PROCRASTINATION AND COMMITMENT

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ABSTRACT: I propose a tractable model of procrastination. A present-biased agent has a task to complete by a fixed deadline. I characterize the agent's effort over time and study the interplay between present bias and task features. The analysis reveals that present bias and adverse task features (i.e., a heavy workload or a close deadline) reinforce each other in affecting the agent's welfare. I then consider a natural remedy to procrastination on a long-term task, namely, committing to a series of short-term goals. I show that short-term goals weakly impair a present-biased agent's welfare. This provides a cautionary counterpoint to the bulk of literature on time inconsistency, where commitment can strictly enhance welfare for present-biased agents.

KEYWORDS: Procrastination, Quasi-Hyperbolic Discounting, Limited Commitment, Time Inconsistency, Present Bias, Naivete

JEL CLASSIFICATION: D81, D83, D91

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1. Introduction

Procrastination prevails among people. From students staying up late before assignment due dates to politicians cramming for agenda deadlines, similar behavioral patterns of self-defeating delay arise across a vast range of scenarios.[1] While individuals may envision an ideal work schedule that smooths the workload over time before they begin a task, they often prioritize immediate gratification over long-term consequences, putting off work to the future.[2] Due to this inconsistency in dynamic choices, people have to catch up with an overwhelming backlog of work as the due date approaches. Intense work at the last minute is usually stressful, error-prone, and thus undesirable ex ante.[3]

Theories (e.g., Gul and Pesendorfer, 2001) suggest that commitment devices can be used to counter dynamic inconsistency and ultimately improve individual well-being. However, in both experimental and market settings, individuals do not purchase commitment devices as much as predicted by theory (e.g., Laibson, 2015). Researchers have approached the enigma of insufficient commitment demand through the lenses of:

(a) naivete — people underestimate their future present bias;[4]
(b) preference for flexibility — payoff-relevant information may arrive later;
(c) the direct cost — the price of commitment exceeds the benefit from it.

In this paper, I find an *alternative* mechanism that is particularly involved in long-term task completion, such that absent these three channels, a present-biased agent is still better off *not* committing herself.

I propose a tractable model in which a present-biased agent needs to complete a long-term task before a fixed deadline. By a long-term task, I mean the task cannot be completed in one shot (such as paying a traffic fine); instead, the agent must arrange workload over time to complete the task (such as working on a project). A difficult task requires more effort (i.e., workload) to complete. The agent can either be sophisticated or (partially) naive in anticipating her future present bias. In the application of the model, I

[1] I use the term "procrastination" to mean the detrimental tendency of delaying work and subsequently rushing to finish the task. The precise definition of procrastination is provided in *Section 2.1*. Anecdotal and experimental evidence abounds for procrastination; see *Section 5.1* for a detailed literature review. Many universities have built special programs to combat academic procrastination, e.g., `https://mcgraw.princeton.edu/understanding-and-overcoming-procrastination`, `https://www.lib.sfu.ca/about/branches-depts/slc/learning/procrastination`. For political procrastination, see, e.g., `https://www.nytimes.com/2021/10/01/us/politics/infrastructure-bill-last-minute.html?searchResultPosition=3`.

[2] In Augenblick, Niederle and Sprenger (2015)'s experiments on time inconsistency regarding real effort tasks, subjects arranged around 9% less work to the present compared to their original plan.

[3] Empirical studies (e.g., Tice and Baumeister, 1997; Burns et al., 2000; Sirois and Pychyl, 2016) show that procrastinators, on average, report lower achievements, self-esteem and poorer health. More broadly, household financial reluctance hinders the effect of macroeconomic policies (Laibson, Maxted and Moll (2021)), and rushed work to meet deadlines can breed careless mistakes and ruin collective goal pursuits.

[4] "Present bias" refers to a tendency to attach a distinctively high weight to the present well-being in the intertemporal tradeoff. See *Section 2* for precise definitions of present bias and naivete.

further allow the agent to use intermediate deadlines as a commitment device. I then investigate how task features affect the agent's work schedule and welfare, and how these effects of task features vary with the agent's present bias and naivete.

The current paper departs from the literature that identifies *individual behavioral frictions* (e.g., present bias, naivete; see *Section 5.1* for a literature review) as the cause of time-inconsistent behaviors. Rather, the main focus of this paper is to study how to manipulate *task features* to curb procrastination, given individual behavioral frictions. It speaks to a major paradigm in social psychology that a nudge in situational factors can overwhelm personal trait differences in affecting people's behaviors (e.g., Ross, 1977). Such a concern motivates O'Donoghue and Rabin (2001) as well. In their paper, an increased value of task options or an expanded menu of tasks may induce procrastination. Following this line of inquiry, I analyze how the workload, the time available, and intermediate deadlines shape an agent's work schedule. The analysis thus informs long-term task design in aspects such as whether or how to insert intermediate deadlines for projects.

1.1. *Overview of Model and Main Results*

In the model, an agent exerts effort in continuous time to complete a task before a fixed deadline. The flow cost of effort is convex, and the agent evaluates future payoffs using quasi-hyperbolic discounting. She optimizes her work schedule dynamically to complete the task on time and minimize her (perceived) continuation effort cost for the task completion. For welfare assessment, I distinguish two overall effort cost measures, both evaluated at the start of the task: the ex-ante perceived cost and the long-run cost. The ex-ante perceived cost is evaluated by the agent, measuring the total effort cost of her *perceived* work schedule under quasi-hyperbolic discounting. In contrast, the long-run cost is evaluated by a time-consistent advisor, measuring the total effort cost of the agent's *actual* work schedule under exponential discounting.

My methodological contribution is to characterize dynamic effort choices under quasi-hyperbolic discounting in a finite horizon. Building on Harris and Laibson (2013), the key to solving dynamic problems under quasi-hyperbolic discounting is a pair of value functions: the value function using quasi-hyperbolic discounting, denoted by $W(\cdot)$, and the continuation value function using exponential discounting, denoted by $V(\cdot)$. Harris and Laibson (2013) study the dynamic consumption-saving model in an infinite horizon. Without the need to keep track of time, they characterize a pair of *stationary* value functions. I apply this framework to the task completion context with a fixed deadline. In a finite horizon, the value function pair (W, V) varies over time and needs to be calculated recursively at every moment before the deadline, which is usually technically challenging. The continuous-time framework grants analytical tractability. In *Proposition 1*, I characterize the value functions and the agent's work schedule in closed form.

Based on *Proposition 1*, I examine how the work schedule and the overall effort costs vary with behavioral types (namely, present bias and naivete) and task features (namely, the workload and the time available). Intuitively, both behavioral frictions (of present bias and naivete) and task frictions (of a heavy workload and little time available) make the agent strictly worse off. I further show that, these frictions reinforce each other in undermining the agent's welfare (*Corollary 1*). For example, an increase in workload impairs welfare for an agent of any time preference since it raises the average effort across time. However, a stronger present bias results in a more disproportionate distribution of this additional workload, thus inflicting an even greater cost in exerting effort. As such, a behaviorally flawed agent suffers more from an adverse task environment compared to a perfectly rational agent. This finding challenges a convenient assumption in behavioral studies that the total cost of action is the sum of the monetary cost and the psychological cost (e.g., Andersen et al., 2020). Instead, it suggests an interactive term of behavioral frictions and environmental frictions when specifying their overall effects on an agent.

Application. The inefficiency arising from procrastination calls for regulation. To overcome procrastination for long-term tasks, one common strategy in practice is to set several short-term goals that break down the total workload. The majority of the existing studies emphasize the positive value of commitment for a present-biased agent. Interestingly, this paper uncovers an unintended negative side effect of commitment that is rarely discussed in the literature. I show that, while committing to short-term goals can mitigate procrastination, it cannot reduce long-run cost or ex-ante perceived cost (*Proposition 2*).

One may imagine this adverse effect results from the fact that commitment shrinks the set of alternatives. This is indeed true for a time-consistent agent. However, commitment has no negative welfare impact as long as it does not preclude the most cost-efficient alternative. Furthermore, for an agent experiencing self-control problems (such as a present-biased agent), tying her hands enables the agent to select an ex-ante better option and thereby improve welfare. So the real question posed here is: what is the lurking opposing effect of commitment on a present-biased agent that offsets this positive effect, ultimately resulting in a net value of zero or even a negative value of commitment?

The logic of my result is as follows. If a present-biased agent can commit her choices at every moment, then by committing exactly to a time-consistent agent's work schedule, she can properly induce early efforts and strictly enhance her welfare. However, when commitment is limited — in the sense that choices are made in continuous time while short-term goals are only finite — the agent can only guarantee the amount of accumulated effort before each intermediate deadline, but cannot guarantee how she will arrange her workload over time to achieve that. Actually, driven by present bias, the agent is bound to procrastinate and rush for every short-term goal. I show that the high effort required near each deadline within the recurrent procrastination cycle incurs a steep cost, and it outweighs the regulatory benefit of committing to short-term goals.

The negative commitment value arises from a combination of (i) present bias and (ii) limited commitment, where the frequency of dynamic choices exceeds that of commitments. Studies on commitment usually discuss cases wherein the agent can (fully or partially) commit her actions *whenever* she gets to make a move. Nevertheless, progress checks in reality are usually less frequent than action choices. For example, an employee can choose whether to work or shirk at any moment, whereas her work is only checked by the manager periodically. Fixing the frequency of commitments, the value of commitment diminishes as the frequency of dynamic choices increases. In the limiting case where choices can be made in continuous time under only finite short-term goals, the negative effect of limited commitment is significant enough to completely neutralize its positive regulatory effect, even under optimal short-term goals.

Outline. The rest of the paper unfolds as follows. I set up the baseline model in *Section 2*, and characterize the agent's dynamic choices in *Section 3*. With the work schedule and individual welfare characterization, I then examine the value of short-term goals in *Section 4*. *Section 5* concludes the paper with a discussion about related literature, a summary of this paper, and avenues for future work. To enrich the task environment, I also explore scenarios where the agent has the option to quit the task halfway or the agent is uncertain about the task difficulty. The main results of this paper are robust to these extensions. The analysis can be found on my website for readers who are interested, and it is omitted in the current paper for brevity.[5]

2. MODEL

I consider a continuous time, finite horizon framework in which an agent optimizes her work schedule dynamically to complete a task under quasi-hyperbolic discounting. The task requires a total workload $w > 0$ by a deadline at time $T > 0$. The agent knows the task features (w, T). Effort into task completion is costly, so the agent's objective is to complete the task on time with the minimal expected overall effort cost.

Payoff. Denote the effort at time $t \in [0, T]$ by $y_t \geq 0$, and denote the work finished (i.e., the accumulated effort) before time t by $x_t \equiv \int_0^t y_s \mathrm{d}s$. For tractability, I assume the flow cost of effort to be $c(y_t) = \gamma y_t^\alpha$ where $\gamma > 0$ and $\alpha > 1$. The convex effort cost captures the idea that smoothing the workload over time is more cost-efficient for the agent.

