, as indicated by having more minor and major assignments, being in more clubs and spending more time socializing (though they are in significantly fewer courses). With regards to psychological factors, subjects who self-impose a deadline also self-report to be less conscientious and more impatient.[40] We interpret lack of conscientiousness as a proxy for present-bias.[41]

[38] A two-sided proportions test comparing the 1T treatment with the equivalent 3T treatment, rejects the hypothesis that the proportion of subjects setting deadlines is the same ($p = 0.026$).

[39] However, a two-sided proportions test just misses marginal significance for this result ($p = 0.102$).

[40] We take as our measure of impatience subjects' response to Question 14 from the survey. This question was taken from Americks, Caplin, Leahy, and Tyler (2007) and was used along with other questions to get an indication of impatience and self-control problems.

[41] In testing for differences between those subjects who do and do not self-impose deadlines for each of our survey questions, it is possible that some variables will be significant purely by chance. To guard against this, we conducted a Monte Carlo exercise. Specifically, for each question and for each of 100,000 trials, we drew random sample of subjects of the same size as our Endogenous Deadlines treatment with the same mean and standard deviation as in our sample. We then tested - both with a $t-$test and a Mann-Whitney rank sum test - for differences between the two simulated populations; results are reported in the last two columns of Table C.1. From this exercise, we can compute the probability of observing six (as we have) or more questions where we reject equality of means at the 10% level or better. For the $t-$test and Mann-Whitney tests, these

Table C.1: Self-Reported Characteristics and Self-Imposed deadlines (3T Treatment, All Survey Questions)

		No Deadline Set	Deadline Set	$p-$value $t-$test	$p-$value MW test
Cost Factors	# of courses	4.06	3.59	0.121	0.197
	GPA	3.42	3.45	0.721	0.509
	# of exams	0.94	0.94	0.994	0.526
	# of major assignments	1.27	1.82	0.079	0.074
	# of minor assignments	2.70	4.24	0.063	0.045
	Have job?	0.55	0.47	0.547	0.543
	# of clubs	1.09	1.68	0.078	0.077
	Time studying	29.65	30.56	0.893	0.816
	Time family	3.55	3.53	0.989	0.641
	Time job	13.80	16.34	0.591	0.990
	Time socializing	12.55	17.55	0.137	0.038
Psychological Factors	Conscientious	4.21	3.76	0.009	0.010
	Often late (assignments)	1.52	1.44	0.688	0.589
	Often on time (appointments)	4.03	4.26	0.312	0.265
	Not dependable	2.55	2.32	0.437	0.406
	Detail oriented	4.03	3.85	0.398	0.355
	Not organized	2.30	2.35	0.860	0.758
	Follow schedule	3.79	3.50	0.247	0.152
	Unexpected events	3.39	3.06	0.129	0.149
	Impatience (Ideal allocation)	5.79	6.85	0.066	0.067
	Temptation allocation	6.06	6.71	0.319	0.422
	Perceived actual allocation	5.82	6.88	0.074	0.110

Higher numbers indicate more of the particular characteristic.

Task Completion

In Tables C.2 and C.3, we look at factors, from the survey subjects completed in Phase 1, which affect task completion. These tables show that both psychological and cost factors affect task completion; however, there is an interesting dichotomy between the 3T and 1T treatments. In 3T psychological factors play a dominant role, while in 1T, cost factors are decisive.

In the 3T treatments (Table C.2), we see that 7 out of 11 psychological characteristics are significantly different at the 10% level and the differences between the groups are all intuitive. In contrast, only one cost factor (number of exams) is significantly different between those subjects who complete zero tasks and those who complete all three tasks. The punchline is that subjects completing three tasks are significantly less disorganized, more punctual, more dependable, more detail oriented, more likely to follow a schedule and have fewer unexpected events than subjects who complete zero tasks.[42] While subjects who fail to complete any

probabilities are 0.029 and 0.027, respectively, supporting our claim that the observed significant differences are not due to chance.

[42]A similar Monte Carlo exercise as the one described in footnote 41 suggests that the number of significant

tasks may be suggestive of procrastination, as noted above and elaborated on in Section 5.3, there may be other behavioral factors at play. It is also interesting to note that none of the factors – psychological or cost – which significantly differentiate between subjects completing 0 or 3 tasks are also significantly different between those who did and did not self-impose a deadline (recall Table C.1) and vice versa. This suggests that there may be factors beyond simply a desire to commit underlying the decision to self-impose a deadline. In contrast, for the 1T treatment (Table C.3), none of the psychological factors differ based on whether not the subject completed the task, while some cost factors do play a role (number of courses and number of minor assignments).