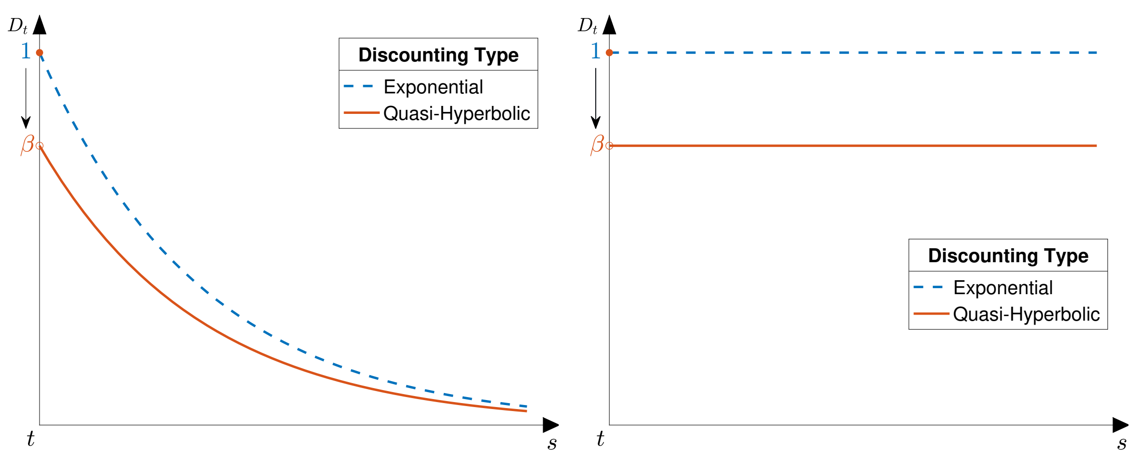
[5] https://drive.google.com/file/d/14zjeM8SH5KE_CouKRF9H813FtsSdsbN2/view?usp=drive_link

Time Preference. To study choices that have influence over time, we need to settle two issues. The first is how the agent evaluates future utility flows at present, which is characterized by her discounting function. The second is how the agent anticipates her future choices, which is captured by the concept of sophistication.

For the first issue, I adopt the instantaneous gratification (IG) model proposed by Harris and Laibson (2013) and specify the discount factor at time t for utility at time $s \geq t$ as

$$D_t(s;\beta,\delta) = \begin{cases} 1 & \text{for } s = t, \\ \beta e^{-\delta(s-t)} & \text{for } s > t, \end{cases} \tag{1}$$

where $\delta \geq 0$ and $\beta \in (0,1]$. It nests the classic exponential discounting when $\beta = 1$. When $\beta < 1$, all future flow payoffs are further discounted by β in addition to the exponential discounting. Hence, the present flow payoff is weighed distinctively higher in the overall utility, capturing the present bias. As illustrated in *Figure 1*, a smaller β corresponds to a sharper immediate drop in the discount factor and thus a larger present bias.



(a) $\beta \in (0,1)$, $\delta > 0$ (b) $\beta \in (0,1)$, $\delta = 0$

FIGURE 1. Discount Factors Evaluated at Time t

Fix an effort trajectory $\boldsymbol{y} = \{y_s : 0 \leq s \leq T\}$. Denote $\boldsymbol{y}^t \equiv \{y_s : t \leq s \leq T\}$ as a continuation path of $\boldsymbol{y}$ starting from time $t \in [0,T]$. The agent's effort cost derived from $\boldsymbol{y}$ evaluated at time t is given by

$$C_t(\boldsymbol{y}^t;\beta) = \int_t^T D_t(s;\beta,\delta)c(y_s)\mathrm{d}s. \tag{2}$$

For the second issue, following O'Donoghue and Rabin (2001), I allow the agent to misperceive $\hat{\beta} \in (0,1]$ as her present bias in the future. Therefore, at time $t \in [0,T)$, the agent anticipates that her effort cost derived from the effort trajectory $\boldsymbol{y}^t$, evaluated at any future moment $r \in (t,T]$, would be $C_r(\boldsymbol{y}^r;\hat{\beta})$.

In the baseline model, I assume the agent discounts all future payoffs equally (i.e., $\delta = 0$),[6] and characterize the agent's time preference by a pair of the actual present bias and the perceived present bias $(\beta, \hat{\beta}) \in (0,1]^2$. We say an agent is sophisticated if she precisely perceives her present bias in the future (i.e., $\hat{\beta} = \beta$), and an agent is naive if she underestimates her present bias in the future (i.e., $\hat{\beta} > \beta$). In particular, a time-consistent agent bears no present bias (i.e., $\hat{\beta} = \beta = 1$), and a fully naive agent is subject to present bias but misperceives that she would be time consistent in the future (i.e., $\beta < \hat{\beta} = 1$).

Work Schedule. I allow the agent to adjust her work schedule dynamically. That is, she has the flexibility to revise her plan at every moment. I denote the work schedule by $(\boldsymbol{x}, \boldsymbol{y}) \equiv \{(x_t, y_t) : t \in [0, T]\}$, where x_t denotes the work that the agent has finished by time $t \in [0, T]$, and y_t denotes her effort at t. At any moment, the agent cares about future payoffs but cannot directly control future choices; she anticipates the choices made by future selves and optimizes her current effort accordingly. The work schedule is thus generated from an intrapersonal sequential game between current self and future selves.

I use Markov-perfect equilibrium as the solution concept for this intrapersonal game. In a Markov-perfect equilibrium, players (i.e., the current self and future selves) base their decisions on the directly payoff-relevant information: (i) the work finished, and (ii) the time spent. Formally, a Markov pure strategy $\mathbf{e} : [0, w] \times [0, T] \to \mathbb{R}_+$ maps the state of the work finished and the time spent to the effort. Denote by $\boldsymbol{y}(x, t|\mathbf{e})$ an effort trajectory such that the agent uses the effort strategy $\mathbf{e}$ starting from the state (x, t). A Markov-perfect equilibrium consists of a pair of the perceived effort strategy $\hat{\mathbf{e}}$ and the actual effort strategy $\mathbf{e}$ such that for any $x \in [0, w]$,

(i) the perceived effort $\hat{\mathbf{e}}(x, t)$ minimizes the effort cost under the perceived present bias $\hat{\beta}$, $C_t(\boldsymbol{y}(x, t|\hat{\mathbf{e}}); \hat{\beta})$, at any time $t \in (0, T]$, and

(ii) given the perceived future effort strategy $\hat{\mathbf{e}}$, the actual effort $\mathbf{e}(x, t)$ minimizes the effort cost under the actual present bias β, $C_t(\boldsymbol{y}(x, t|\mathbf{e}'); \beta)$, at any time $t \in [0, T]$, where $\mathbf{e}' = \mathbf{e}$ at the current time t and $\mathbf{e}' = \hat{\mathbf{e}}$ at any future time $s > t$.

Here, $C_t(\cdot)$ is given by (2). Thus, the work schedule $(\boldsymbol{x}, \boldsymbol{y})$ derived from a Markov-perfect equilibrium $(\mathbf{e}, \hat{\mathbf{e}})$ is as follows: for any $t \in [0, T]$, $x_0 = 0$, $y_t = \mathbf{e}(x_t, t)$, and $x_t = \int_0^t y_s \mathrm{d}s$.

2.1. *Benchmark: Full Sophistication & Full Commitment*

Before solving the model, I provide the first-best benchmark in which the agent is sophisticated and can fully commit to her initial plan. Against this benchmark, I define

[6] The general case when $\delta \geq 0$ is provided in the online appendix available from the author's webpage. The case $\delta = 0$ is of particular interest. First, due to convex flow effort cost, the most cost-efficient work schedule is to distribute the work evenly over time. Against this benchmark, we can easily detect procrastination by an increasing effort trajectory. Second, the exponential discount rate δ is calibrated at approximately 0 in empirical studies (e.g., Andreoni and Sprenger, 2012; Augenblick, Niederle and Sprenger, 2015).

procrastination in the long-term task completion and give a measure for the degree of procrastination.

In this benchmark case, the agent commits to an effort trajectory $\boldsymbol{y}$ that minimizes

$$C_0(\boldsymbol{y};\beta) = \int_0^T D_0(t;\beta)c(y_t)\mathrm{d}t \quad \text{subject to} \quad \int_0^T y_t \mathrm{d}t = w$$

before she starts the task, which yields the most cost-efficient work schedule to complete the task on time. By the variational approach, it is easy to see that, regardless of the magnitude of present bias, the first-best work schedule $(\boldsymbol{x}^*, \boldsymbol{y}^*)$ is always to spread out the workload evenly over the time available, that is, for $t \in [0, T]$,

$$x_t^* = \frac{w}{T}t, \quad y_t^* = \frac{w}{T}. \tag{3}$$

Intuitively, since the flow cost of effort is strictly convex, any deviation from an evenly-distributed workload over time would incur a higher overall effort cost.

I say an agent procrastinates if she falls behind her first-best work schedule $(\boldsymbol{x}^*, \boldsymbol{y}^*)$; an agent procrastinates more than another agent if she finishes strictly less work at any time before the deadline. Formally, I provide the following measure of procrastination.

DEFINITION (Procrastination)**.** *Fix any task $(w, T) \in \mathbb{R}^2_{++}$.*

(i) An agent with the work schedule $(\boldsymbol{x}, \boldsymbol{y})$ exhibits procrastination if

$$x_t \leq x_t^* \text{ for any } t \in [0, T], \text{ and } x_t < x_t^* \text{ for some } t \in (0, T),$$

where x_t^* is given by (3).

(ii) An agent with the work schedule $(\boldsymbol{x}, \boldsymbol{y})$ procrastinates more than an agent with the work schedule $(\boldsymbol{x}', \boldsymbol{y}')$ if $x_t \leq x_t'$ for any $t \in [0, T]$, and $x_t < x_t'$ for some $t \in (0, T)$.

3. DYNAMIC WORK SCHEDULE

Now we turn to the case where the agent has the discretion about her effort at any moment. Let $\mathcal{T} = \langle w, T \rangle$ represent task features and let $\mathcal{B} = \langle \beta, \hat{\beta} \rangle$ represent behavioral frictions of the agent. *Proposition 1* presents the main result of this paper, which characterizes the agent's work schedule and effort costs to complete a task before the deadline.[7]

PROPOSITION 1 (Work Schedule and Effort Costs for a Long-Term Task)**.**

Let $B = (\beta/\hat{\beta})^{\frac{1}{\alpha-1}}(\alpha - 1)/(\alpha - \hat{\beta})$. The agent's work schedule is: for any $t \in [0, T)$,

$$x_t(\mathcal{T}, \mathcal{B}) = w\left[1 - \left(1 - \frac{t}{T}\right)^B\right], \tag{4}$$

$$y_t(\mathcal{T}, \mathcal{B}) = \frac{wB}{T}(1 - \frac{t}{T})^{B-1}. \tag{5}$$

[7] All proofs are omitted in the main text and can be found in the appendix.

The cost function (or the ex-ante perceived cost) is

$$C(\mathcal{T},\mathcal{B}) = \frac{\gamma B^{\alpha-1} w^{\alpha}}{T^{\alpha-1}}. \tag{6}$$

The long-run cost associated with the work schedule is

$$LC(\mathcal{T},\mathcal{B}) = \frac{\gamma B^{\alpha} w^{\alpha}}{[1-\alpha(1-B)]T^{\alpha-1}} \tag{7}$$

if $\alpha(1-B) < 1$, *and* $LC(\mathcal{T},\mathcal{B}) = \infty$ *otherwise.*

Here, $B \in (0,1]$ decreases in present bias and naivete, indicating behavioral frictions borne by the agent. *Proposition 1* implies that the first-best benchmark is attained by dynamic choices if and only if the agent is time consistent ($B = 1$). If $B < 1$, the agent bunches effort near the deadline, and the long-run cost of the agent's work schedule exceeds the total effort cost perceived by the agent ex ante.

For a sophisticated agent, $B = (\alpha-1)/(\alpha-\beta) > 1 - 1/\alpha$ for any $\beta \in (0,1]$. Only for a highly naive agent, B could possibly go below $1 - 1/\alpha$. In this case, excessive work is concentrated around the deadline and incurs an extremely high long-run cost such that no task is worth taking in the first place. Therefore, in the main body of the paper, I restrict attention to the situation when $\alpha(1-B) < 1$.[8]

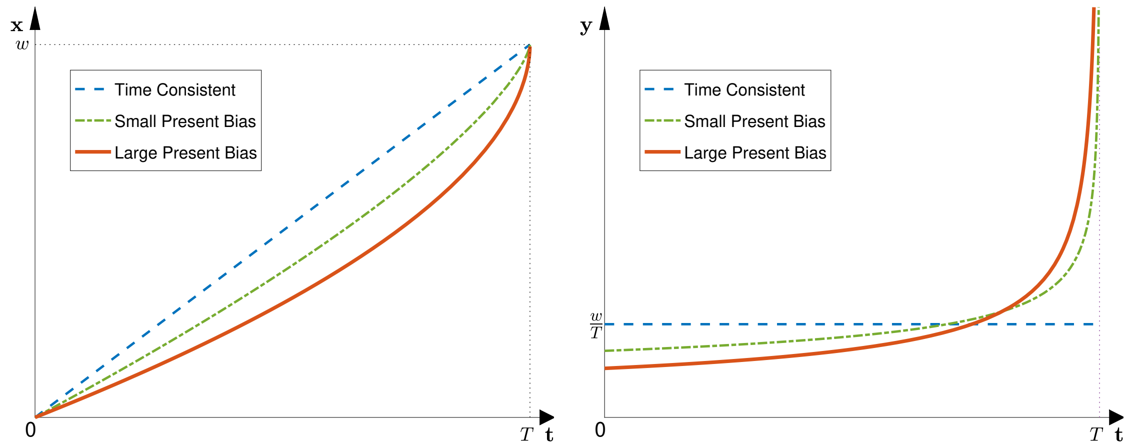
Drawing on *Proposition 1*, I first illustrate the key findings regarding the interactive impacts of behavioral frictions and task features, and demonstrate that present bias and naivete cannot be jointly identified. At the end of this section, I provide the techniques to solve finite-horizon dynamic optimization under quasi-hyperbolic discounting.

3.1. *The Interactive Impacts of Behavioral Frictions and Task Features*

Figure 2 illustrates how present bias affects the agent's work schedule. Observe that the work schedule for a time-consistent agent is to spread the total workload evenly over the time available, which achieves the first best for the agent. When present bias comes in, procrastination emerges. The agent's effort into the task is initially low and then rises over time. As the present bias increases, the agent puts off more of the workload towards the deadline and exhibits more severe procrastination. Similarly, a larger naivete corresponds to a work trajectory that is tilted more towards the deadline — I show later in *Section 3.2* that present bias and naivete are observationally equivalent for a fixed task.

I use the long-run cost LC to measure individual welfare, as in O'Donoghue and Rabin (2001). It represents the overall cost of a work schedule from the perspective of an outsider

[8] In the online appendix, I allow for $\alpha(1-B) < 1$ and allow the agent to quit at any time if her perceived continuation cost overwhelms the reward for task completion. In this case, I show that a naive agent may too readily undertake a task and then fail to complete it despite her foregone effort. Additionally, under short-term goals, a naive agent can complete a task that inflicts a higher long-run cost than its reward.



(a) Work Trajectory (b) Effort Trajectory

FIGURE 2. Work Schedule: Sophisticated Agent

(or the agent herself in reflection), exempt from present bias. Intuitively, a higher long-run cost is inflicted by a more demanding task (with a heavier workload w and shorter time available T) and more intense behavioral frictions (with a larger present bias and naivete). More importantly, $\partial LC/\partial w$ and $|\partial LC/\partial T|$ strictly decrease in B. This implies that present bias and naivete magnify the harm of adverse task features to the agent. Conversely, $|\partial LC/\partial B|$ grows as w/T gets larger. Therefore, a demanding task intensifies the welfare loss due to behavioral frictions.

COROLLARY 1 (Interaction between Behavioral and Task Features)**.** *Behavioral frictions $\mathcal{B} = (\beta, \hat{\beta})$ and task features $\mathcal{T} = (w, T)$ reinforce each other in affecting the agent's welfare:*

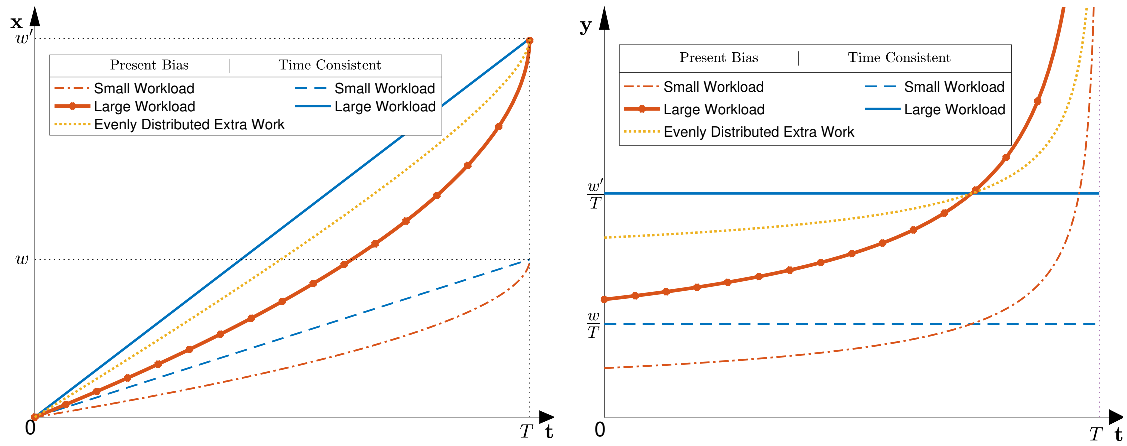
(1) the welfare impact of task features $\mathcal{T}$ is amplified by the agent's present bias and naivete;

(2) the welfare loss due to behavioral frictions $\mathcal{B}$ is aggravated by demanding task requirements (i.e., a difficult task and a close deadline).

The interaction between behavioral frictions and task features in affecting the agent's welfare is a testable prediction of this model. It is caused by the interdependence of these two factors in shaping the agent's work schedule. For example, a higher workload raises the average effort across time for both a time-consistent agent and a present-biased agent, thus impairing welfare to both. However, while the time-consistent agent evenly distributes the additional workload over time, the present-biased agent tends to postpone more of the additional workload to the future, engendering an extra cost (see *Figure 3*).

3.2. *Identify the Sources of Procrastination*

People may procrastinate because: (i) they particularly value immediate gratification; (ii) they think naively about future choices; and (iii) they are not very averse to rushing



(a) Work Trajectory (b) Effort Trajectory

FIGURE 3. Interactive Impacts: Present Bias & Increased Workload

at the last moment after all. A natural question to ask is: can we disentangle these three potential driving forces empirically from an observed work trajectory? This inquiry can concern researchers who seek to structurally pin down people's task completion patterns and design the optimal long-term task accordingly. It can also be relevant when an agent, with an imperfect memory of her decision-making process, reflects on her previous work schedule and tries to identify the cause of her undesirable procrastination.

In the model, these three forces correspond to (i) present bias $\beta < 1$, (ii) naivete $\beta/\hat{\beta} < 1$, and (iii) rush aversion $\alpha < \infty$.[9] I can thus reformulate the identification issue more explicitly: can we recover unobserved parameters of interest $(\beta, \hat{\beta}, \alpha)$ from observed data of a work trajectory $\boldsymbol{x} = \{x_t : t \in [0, T]\}$? Using the model, I show that a measure of preferences $B = (\beta/\hat{\beta})^{\frac{1}{\alpha-1}}(\alpha - 1)/(\alpha - \hat{\beta})$ can be identified. However, present bias and naivete are observationally equivalent.

Identification of B. By *Proposition 1*, time preference parameters $(\beta, \hat{\beta})$ are summarized in B, and B controls the curvature of the work trajectory.

Assume a researcher observes an agent's work trajectory $\{x_t : t \in [0, T]\}$. Since

$$\frac{1 - (1 - s/T)^B}{1 - (1 - t/T)^B} = \frac{x_s}{x_t} \in (0, 1),$$

[9]The parameter $\alpha > 1$ captures the agent's aversion to variation in the work intensity (or flow effort); I take it as a measure of "rush aversion". By *Proposition 1*, when α goes to 1, a present-biased agent tends to leave all the work to the last moment ($\lim_{\alpha \downarrow 1} x_t = 0$ for all $t < T$, $\beta < 1$). On the other extreme, when α goes to infinity, a present-biased agent tends to distribute the workload evenly, acting like a time-consistent agent. In general, procrastination worsens as rush aversion decreases. I show in the online appendix that rush aversion α cannot be identified from any observed work trajectory. In particular, any rush aversion is observationally equivalent to a larger rush aversion with a larger present bias. This result echoes the general finding that time preferences cannot be identified without knowing or assuming the payoff function (see, e.g., Andersen et al., 2008; Heidhues and Strack, 2021).

and the function $\varphi(B) \equiv \frac{1-(1-s/T)^B}{1-(1-t/T)^B}$ is strictly increasing in B, we obtain $B = \varphi^{-1}(x_s/x_t)$.

Observational Equivalence of Present Bias β and Naivete $\hat{\beta}$. Given that B can be identified from an observed work trajectory, I show that present bias β and naivete $\hat{\beta}$, nevertheless, cannot be identified separately. This is true even if the agent's payoff function (especially, α) is known.

To see this, for any time preference $(\beta, \hat{\beta})$ with $0 < \beta \leq \hat{\beta} < 1$, there always exists an alternative time preference $(\beta', 1)$ that yields the same work trajectory, in which $\beta' = \beta/\hat{\beta}\left[(\alpha-1)/(\alpha-\hat{\beta})\right]^{\alpha-1} \in (\beta, 1)$. Therefore, the work trajectory for a sophisticated or partially naive agent is the same as that for a fully naive agent with a smaller present bias.

Besides, the work trajectory for any naive agent is the same as that for a sophisticated agent with a larger present bias. Specifically, for any time preference $(\beta, \hat{\beta})$ such that $0 < \beta < \hat{\beta} \leq 1$, there always exists an alternative time preference (β', β') that yields the same work schedule, in which $\beta' = \alpha - (\alpha - \hat{\beta})(\hat{\beta}/\beta)^{\frac{1}{\alpha-1}} \in (0, \beta)$.

COROLLARY 2 (Identification). *Suppose a work trajectory $\boldsymbol{x} = \{x_t : t \in [0, T]\}$ is observed.*

(i) A measure of individual preference $B = \left(\beta/\hat{\beta}\right)^{\frac{1}{\alpha-1}} (\alpha-1)/(\alpha-\hat{\beta})$ can be identified.

(ii) The present bias parameter β and the naive parameter $\hat{\beta}$ cannot be jointly identified from any observed work trajectory. In particular, partial naivete is observationally equivalent to full sophistication with a larger present bias, and is also observationally equivalent to full naivete with a smaller present bias.

3.3. *Technical Discussion*

In this section, I present the main steps in deriving *Proposition 1*. The procedure below applies Harris and Laibson (2013) to task completion in finite horizon, and accommodates (partial/full) naivete in the dynamic effort choices under quasi-hyperbolic discounting. Readers who prefer to skip this technical content can proceed directly to *Section 4* without loss of continuity.