Table C.2: Self-Reported Characteristics and Task Completion (3T Treatment)

		0 Tasks	3 Tasks	$p-$val. ($t-$test)	$p-$val. (MW test)
Cost Factors	# of courses	4.15	4.05	0.724	0.931
	GPA	3.41	3.49	0.176	0.100
	# of exams	1.31	1.00	0.079	0.070
	# of major assignments	1.58	1.45	0.532	0.591
	# of minor assignments	3.27	3.30	0.959	0.953
	Have job?	0.50	0.55	0.506	0.504
	# of clubs	1.56	1.23	0.149	0.291
	Time studying	34.88	31.53	0.536	0.238
	Time family	2.86	4.30	0.097	0.283
	Time job	12.33	12.53	0.937	0.852
	Time socializing	15.87	16.51	0.794	0.794
Psychological Factors	Conscientious	3.99	4.03	0.715	0.648
	Often late (assignments)	1.51	1.33	0.202	0.055
	Often on time (appointments)	4.09	4.50	0.007	0.006
	Not dependable	2.64	2.20	0.032	0.016
	Detail oriented	3.92	4.17	0.090	0.061
	Not organized	2.46	1.90	0.001	0.001
	Follow schedule	3.58	3.95	0.027	0.039
	Unexpected events	3.31	3.03	0.076	0.048
	Impatience (Ideal allocation)	6.20	5.92	0.446	0.801
	Temptation allocation	6.47	6.25	0.593	0.567
	Perceived actual allocation	6.43	6.12	0.425	0.519

Higher numbers indicate more of the particular characteristic.

Finally, we are also interested in the factors which affect, conditional on completing a task, *when* the task gets done. Table C.4 reports regressions (random effects in the case of 3T) where the dependent variable is the time remaining before the end of the experiment that the task is completed and the explanatory variables come from the pre-experiment survey. Negative coefficients imply that higher values of the variable lead to **earlier** task completion. Similar to the results on completions, in the 1T treatments, only cost factors have explanatory power, while in the 3T treatments, it is primarily psychological factors that influence when the task gets completed. In all cases, the signs of the coefficients are

differences found is highly unlikely to be due to chance ($p < 0.0001$).

Table C.3: Self-Reported Characteristics and Task Completion (1T Treatment)

		0 Tasks	1 Task	$p-$val. ($t-$test)	$p-$val. (MW test)
Cost Factors	# of courses	3.78	4.63	0.062	0.125
	GPA	3.37	3.52	0.070	0.167
	# of exams	0.40	0.46	0.654	0.771
	# of major assignments	0.75	0.76	0.973	0.996
	# of minor assignments	2.13	2.83	0.096	0.085
	Have job?	0.40	0.56	0.151	0.150
	# of clubs	1.33	1.37	0.881	0.855
	Time studying	15.58	20.27	0.644	0.582
	Time family	1.93	2.61	0.682	0.187
	Time job	5.58	5.63	0.972	0.666
	Time socializing	9.43	8.39	0.592	0.407
Psychological Factors	Conscientious	4.03	4.07	0.797	0.852
	Often late (assignments)	1.80	1.59	0.335	0.441
	Often on time (appointments)	4.13	4.24	0.587	0.321
	Not dependable	2.30	2.44	0.598	0.404
	Detail oriented	3.90	4.10	0.273	0.286
	Not organized	2.48	2.15	0.158	0.120
	Follow schedule	3.50	3.78	0.253	0.312
	Unexpected events	3.10	2.93	0.398	0.480
	Impatience (Ideal allocation)	5.90	6.20	0.533	0.613
	Temptation allocation	6.15	6.80	0.282	0.428
	Perceived actual allocation	6.03	6.51	0.376	0.695

Higher numbers indicate more of the particular characteristic.

intuitive. More conscientious and more punctual subjects complete tasks earlier. Similarly, more impatient subjects and subjects who anticipate more unexpected events also complete the task earlier. Both of these are intuitive because the option value of delaying is lower for such subjects. The cost factors for the 1T treatment also have intuitive signs. Subjects with more major assignments and subjects who spend more time socializing complete tasks later. Interestingly, having a job implies earlier task completion – perhaps because such subjects are better at managing their time – but the more time subjects anticipate working, the later they complete the tasks.

Table C.4: Self-Reported Characteristics and Timing (Conditional on Completion)

	3T Treatment		1T Treatment	
Task	2.080^{***}	(0.196)		
# of major assign.			0.925^{**}	(0.395)
# of minor assign.	-0.284^{**}	(0.111)		
Have job?			-2.274^{**}	(0.962)
Time job			0.261^{***}	(0.073)
Time socializing			0.099^{**}	(0.043)
Conscientious	-0.993^{**}	(0.479)		
Unexpected events	-0.795^{**}	(0.369)		
Often on time (appts.)	-0.985^{***}	(0.381)		
Impatience (ideal alloc.)	-0.325^{*}	(0.168)		
Beliefs: All tasks			-0.047^{**}	(0.019)
Constant	0.028	(3.269)	-2.018	(1.741)
Observations	244		41	
LL	-627.958		-84.055	

Standard errors in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$