3.3.1. *Sophiscated Agent.* The dynamic programming problem is formulated as follows. Let $W^S(x, t; w, T, \beta)$ be the perceived cost function at any state $(x, t) \in [0, w] \times [0, T]$, and let $\mathbf{e}^S(x, t; w, T, \beta)$ be a corresponding policy function. Here, the superscript S indicates that the agent is sophisticated; the work state x denotes the work finished, and the time state t denotes the time spent. In what follows, I suppress the dependence of W^S and $\mathbf{e}^S$ on the fixed parameter (w, T, β) for convenience of exposition. Let $\langle \boldsymbol{x}(x,t), \boldsymbol{y}(x,t)\rangle$ be the corresponding work and effort trajectories starting from the state (x, t). The cost function at state (x, t) is thus given by

$$W^S(x,t) \equiv C_t(\boldsymbol{y}(x,t); \beta) = \int_t^T D_t(s;\beta) c(y_s(x,t)) \mathrm{d}s. \tag{8}$$

Step 1. Define the sophisticated agent's continuation cost in the state (x,t) as

$$V^S(x,t) \equiv C_t(\boldsymbol{y}(x,t);1) = \int_t^T c(y_s(x,t))\mathrm{d}s. \tag{9}$$

In the classic dynamic programming under exponential discounting, there is no present bias (i.e., $\beta = 1$); thus the continuation cost function $V^S(\cdot)$ amounts to the cost function $W^S(\cdot)$. Under present bias β, we can still relate $W^S(\cdot)$ to $V^S(\cdot)$ using (8) and (9) as follows,

$$W^S(x,t) = \beta V^S(x,t), \tag{10}$$

for all $x \in [0,w], t \in [0,T]$. Intuitively, (10) holds because (i) the IG discounting factor (1) coincides with the exponential discount factor only at the current instant and the current effort cost is negligible in the integral of the overall cost; (ii) all future payoffs are further discounted by β in the IG discounting, as opposed to the exponential discounting.

Step 2. Derive the first-order condition for the policy function.

The agent optimizes effort, trading off the cost of the current effort against the benefit from workload reduction in the future. By (10), the F.O.C. for the optimal effort $\hat{y} > 0$ in any state (x,t) gives us

$$c'(\hat{y}) = -\beta V_x^S(x,t),$$

where $V_x^S(\cdot)$ stands for the partial derivative of $V^S(\cdot)$ with respect to x. The F.O.C. equalizes the marginal cost of effort with the marginal reduction in the perceived cost to go. Thus, for all $(x,t) \in [0,w] \times [0,T]$, the policy function is given by

$$\mathbf{e}^S(x,t) = \begin{cases} \hat{y} = \left[-\frac{\beta}{\alpha\gamma} V_x^S(x,t)\right]^{\frac{1}{\alpha-1}} & \text{if } V_x^S(x,t) < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

Step 3. Derive the Hamilton–Jacobi–Bellman (HJB) equation to characterize the dynamics of continuation cost $V^S(\cdot)$: for any $x \in [0,w], t \in [0,T]$,

$$c(\mathbf{e}^S(x,t)) + V_t^S(x,t) + V_x^S(x,t)\mathbf{e}^S(x,t) = 0, \tag{12}$$

where $V_t^S(\cdot)$ stands for the partial derivative of $V^S(\cdot)$ with respect to t. The HJB equation of $V^S(\cdot)$ indicates that at the optimal effort level, the flow cost of effort equals the instantaneous reduction in the continuation cost.

Step 4. Use boundary conditions on the work trajectory and value matching condition to pin down the solution to the dynamic optimization.

Boundary conditions on the initial and terminal states are as follows: for any $(x,t) \in [0,w] \times [0,T]$,

$$x_t(x,t) = x, \quad x_T(x,t) = w. \tag{13}$$

Additionally, we have the value matching condition

$$V^S(w,t) = 0, \tag{14}$$

for any $t \in (0, T]$, since the agent exerts no further effort once the task is completed.

LEMMA 1 (Value and Policy Characterization)**.** *If* $(W^S, V^S, \mathbf{e}^S)$ *satisfies* (10), (11), (12), (13) *and* (14), *then* $C(w,T,\beta) = W^S(0,0;w,T,\beta)$ *is the (perceived) cost function for the dynamic optimization,* $LC(w,T,\beta) = V^S(0,0;w,T,\beta)$ *is the long-run cost function, and* $\boldsymbol{y}(w,T,\beta) = \boldsymbol{y}(0,0;w,T,\beta)$ *is the* ***unique*** *optimal effort trajectory (up to Lebesgue measure 0).*

Lemma 1 asserts that the above conditions fully characterize the dynamic work schedule for a sophisticated agent. Using the *"Specify and Verify"* technique, I then solve the dynamic programming analytically. In particular, I obtain for any $(x,t) \in [0,w] \times [0,T)$,

$$V^S(x,t;w,T,\beta) = \frac{\gamma}{\beta}\left[\frac{\alpha-1}{(\alpha-\beta)(T-t)}\right]^{\alpha-1}(w-x)^{\alpha}. \tag{15}$$

3.3.2. *Allowing for Naivete.* For a naive agent $(\beta, \hat{\beta})$, she anticipates the future self would act as a sophisticated agent with less present bias, i.e., $\hat{\beta} \in (\beta, 1]$. This misperception links her cost function $W(\cdot)$ to the continuation cost $V^S(\cdot)$ for a sophisticated agent $\hat{\beta}$ as

$$W(x,t;;w,T,\beta,\hat{\beta}) = \beta V^S(x,t;w,T,\hat{\beta}),$$

for $x < w_L$, where $V^S(\cdot)$ is given by (15). Following the procedure in *Section 3.3.1*, I characterize the work schedule and overall effort costs for the agent, as in *Proposition 1*.

4. COMMITTING TO SHORT-TERM GOALS

Welfare loss due to procrastination calls for regulation — either from self-discipline or from external supervision. A popular commitment device used to combat procrastination for a long-term project is to insert a series of short-term goals. For example, Ph.D. students must achieve milestones throughout their graduate study to earn the doctorate degree; an employer can set down a timetable at the start of a project, requiring workers to report their work progress. The basic idea in these scenarios is to smooth the workload over time, thereby preventing the last-minute rush right before the deadline. Now, a big task breaks down into several small tasks by intermediate deadlines; one long-term goal becomes a series of successive short-term goals.

In this section, I examine the value of such short-term goals using the schedule and welfare characterized in *Proposition 1*. I proceed by asking:

(i) How would a present-biased agent set short-term goals for herself to minimize her ex-ante perceived cost?

(ii) How would a time-consistent advisor set short-term goals for the agent to minimize the agent's long-run cost?

(iii) Can any short-term goals strictly enhance the agent's welfare?

Formally, fix the task $\mathcal{T} = (w, T)$. A commitment device is available at the start of the project $t = 0$ to set $k \in \mathbb{N}_+$ goals

$$\boldsymbol{G}_k = \{(\hat{w}_1, \hat{\tau}_1), (\hat{w}_2, \hat{\tau}_2), \ldots, (\hat{w}_k, \hat{\tau}_k)\}.$$

For any $1 \le i \le k$, $(\hat{w}_i, \hat{\tau}_i)$ is a short-term goal requiring the agent to complete at least $\hat{w}_i$ by time $\hat{\tau}_i$, and $0 \le \hat{w}_{i-1} \le \hat{w}_i \le w, 0 < \hat{\tau}_{i-1} < \hat{\tau}_i \le T$ with the convention that $(\hat{w}_0, \hat{\tau}_0) = (0, 0)$, $(\hat{w}_k, \hat{\tau}_k) = (w, T)$. In particular, when $k = 1$, the agent only commits to the final goal (w, T) as in the baseline model.

If a short-term goal is lower than what the agent would have finished without it (i.e., $\hat{w}_i \le \hat{w}_{i-1} + x_{\hat{\tau}_i - \hat{\tau}_{i-1}}(w - \hat{w}_{i-1}, T - \hat{\tau}_{i-1}, \mathcal{B})$ for some $1 \le i < k$), the goal does not affect work schedule, which is a trivial case. In what follows, I focus on *effective goals* such that the agent completes more work at each goal than the case without short-term goals. On this basis, every short-term goal is made urgent to the agent, and the work schedule is now characterized by phase-wise task completion.

4.1. *Optimal Short-Term Goals*

The agent aims to minimize her ex-ante perceived cost to complete the task, whereas her time-consistent advisor aims to minimize her long-run cost. In each goal phase i spanning from $\hat{\tau}_{i-1}$ to $\hat{\tau}_i$, the agent completes the work margin $\hat{w}_i - \hat{w}_{i-1}$. Thus, the ex-ante perceived cost and long-run cost of task completion under short-term goals $\boldsymbol{G}_k$ are

$$\hat{C}(\boldsymbol{G}_k) = \sum_{i=1}^{k} C(\hat{w}_i - \hat{w}_{i-1}, \hat{\tau}_i - \hat{\tau}_{i-1}, \mathcal{B}) = \gamma B^{\alpha-1} \sum_{i=1}^{k} \frac{(\hat{w}_i - \hat{w}_{i-1})^\alpha}{(\hat{\tau}_i - \hat{\tau}_{i-1})^{\alpha-1}}, \tag{16}$$

$$\begin{aligned} \hat{LC}(\boldsymbol{G}_k) &= \sum_{i=1}^{k} LC(\hat{w}_i - \hat{w}_{i-1}, \hat{\tau}_i - \hat{\tau}_{i-1}, \mathcal{B}) \\ &= \sum_{i=1}^{k} \frac{B}{\alpha B + 1 - \alpha} C(\hat{w}_i - \hat{w}_{i-1}, \hat{\tau}_i - \hat{\tau}_{i-1}) = \frac{B}{\alpha B + 1 - \alpha} \hat{C}(\boldsymbol{G}_k), \end{aligned}$$

where $C(\cdot)$ and $LC(\cdot)$ are given by *Proposition 1*. Since $B/(\alpha B + 1 - \alpha)$ is a positive constant to the agent, the optimal short-term goals for the agent coincide with the optimal short-term goals for her time-consistent advisor.

I then derive the optimal k short-term goals, selected by both the agent $(\beta, \hat{\beta})$ and her advisor. For all $1 \le i \le k-1$, F.O.C. of (16) with regard to $\hat{\tau}_i$ gives us

$$-(\alpha - 1)\frac{(\hat{w}_i - \hat{w}_{i-1})^\alpha}{(\hat{\tau}_i - \hat{\tau}_{i-1})^\alpha} + (\alpha - 1)\frac{(\hat{w}_{i+1} - \hat{w}_i)^\alpha}{(\hat{\tau}_{i+1} - \hat{\tau}_i)^\alpha} = 0 \quad \Rightarrow \quad \frac{\hat{\tau}_{i+1} - \hat{\tau}_i}{\hat{\tau}_i - \hat{\tau}_{i-1}} = \frac{\hat{w}_{i+1} - \hat{w}_i}{\hat{w}_i - \hat{w}_{i-1}}.$$

Since $(\hat{w}_0, \hat{\tau}_0) = (0, 0)$, $(\hat{w}_k, \hat{\tau}_k) = (w, T)$, we have $\hat{w}_i = \frac{w}{T}\hat{\tau}_i$. Therefore, the set of optimal k short-term goals — which minimize both the agent's ex-ante perceived cost and the long-run cost — is given by

$$\mathcal{G}_k^* = \left\{ \boldsymbol{G}_k : \frac{\hat{w}_i}{\hat{\tau}_i} = \frac{w}{T} \text{ for } i = 1, 2, \ldots, k \right\}.$$

I denote any selection $\boldsymbol{G}_k^* \in \mathcal{G}_k^*$ as the optimal k short-term goals.

Note that the set of optimal short-term goals $\mathcal{G}_k^*$ is invariant to the agent's time preferences. This result implies that if the agent or her advisor can choose short-term goals at the start of the project, they would choose the same as a time-consistent agent, trying to distribute workload evenly across phases, as illustrated in *Figure 4*.

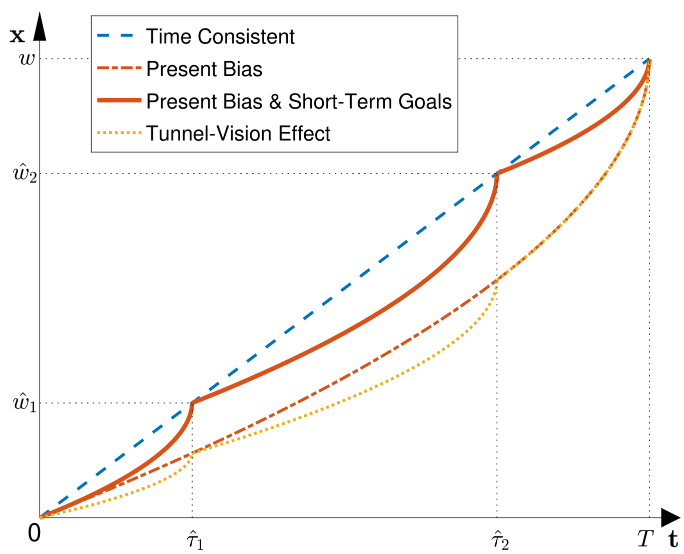


FIGURE 4. Work Trajectory under Optimal Short-Term Goals

4.2. *Value of Short-Term Goals*

Indeed, optimal short-term goals can reduce procrastination for the present-biased agent. Formally, the work finished by any time $t \in [0, T]$ under the short-term goals $\boldsymbol{G}_k$ is as follows:

$$\hat{x}_t(\boldsymbol{G}_k) = \hat{w}_{i-1} + x_{t-\hat{\tau}_{i-1}}(\hat{w}_i - \hat{w}_{i-1}, \hat{\tau}_i - \hat{\tau}_{i-1}, \mathcal{B}),$$

for $i \in [1, k]$ such that $t \in [\hat{\tau}_{i-1}, \hat{\tau}_i]$, where $x_t(\cdot)$ is given by (4). By calculation, the agent completes more of the work before any time $t \in (0, T)$ under the optimal short-term goals $\boldsymbol{G}_k^*$; that is, for any optimal goals $\boldsymbol{G}_k^* \in \mathcal{G}_k^*$, and any task-behavioral features $(\mathcal{T}, \mathcal{B})$,

$$\hat{x}_t(\boldsymbol{G}_k^*) > x_t(\mathcal{T}, \mathcal{B}).$$

However, less procrastination under short-term goals does not reduce the overall effort cost. To see this, I first calculate the minimal perceived cost under short-term goals:

$$\begin{aligned}\hat{C}_k^* &\equiv \min_{\boldsymbol{G}_k} \hat{C}(\boldsymbol{G}_k) = \hat{C}(\boldsymbol{G}_k^*) \\ &= \gamma B^{\alpha-1}\left(\frac{w}{T}\right)^{\alpha-1}\sum_{i=1}^{i=k}(\hat{w}_i - \hat{w}_{i-1}) = \gamma B^{\alpha-1}\frac{w^\alpha}{T^{\alpha-1}} = C(\mathcal{T},\mathcal{B}).\end{aligned}$$

Likewise, the minimal long-run cost under short-term goals is

$$\begin{aligned}\hat{LC}_k^* &\equiv \min_{\boldsymbol{G}_k} \hat{LC}(\boldsymbol{G}_k) = \hat{LC}(\boldsymbol{G}_k^*) \\ &= \frac{B}{\alpha B + 1 - \alpha}\hat{C}_k^* = \frac{B}{\alpha B + 1 - \alpha}C(\mathcal{T},\mathcal{B}) = LC(\mathcal{T},\mathcal{B}).\end{aligned}$$

Therefore, although full commitment to the first-best schedule restores efficiency, committing to finite short-term goals cannot lower either the perceived cost or the long-run cost for a present-biased agent. Worse still, if not set optimally, the intervention of short-term goals would strictly increase these overall effort costs. Hence, both the agent and her advisor would rather *not* set short-term goals for the agent, regardless of the task features and the agent's time preferences.

Note also that the value of short-term goals does not vary with the number of goals. Hence, even arbitrarily many short-term goals cannot improve individual welfare.

4.3. *Two Effects Generated by Short-Term Goals*

To understand why the value for finite commitments is weakly negative, I isolate the following two opposite forces at play:

(i) *Keep on Track* $(+)$: smooth out the workload over phases so that work is not accumulated near the final deadline.
(ii) *Tunnel Vision* $(-)$: rush to finish the short-term goals in every phase.

The *Keep-on-Track Effect* is easy to understand; after all, this is the main purpose of arranging these short-term goals in the first place. However, the *Tunnel-Vision Effect* is an unintended side effect when applying short-term goals and requires more explanation. Effective short-term goals urge the agent to finish more work by intermediate deadlines compared to the case when she is not subject to any short-term goals. As a result, the agent is prompted to be myopic and focus exclusively on the urgent short-term goal at each phase. Additionally, the existence of subsequent short-term goals streamlines future work and guarantees that a proportional workload is completed over time. This anticipation allows the current self to slack off at the start of each phase and justifies the tunnel vision.

The *Tunnel-Vision Effect* precisely captures the adverse effect arising from being myopic in achieving short-term goals. To see this negative effect, consider an agent who sets short-term goals aligned with what she would have done without these goals (i.e.,

$\hat{w}_i = x_{\hat{\tau}_i}(\mathcal{T}, \mathcal{B}))$ but narrows her attention solely to the upcoming short-term goals in each phase; see *Figure 4* for an illustration. We can calculate her ex-ante perceived cost and long-run cost as follows:

$$\begin{aligned}
\hat{C}(\boldsymbol{G}_k) &= \gamma B^{\alpha-1} w^{\alpha} \sum_{i=1}^{k} \frac{[(1-\frac{\hat{\tau}_{i-1}}{T})^B - (1-\frac{\hat{\tau}_i}{T})^B]^{\alpha}}{(\hat{\tau}_i - \hat{\tau}_{i-1})^{\alpha-1}} \\
&\geq \gamma B^{\alpha-1} w^{\alpha} / T^{\alpha-1} = C(\mathcal{T}, \mathcal{B}), \qquad (17) \\
\hat{LC}(\boldsymbol{G}_k) &= \frac{B}{\alpha B + 1 - \alpha} \hat{C}(\boldsymbol{G}_k) \geq \frac{B}{\alpha B + 1 - \alpha} C(\mathcal{T}, \mathcal{B}) = LC(\mathcal{T}, \mathcal{B}),
\end{aligned}$$

where the equality in (17) holds if and only if the agent is time consistent (i.e., $B = 1$). In other words, the adverse *Tunnel-Vision Effect* only exists for a present-biased agent. A time-consistent agent constantly exerts effort w/T over time, so her overall cost is invariant to her consideration horizon for dynamic decisions. However, if a present-biased agent focuses solely on the most urgent short-term goal, the repeated procrastination for each short-term goal entails higher overall costs to her.

On the whole, the *Keep-on-Track Effect* smooths the workload over time by setting short-term goals as checkpoints; however, the *Tunnel-Vision Effect* increases overall costs by inducing repeated rushing for deadlines. If the short-term goals are chosen optimally, these two effects exactly cancel out each other; otherwise, the *Tunnel-Vision Effect* dominates the *Keep-on-Track Effect* for a present-biased agent. As effective short-term goals (weakly) increase overall effort costs for the agent, the agent and her advisor prefer to work only under an end goal rather than a series of short-term goals.

4.4. *Limited Commitment in Discrete-Time Case.*

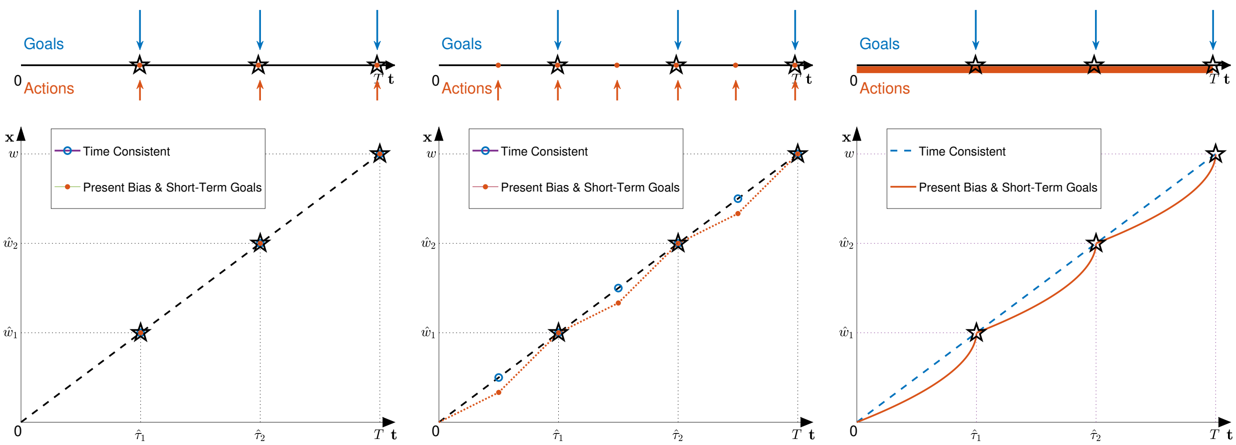
I further examine the nature of the *Tunnel-Vision Effect* by viewing continuous-time choices as a limiting case of discrete-time choices when the choice frequency goes to infinity. I will show that the value of short-term goals to a present-biased agent can be positive in discrete time. However, the commitment value is attenuated as the frequency of actions relative to the frequency of goals grows. It eventually dissipates when dynamic choices are made in continuous time under only finite short-term goals.

Suppose $t = 1, 2, \ldots, T$, and a sophisticated agent with present bias $\beta \in [0, 1]$ has a task (w, T) to complete. Denote $y_t > 0$ as the effort at the period t, and denote $x_t = \sum_{\tau=1}^{t} y_\tau$ as the accumulated effort (or the work finished) up to period t. The quasi-hyperbolic discounting factor at time t for utility at time $s \geq t$ is specified by $D_t(s, \beta, \delta) = \beta\delta^{s-t}$. As in the baseline model, I further assume $\delta = 1$ so that future payoffs are uniformly discounted by $\beta \in (0, 1]$.

Let $\mathbf{e}(x, t)$ be the agent's optimal effort when work finished is x in the period t. By backward induction, I solve the dynamic optimization that minimizes the overall perceived effort cost, subject to the boundary constraints $x_0 = 0, x_T = w$, and characterize

$$\mathbf{e}(x, T-k) = A_k(w-x)\mathbb{1}\{x < w\},$$

where $A_0 = 1, A_k = \left\{1 + [A_{k-1}^{\alpha-1} - (1-\beta)A_{k-1}^{\alpha}]^{-\frac{1}{\alpha-1}}\right\}^{-1}$, and $\mathbb{1}\{\cdot\}$ is an indicator function. In particular, $A_k = 1/(k+1)$ for $\beta = 1$, indicating that a time-consistent agent distributes the remaining workload evenly among the remaining periods. Moreover, A_k is strictly increasing in β for $k \geq 1$. Therefore, given the remaining work and time, an agent with a larger present bias exerts strictly less effort in the current period.



(a) Full Commitment $\frac{\#(\text{actions})}{\#(\text{goals})} = 1$

(b) Limited Commitment $\frac{\#(\text{actions})}{\#(\text{goals})} > 1$

(c) Continous Time $\frac{\#(\text{actions})}{\#(\text{goals})} = \infty$

FIGURE 5. Variation in Relative Frequency of Actions to Goals

Figure 5 shows how the agent's work trajectory varies with the frequency of actions. *Figure 5(a)* depicts the full commitment case when the frequency of actions matches the frequency of goals. Here, short-term goals enable the agent to attain her first best by completely binding her effort choices. This manifests the positive *Keep-on-Track* effect of commitment.

Now fix the number of short-term goals and increase the frequency of dynamic choices. The commitment becomes inadequate to bind the agent's every choice. As depicted in *Figure 5(b)*, the agent procrastinates in achieving each goal whenever she is left unchecked — this is where the *Tunnel-Vision Effect* comes in.

Unlike the continuous-time case, short-term goals in discrete time can indeed bring down the long-run cost. However, the commitment value vanishes as T gets sufficiently large. For example, take $T = 52$ (weeks), $\beta = 0.8$ (estimated present bias in unpleasant task completion by Augenblick and Rabin (2019)). Although full commitment (weekly checks) can fully recover the welfare loss caused by present bias and reduce the long-run cost by 8.9%, quarterly checks ($k = 4$) merely result in a savings of 0.54% in the long-run cost. If the agent works daily instead ($T = 365$), then the value of quarterly checks becomes even more negligible, only reducing the long-run cost by roughly 0.12%. In this light, the baseline continuous-time model approximates the discrete-time case when the dynamic choices are far more frequent than short-term goals.

Intuitively, increasing the relative frequency of dynamic choices gives the present-biased agent more freedom to procrastinate before each short-term goal. This freedom amplifies the *Tunnel-Vision Effect* — rushing more towards the end of each phase. In the limiting continuous-time case when the relative frequency of dynamic choices to short-term goals goes to infinity, the *Tunnel-Vision Effect* completely offsets the *Keep-on-Track Effect*, causing a weakly negative value of short-term goals.

Proposition 2 summarizes my findings about the impact of short-term goals.

PROPOSITION 2 (The Value of Short-Term Goals)**.**

(i) The optimal short-term goals are chosen along the first-best work trajectory.
(ii) Finite short-term goals alleviate procrastination for a present-biased agent.
(iii) In terms of both the ex-ante perceived cost and the long-run cost, finite short-term goals are at best of no value to the agent, if not harmful.
(iv) Present bias and limited commitment combined give rise to the Tunnel-Vision Effect. This negative effect grows as the ratio of the action frequency to the goal frequency increases, and it completely neutralizes the positive Keep-on-Track Effect when the choices are made in continuous time under finite short-term goals.

REMARK 1. *The result that intermediate deadlines entail weakly higher effort costs is consistent with experimental findings documented in Ariely and Wertenbroch (2002).*[10] *They assigned participants to complete unpleasant tasks in different deadline settings, and asked them to evaluate their overall experience afterward. The group with the mandatory evenly-spaced deadlines was reported to suffer the most from the task, whereas the group with only one end deadline was reported to dislike the task the least.*

REMARK 2. *It has been well-explored that limited commitment can backfire if the agent is (partially) naive. For example, Heidhues and Kőszegi (2009) investigate costly yet ineffective attempts at self-control when a present-biased agent does not fully appreciate her future taste. In their paper, the agent takes insufficient action to prevent herself from indulging in harmful consumption, resulting in a futile attempt at self-control. In contrast, I emphasize a negative effect of limited commitment that can be caused by present bias alone (i.e., the Tunnel-Vision Effect). I show that,*

[10] I further show in the online appendix that a present-biased agent incurs strictly higher effort costs under all short-term goals when the exponential discount rate $\delta > 0$.

even if the present-biased agent is fully sophisticated (i.e., $\hat{\beta} = \beta < 1$), Proposition 2 still holds and the value of the limited commitment remains weakly negative for the present-biased agent.

REMARK 3. *In Appendix D, I investigate the reason why the long-run cost under the optimal short-term goals is precisely the same as without any short-term goal. The key finding is that, the accumulated time during which the flow effort is no more than any effort level y is homogeneous of degree 1 in the task requirement (w, T). This implies that the total time the agent spends on each flow effort level remains unchanged when short-term goals are proportionally inserted. Consequently, the overall effort cost remains the same under the optimal short-term goals.*

5. DISCUSSION

5.1. *Related Literature*

***Experimental and Empirical Evidence*.** The classic exponential discounting model implies time consistency: preferences over alternatives are independent of the time of evaluation; thus, the best plan for the future remains optimal when the future arrives. However, both laboratory experiments and empirical work suggest that this implication about human behaviors is often descriptively inaccurate (e.g., Mischel, 1974; Loewenstein and Prelec, 1992; Frederick, Loewenstein and O'Donoghue, 2002; DellaVigna and Malmendier, 2006; Steel, 2007; DellaVigna, 2009; Mullainathan and Shafir, 2013; Thaler, 2015; Sirois and Pychyl, 2016; Cohen et al., 2020). Augenblick, Niederle and Sprenger (2015) show that, as opposed to the insignificant present bias exhibited in intertemporal monetary choices, subjects exhibit substantial present bias in real effort tasks.

***Time Inconsistency Models*.** Procrastination manifests the time inconsistency between ex-ante plans and ex-post choices. Early economic work on time inconsistency is pioneered by Strotz (1956) and Thaler and Shefrin (1981). Then, a growing body of theoretical models arises to account for time-inconsistent choices. This literature has three main paradigms: (quasi-)hyperbolic discounting (e.g., Laibson, 1997; O'Donoghue and Rabin, 1999, 2001; Ahn, Iijima and Sarver, 2020), temptation (e.g., Gul and Pesendorfer, 2001; Ahn et al., 2019; Banerjee and Mullainathan, 2010) and multi-self models (e.g., Fudenberg and Levine, 2006), each explaining time-inconsistent choices based on different assumptions about dynamic preferences. In hyperbolic discounting models, the short-term discount rate is greater than the long-run discount rate, capturing the diminishing impatience over time. For tractability, Laibson (1997) proposes the quasi-hyperbolic discounting model in discrete time and characterizes time preferences with only two parameters: the exponential discount factor δ as in exponential discounting, and the present bias parameter β, attaching the additional weight to the present. Harris and Laibson (2013) then extend the quasi-hyperbolic discounting model from discrete time to continuous time.

To further explain the planning fallacy, this strand of literature accommodates bounded rationality such as naivete, perfectionism and imperfect memory (e.g., O'Donoghue and Rabin, 2001; Kopylov, 2012; Ericson, 2017; Ericson and Laibson, 2019, for a survey).

The most closely related paper is Maxted (2023), who studies consumption-saving choices for a household under present bias in the infinite horizon. Using the IG model, the author also finds that self-imposed financial commitment devices (e.g., asset illiquidity and high-cost borrowing) cannot reduce the welfare loss arising from present bias. My paper differs from it in the application context; namely, I study a present-biased agent's dynamic effort choices for a task featuring a deadline. The finite-horizon frame is more suited for many task completion scenarios, and it enables us to study the effect of the deadline, especially the key finding of the *Tunnel-Vision Effect*.

Commitment Contracts. A general lesson from the time inconsistency literature is that commitment can alleviate self-control problems and thus enhance a time-inconsistent agent's long-run welfare (e.g., Himmler, Jäckle and Weinschenk, 2019; Schilbach, 2019). A market has arisen to provide desired commitment devices, which motivates a burgeoning strand of literature (e.g., Amador, Werning and Angeletos, 2006; Ambrus and Egorov, 2013; Laibson, 2015; Bond and Sigurdsson, 2018; Bryan, Karlan and Nelson, 2010, for a survey). The key tension under study is between the demand for commitment (due to present bias) and the demand for flexibility (due to taste shocks). Another concern in this literature is around exploitative contract design (e.g., DellaVigna and Malmendier, 2004; Heidhues and Kőszegi, 2010; Kőszegi, 2014; Galperti, 2015). These papers point out that firms can design contracts to screen and exploit naive consumers, creating market inefficiency — although Gottlieb and Zhang (2021) show that the inefficiency asymptotically disappears for a long-term contract.

My contribution to this literature is introducing the *Tunnel-Vision Effect*, a negative effect of commitment even in the absence of taste shocks, naivete, and costs of device purchases. Committed to a series of short-term goals, a present-biased agent needs to prioritize the most urgent short-term goal. In this light, one may resort to short-term goals to arrange the workload more evenly across periods. Welfare-enhancing as this commitment device appears at first glance, yet it backfires and impairs her welfare. Now, the agent would repeatedly rush to meet every short-term goal, prolonging the total duration of high effort.

Task Completion. The current paper resembles Ely and Szydlowski (2020) in that task difficulty is modeled as the accumulated effort required to complete the task. They fully characterize the optimal information disclosure about the workload to induce effort. Instead, this paper highlights time inconsistency in dynamic choices and assumes the flow effort cost is convex in the work intensity, capturing the aversion to rushed work. Saez-Marti and Sjögren (2008) study the optimal deadline choice for a principal of a task. In their model, a time-consistent agent needs two periods to complete the task. The opportunity cost of effort at each period is random, with a high effort cost interpreted as distractions. Heidhues and Strack (2021) study a quasi-hyperbolic discounting model for task completion with a deadline and taste shocks over time. In their model, only the timing of task completion is observed. Logically, their results share some common features with my work: the task completion rate in their paper and the effort level in my paper are both increasing before the deadline. They establish that present bias is pinned down by payoff distribution for any observed data with an increasing task-completion rate. Without knowing the payoff distribution, time preference parameters cannot be identified. I further show that, even if the entire path of effort is observed, time preference cannot be identified under an unknown payoff function.

5.2. *Concluding Remarks*

I propose a tractable dynamic model in which a present-biased and potentially naive agent works on a long-term task with a fixed deadline. The paper yields two key insights into the study of time inconsistency. First, behavioral frictions (of present bias and naivete) intensify the welfare loss due to task features (of a difficult task and a close deadline), and vice versa. Second, commitment to short-term goals, even if optimally chosen (by the agent or by her advisor), cannot reduce the welfare loss caused by present bias.

The second point is particularly noteworthy and novel to the literature. The intervention of short-term goals is designed to correct behaviors and benefit the agent. However, the unchanged motive of procrastination (e.g., present bias and naivete) finds its way to rebound during unregulated times; the agent would focus on achieving the most urgent short-term goal and undergo repeated procrastination. This side effect arises when (i) the agent has present bias, and (ii) the commitment is inadequate to bind her every choice. The negative effect counteracts the benefit of keeping the agent on track, and it looms as dynamic choices become increasingly more frequent relative to the commitments. In the limit as the choices are made in continuous time while the commitments are finite, the negative effect eliminates the positive effect under the optimal short-term goals, and it strictly dominates the positive effect if the short-term goals are not chosen optimally. Therefore, although full commitment strictly enhances the welfare of a present-biased agent, the limited commitment of short-term goals leaves the agent at best as well-off as she would be without any commitment.

I conclude the paper by listing three avenues for future investigation into procrastination. The first is to examine alternative commitment device (e.g., random checking on progress instead of explicit intermediate deadlines), and further characterize the properties of limited commitment that improves a present-biased agent's welfare. The second is to enrich the payoff structure such that the reward for task completion varies with the total effort exerted on the task before the deadline. The third is to incorporate insights from recent psychological studies (e.g., Fee and Tangney, 2000; Tice, Bratslavsky and Baumeister, 2001; Sirois and Pychyl, 2016), viewing procrastination as more of a self-protection strategy for coping with anxiety than a time management problem. The psychological cost incurred by anxiety works differently than the effort cost modeled in this paper. It may suggest that chunking, breaking down a big task into several manageable pieces, could promote steady progress and motivate incremental effort.

APPENDIX A. PROOF OF LEMMA 1

Fix the initial state $(x,t) \in [0,w) \times [0,T)$, and let $(\bar{\boldsymbol{x}}(x,t), \bar{\boldsymbol{y}}(x,t))$ be an admissible work schedule for a sophisticated agent starting from (x,t). Denote the perceived cost

$$\bar{W}(x,t) = \int_t^T D_t(s;\beta,\delta)c(\bar{y}_s(x,t))\mathrm{d}s,$$

and the long-run cost

$$\bar{V}(x,t) = \int_t^T D_t(s;1,\delta)c(\bar{y}_s(x,t))\mathrm{d}s.$$

First, I show that $(\bar{\boldsymbol{x}}(x,t), \bar{\boldsymbol{y}}(x,t))$ must satisfy (10), (13) and (14). (10) relates the perceived cost $\bar{W}(\cdot)$ to the long-run cost $\bar{V}(\cdot)$ by definition. Intuitively, the long-run cost $\bar{V}(\cdot)$ evaluates continuation effort costs of the work schedule $(\bar{\boldsymbol{x}}(x,t), \bar{\boldsymbol{y}}(x,t))$ by exponential discounting. In contrast, the perceived cost $\bar{W}(\cdot)$ discounts all future payoffs further by β (besides exponential discounting). Since the impact of the current payoff only lasts for an instant and is thus negligible, we can obtain $\bar{W}(\cdot) = \beta\bar{V}(\cdot)$. The boundary conditions (13) and value matching condition (14) describe the initial and terminal state of the dynamic problem. They guarantee that the agent finishes the remaining workload $w - x$ within the time available $T - t$, and she does not need to incur any effort cost once she finishes the workload w.

Next I prove that an optimal work schedule $(\boldsymbol{x}^S, \boldsymbol{y}^S)$ for a sophisticated agent must satisfy (12). Since a sophisticated agent correctly anticipates her present bias in the future, all her predictions about future choices are realized. Therefore, the continuation cost along the sophisticated agent's work schedule $(\boldsymbol{x}^S, \boldsymbol{y}^S)$ is given by

$$V(x_t^S, t) = \int_t^T c(y_\tau^S)\mathrm{d}\tau \tag{A.1}$$

for all $t \in [0,T]$. Differentiating both sides of (A.1) with regard to t, we have

$$V_x(x_t^S,t)y_t^S + V_t(x_t^S,t) = -c(y_t^S),$$

which is the HJB equation (12) for the initial state $(0,0)$. Since the preceding argument can be repeated for any initial state $(x,t) \in [0,w) \times [0,T)$, we can establish that (12) holds for any sophisticated agent's continuation cost $V^S(x,t)$ and the policy function $\mathbf{e}^S(x,t)$.

Then it suffices to show that the F.O.C. (11) characterizes an optimal work schedule for a sophisticated agent. To see this, note that the flow cost function $c(\cdot)$ is strictly convex and the continuation cost $V^S(\cdot)$ is differentiable. Therefore, the F.O.C. (11) gives us the optimal solution to the corresponding unconstrained cost minimization problem in scheduling.

Combining these pieces, if a work schedule $(\boldsymbol{x}^S, \boldsymbol{y}^S)$ satisfies the F.O.C. (11) and also satisfies the constraints (10), (12), (13) and (14), it is the most cost-efficient work schedule that is implementable for a sophisticated agent.

To prove the uniqueness of the optimal work schedule $(\boldsymbol{x}^S, \boldsymbol{y}^S)$, first note that the cost function $W^S(\cdot)$, which is the minimized perceived cost subject to constraints (10), (12), (13) and (14), must be unique. Then the continuation cost function $V^S(\cdot)$ is uniquely pinned down by (10), which in turn uniquely pin down the policy function $\mathbf{e}^S(\cdot)$ by the F.O.C. (11). Since the optimal work schedule $(\boldsymbol{x}^S, \boldsymbol{y}^S)$ is generated by the unique policy function $\mathbf{e}^S(\cdot)$ with the initial state at $(0,0)$, the optimal work schedule that satisfies (10), (11),(12), (13) and (14), if it ever exists, must be unique.

Appendix B. Proof of Proposition 1

To derive *Proposition 1*, I first characterize a sophisticated agent's work schedule and welfare (*Lemma B.1*). I then allow the agent to be naive, (mis)perceiving that her future selves are sophisticated and exhibit a smaller present bias.

Lemma B.1. *The unique work schedule for a sophisticated agent with present bias $\beta \in (0,1]$ and a certain task $\mathcal{T} = (w, T)$ is: for all $t \in [0, T]$,*

$$x_t(\mathcal{T}, \beta) = w\left[1 - (1 - t/T)^{\frac{\alpha-1}{\alpha-\beta}}\right],$$
$$y_t(\mathcal{T}, \beta) = [(\alpha-1)w/(\alpha-\beta)T]\,(1 - t/T)^{\frac{\beta-1}{\alpha-\beta}}.$$

The cost function (or ex-ante perceived cost) is

$$C(\mathcal{T}, \beta) = \gamma w^\alpha/(T^{\alpha-1})\,[(\alpha-1)/(\alpha-\beta)]^{\alpha-1}.$$

The continuation cost (or long-run cost) is $LC(w, T, \beta) = C(w, T, \beta)/\beta$.

Proof of Lemma B.1. The dynamic programming problem is formulated as follows. Fix the initial state $(x, t) \in [0, w] \times [0, T]$. Let $W^S(x, t)$ be the perceived cost function at any state (x, t); let $\mathbf{e}^S(x, t)$ be the corresponding policy function; and let $\langle \boldsymbol{x}^S(x, t), \boldsymbol{y}^S(x, t)\rangle$ be the corresponding work and effort trajectories starting from the state (x, t).

Suppose $V^S(x, t) = f(t)g(x)$ where $f(\cdot), g(\cdot)$ are two continuously differentiable functions, and $f' > 0, g' < 0$. Then equation (11) yields

$$\mathbf{e}^S(x, t) = \left[-\frac{\beta}{\alpha\gamma} f(t) g'(x)\right]^{\frac{1}{\alpha-1}}.$$

Plugging in the HJB equation (12) and rearranging terms, we have

$$\frac{f'(t)}{[f(t)]^{\frac{\alpha}{\alpha-1}}} = \left(\frac{1}{\gamma}\right)^{\frac{1}{\alpha-1}} \left[\left(\frac{\beta}{\alpha}\right)^{\frac{1}{\alpha-1}} - \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha-1}}\right] \frac{(-g'(x))^{\frac{\alpha}{\alpha-1}}}{g(x)}. \tag{B.1}$$

Note that the left-hand side of (B.1) is unrelated to x, and the right-hand side is unrelated to t. Therefore, there exists a constant $H > 0$ such that

$$\frac{f'(t)}{f(t)^{\frac{\alpha}{\alpha-1}}} = H = \left(\frac{1}{\gamma}\right)^{\frac{1}{\alpha-1}} \left[\left(\frac{\beta}{\alpha}\right)^{\frac{1}{\alpha-1}} - \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha-1}}\right] \frac{(-g'(x))^{\frac{\alpha}{\alpha-1}}}{g(x)}.$$

Solving these two first-order differential equations, we can obtain

$$f(t) = \left(\frac{\alpha-1}{-Ht+J}\right)^{\alpha-1},$$
$$g(x) = (Ax+B)^{\alpha},$$

where $A = -\frac{\gamma^{\frac{1}{\alpha}}}{\beta}\left(\frac{H\beta}{\alpha-\beta}\right)^{\frac{\alpha-1}{\alpha}}$, and $B, J \in \mathbb{R}$ are two constants. Therefore,

$$V^S(x,t) = f(t)g(x) = \left(\frac{\alpha-1}{-Ht+J}\right)^{\alpha-1}(Ax+B)^{\alpha},$$
$$\mathbf{e}^S(x,t) = \left[-\frac{\beta}{\alpha\gamma}f(t)g'(x)\right]^{\frac{1}{\alpha-1}} = \frac{\alpha-1}{-Ht+J}(Ax+B)\left(-\frac{\beta A}{\gamma}\right)^{\frac{1}{\alpha-1}}.$$

Then the value matching condition $V^S(w,t) = 0$, implies that

$$V^S(w,t) = \left(\frac{\alpha-1}{-Ht+J}\right)^{\alpha-1}(Aw+B)^{\alpha}$$

for all $t \in [0,T]$. Thus, we have $B = -Aw$.

Since for any $s \in [t,T]$, $\dot{x}_s^S(x,t) = y_s^S(x,t) = \mathbf{e}^S(x_s(x,t),s) = \frac{\alpha-1}{-Hs+J}(Ax_s^S(x,t) + B)(-\frac{\beta A}{\gamma})^{\frac{1}{\alpha-1}}$, we have

$$x_s^S(x,t) = E\left[(-Hs+J)/A\right]^{\frac{\alpha-1}{\alpha-\beta}} + w,$$

where E is a function of the initial state variables (x,t) and is invariant to s. Then by the boundary conditions $x_T^S(x,t) = w$ and $x_t^S(x,t) = x$,

$$x_T^S(x,t) = E\left[(-HT+J)/A\right]^{\frac{\alpha-1}{\alpha-\beta}} + w = w,$$
$$x_t^S(x,t) = E\left[(-Ht+J)/A\right]^{\frac{\alpha-1}{\alpha-\beta}} + w = x.$$

Therefore, $J = HT, E = (x-w)/[H(T-t)/A]^{\frac{\alpha-1}{\alpha-\beta}}$.

Finally, we can derive the cost function, the continuation cost, the policy function, and the corresponding optimal state and control trajectories in any state $(x,t) \in [0,w] \times [0,T]$ as follows:

$$W^S(x,t) = \beta V^S(x,t),$$

$$V^S(x,t) = \frac{\gamma}{\beta}\left[\frac{\alpha-1}{(\alpha-\beta)(T-t)}\right]^{\alpha-1}(w-x)^\alpha,$$

$$x_s^S(x,t) = w-(w-x)\left(\frac{T-s}{T-t}\right)^{\frac{\alpha-1}{\alpha-\beta}} \text{ for any } s\in[t,T],$$

$$y_s^S(x,t) = \dot{x}_s(x,t) = \frac{\alpha-1}{\alpha-\beta}(w-x)\frac{(T-s)^{\frac{\alpha-1}{\alpha-\beta}-1}}{(T-t)^{\frac{\alpha-1}{\alpha-\beta}}} \text{ for any } s\in[t,T].$$

Taking the initial state (x,t) as $(0,0)$, we obtain *Lemma B.1*.

■

Now, we are in a position to characterize dynamic work schedule and welfare for a potentially naive agent. Fix the initial state $(x,t)\in[0,w_L)\times[0,T]$. Let $\langle \boldsymbol{x}(x,t), \boldsymbol{y}(x,t)\rangle$, $W(x,t)$ and $V(x,t)$ be the work schedule, cost function, and continuation cost function starting from the state (x,t), respectively.

I first relate the cost function for a naive agent $(\beta,\hat{\beta})$, $W(\cdot)$, to the continuation cost for a sophisticated agent $\hat{\beta}$, $V^S(\cdot)$:

$$W(x,t;\mathcal{T},\mathcal{B}) = \beta V^S(x,t;\mathcal{T},\hat{\beta}) = \gamma\beta\left[(\alpha-1)/(\alpha-\hat{\beta})\right]^{\alpha-1}(w-x)^\alpha/\left[\hat{\beta}(T-t)^{\alpha-1}\right]$$

for $x<w_L$, where $w=w_L+(1-\mu)^{\frac{1}{\alpha}}(w_H-w_L)$. Thus, the cost function at the start is

$$C(\mathcal{T},\mathcal{B}) = W(0,0;\mathcal{T},\mathcal{B}) = \frac{\gamma\beta}{\hat{\beta}}\left(\frac{\alpha-1}{\alpha-\hat{\beta}}\right)^{\alpha-1}\frac{w^\alpha}{T^{\alpha-1}}.$$

We can then obtain the optimal current effort by the F.O.C. as

$$\mathbf{e}(x,t;\mathcal{T},\mathcal{B}) = \left[-\frac{\beta}{\alpha\gamma}V_x^S(x,t;\mathcal{T},\hat{\beta})\right]^{\frac{1}{\alpha-1}} = B\frac{w-x}{T-t},$$

where $B=(\beta/\hat{\beta})^{\frac{1}{\alpha-1}}(\alpha-1)/(\alpha-\hat{\beta})$. Therefore,

$$\dot{x}_s(x,t) = \mathbf{e}(x_s(x,t),s;\mathcal{T},\mathcal{B}) = B\,(w-x_s(x,t))/\,(T-s).$$

Solving this first-order differential equation with the boundary condition $x_t(x,t)=x$, we obtain the work trajectory starting from the state $(x,t)\in[0,w_L)\times[0,T]$ as follows:

$$x_s(x,t) = w-(w-x)\left(1-\frac{s-t}{T-t}\right)^B.$$

Finally taking the initial state $(x,t)=(0,0)$, we can obtain *Proposition 1*.

Appendix C. Dynamic Effort Choices in the Discrete Time

Denote $y_k(x)$ as the effort at period $T-k$ when the remaining work is x. Fix the remaining work $x\in(0,w]$. In this section, I prove when $x>0$, $y_k(x)\equiv y(w-x,T-k)=A_kx$

where $A_0 = 1$ and for $k = 1, 2, \ldots, T$,

$$A_k = \frac{1}{1 + [A_{k-1}^{\alpha-1} - (1-\beta)A_{k-1}^{\alpha}]^{-\frac{1}{\alpha-1}}}.$$

Lemma C.1. *For any $x \in [0, w]$, $y_k(x) = A_k x$ where $A_0 = 1$, and for $k = 1, 2, \ldots, T$,*

$$\frac{1}{\beta}(A_k^{-1} - 1)^{1-\alpha} = \sum_{i=0}^{k-1} A_i^{\alpha} \prod_{j=i+1}^{k-1} (1 - A_j)^{\alpha}, \tag{C.1}$$

with the convention that $\Pi_{i=k}^{k-1}(1 - A_i)^{\alpha} = 1$.

Proof of Lemma C.1. The proof is conducted by mathematical induction.

(i) For $k = 0$ (the last period), the agent needs to finish all the remaining work $y_0(x) = x$, and therefore $A_0 = 1$.

(ii) For $k = 1$ (the second-to-last period), the agent minimizes $c(y) + \beta c(y_0(x - y))$ over $y \in [0, w]$. By F.O.C, we have

$$c'(y^*) - \beta c'(x - y^*) = 0 \;\Rightarrow\; y_1(x) = y^* = x/\left(1 + \beta^{-\frac{1}{\alpha-1}}\right).$$

Therefore, $A_1 = 1/\left(1 + \beta^{-\frac{1}{\alpha-1}}\right)$ and thus $\frac{1}{\beta}(A_1^{-1} - 1)^{1-\alpha} = 1 = A_0^{\alpha}$, showing that $y_k(x) = A_k x$ and (C.1) holds for $k = 1$.

(iii) Take any $m = 1, 2, \ldots, T$. Suppose $y_k(x) = A_k x$ and (C.1) holds for all $k = 1, 2, \ldots, m-1$. I show in this step that $y_m(x) = A_m x$ and (C.1) holds for $k = m$. At this period, the agent minimizes $c(y) + \sum_{i=0}^{m-1} \beta c(y_i)$ over $y \in [0, w]$, where

$$\begin{aligned}
y_{m-1} &= A_{m-1}(x - y), \\
y_{m-2} &= A_{m-2}(x - y - y_{m-1}) = A_{m-2}(1 - A_{m-1})(x - y), \\
y_{m-3} &= A_{m-3}(x - y - y_{m-1} - y_{m-2}) = A_{m-3}(1 - A_{m-2})(1 - A_{m-1})(x - y),
\end{aligned}$$

and I can then prove by induction that $y_i = A_i \prod_{j=i+1}^{m-1}(1 - A_j)(x - y)$ for $i = 0, 1, \ldots, m-1$. Then by F.O.C. of the cost minimization, we have

$$\begin{aligned}
0 &= c'(y^*) + \sum_{i=0}^{m-1} \beta c'(y_i) \left.\frac{dy_i}{dy}\right|_{y=y^*} \\
&= \gamma\alpha(y^*)^{\alpha-1} - \sum_{i=0}^{m-1} \beta\gamma\alpha \left[A_i \prod_{j=i+1}^{m-1}(1 - A_j)(x - y^*)\right]^{\alpha-1} A_i \prod_{j=i+1}^{m-1}(1 - A_j) \\
&= \gamma\alpha \left\{ (y^*)^{\alpha-1} - \sum_{i=0}^{m-1} \beta \left[A_i \prod_{j=i+1}^{m-1}(1 - A_j)\right]^{\alpha} (x - y^*)^{\alpha-1} \right\}.
\end{aligned}$$

Therefore, $y_m(x) = y^* = x/\left\{1+\beta^{-\frac{1}{\alpha-1}}\sum_{i=0}^{m-1}\left[A_i\prod_{j=i+1}^{m-1}(1-A_j)\right]^{-\frac{\alpha}{\alpha-1}}\right\}$. So we have $y_m(x) = A_m x$ where

$$A_m = \frac{1}{1+\beta^{-\frac{1}{\alpha-1}}\sum_{i=0}^{m-1}\left[A_i\prod_{j=i+1}^{m-1}(1-A_j)\right]^{-\frac{\alpha}{\alpha-1}}},$$

and (C.1) holds for $k = m$.

In sum, I establish that $y_k(x) = A_k x$, $A_0 = 1$ and (C.1) holds for all $k = 1, 2, \ldots, T$.

■

Lemma C.1 above implies that

$$\begin{aligned}(A_k^{-1}-1)^{1-\alpha} &= \beta\sum_{i=0}^{k-1}A_i^\alpha\prod_{j=i+1}^{k-1}(1-A_j)^\alpha = \beta A_{k-1}^\alpha + \beta(1-A_{k-1})^\alpha\sum_{i=0}^{k-2}A_i^\alpha\prod_{j=i+1}^{k-2}(1-A_j)^\alpha \\ &= \beta A_{k-1}^\alpha + (1-A_{k-1})^\alpha(A_{k-1}^{-1}-1)^{1-\alpha} = A_{k-1}^{\alpha-1} - (1-\beta)A_{k-1}^\alpha,\end{aligned}$$

where the second equality follows from the convention $\Pi_{i=k}^{k-1}(1-A_i)^\alpha = 1$, and the third equality holds using (C.1) for A_{k-1}. Therefore, $A_k = 1/\left\{1+[A_{k-1}^{\alpha-1}-(1-\beta)A_{k-1}^\alpha]^{-\frac{1}{\alpha-1}}\right\}$.

APPENDIX D. CONSTANT RETURN TO (TASK) SCALE

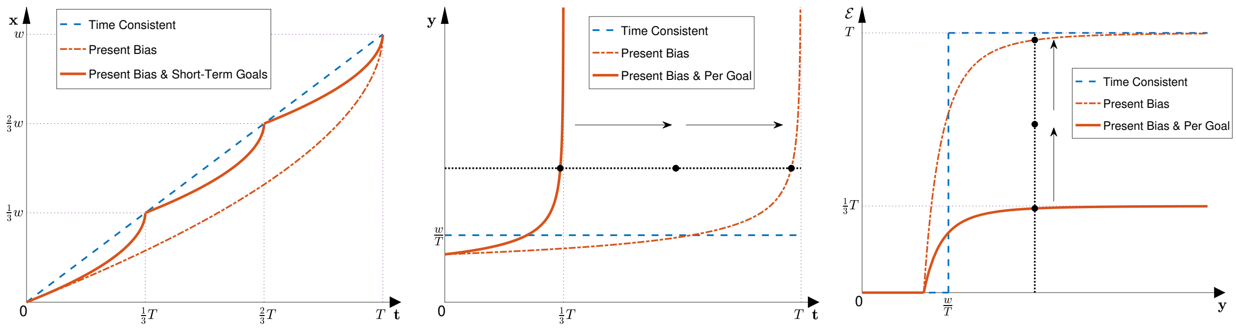
By *Proposition 1*, both cost functions, $C(\cdot)$ and $LC(\cdot)$, are homogeneous of degree 1 in the task requirement (w, T). In other words, ex-ante perceived cost and long-run cost are both constant return to (task) scale. This implies that optimal short-term goals, which distribute the total workload proportionally to the duration of each short-term task phase, do not affect the overall effort costs. In this appendix, I will demonstrate the reason behind this result.

I define the "effort time distribution" function $\mathcal{E}(\cdot)$ as follows: for any $y \geq Bw/T$,

$$\mathcal{E}(y;\mathcal{T},\mathcal{B}) \equiv \psi^{-1}(t;\mathcal{T},\mathcal{B}) = T - T\left[Ty/(Bw)\right]^{-\frac{1}{1-B}}, \tag{D.1}$$

where $B < 1$ and $\psi(t;\mathcal{T},\mathcal{B}) = y_t(\mathcal{T},\mathcal{B})$. Since ψ is strictly increasing in $t \in [0, T)$ for a present-biased agent, $\mathcal{E}$ is well defined for $y \in [y_0(\mathcal{T},\mathcal{B}), \infty) = [Bw/T, \infty)$. The effort time distribution is given by the inverse function of y_t characterized in (5). It represents the accumulated time when the flow effort is no more than y.

Observe that the effort time distribution function $\mathcal{E}(y;\mathcal{T},\mathcal{B})$ is homogeneous of degree 1 in the task requirement (w, T). This implies that the time spent below any flow effort level y is prolonged proportionally to the task requirement (w, T). For example, suppose the workload and the time available to complete the task are both tripled; then the time spent below any flow effort, and thus the aggregated effort cost, are also tripled (see *Figure D.1* for an illustration).



(a) Level Comparison (b) Slope Aggregation (c) Effort Time Distribution

FIGURE D.1. Constant Effort Cost to Task Scale

Under the optimal short-term goals, workload is distributed proportionally to the duration of each short-term task phase. Therefore, although less work is left to finish near the final due date compared to working without these goals, the total time that the agent spends on every flow effort level, measured by the effort time distribution function $\mathcal{E}$, remains unchanged.

Given that $\mathcal{E}$ is homogeneous of degree 1 in the task requirement (w, T), now I will show that the same holds true for C and LC, which in turn implies that the value of the optimal short-term goals is null. By the definition of the long-run cost (9) and the definition of the effort time distribution function (D.1), we obtain

$$LC(w, T, \mathcal{B}) = \int_0^T c(y_t(w, T, \mathcal{B}))\mathrm{d}t = \int_{\frac{Bw}{T}}^{\infty} c(y)d\mathcal{E}(y; w, T, \mathcal{B}),$$

where the second equality holds by the change of integrated variable. Therefore, when $\mathcal{E}(y; w, T, \beta)$ is homogeneous of degree 1 in (w, T), for any $\lambda > 0$, we have

$$\begin{aligned} LC(\lambda w, \lambda T, \mathcal{B}) &= \int_{\frac{Bw}{T}}^{\infty} c(y)d\mathcal{E}(y; \lambda w, \lambda T, \mathcal{B}) = \int_{\frac{Bw}{T}}^{\infty} c(y)d\left(\lambda \mathcal{E}(y; w, T, \mathcal{B})\right) \\ &= \lambda LC(w, T, \mathcal{B}), \end{aligned}$$

which implies the constant return to task scale of LC (and thus $C = \frac{\alpha B + 1 - \alpha}{B} LC$) as desired.

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