BAD HABITS AND ENDOGENOUS DECISION POINTS*

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ABSTRACT

This paper introduces a theory of bad habits (namely, addiction) based on endogenous "decision points" — i.e. the times a recurring decision is faced. Cravings are decision points that force an individual to consider consumption while inflicting an opportunity cost. Consumption provides a temporary break from unwanted cravings, which is the incentive that sustains addiction. Habit strength is jointly characterized by the frequency and the per-occasion level of consumption, matching evidence unaddressed by prevailing models. Incorporating random external cues as decision points, routines become regimented as addiction develops; light users are most responsive to cues, while addicts are comparatively immune. While cues are generally associated with higher consumption frequencies, the model also shows how cues can deter consumption. In fact, "overexposure" can fully desensitize the agent in that cue-induced consumption levels fall to zero. (*JEL* D01, D03, D11, I12)

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1 INTRODUCTION

The choices we make crucially depend on the *decisions* we consider — I cannot choose to buy a product without *considering the decision* to buy it. What then causes someone to consider a decision? Why do certain decisions arise when they do? Can our choices influence the timing of future decisions? These questions have remained outside the scope of economic analysis because standard practice takes the times decisions are faced as given. In models with a repeated choice, it is customary to assume time is *metronomic*. An inherent feature of the standard discrete-time ($t = 0, 1, 2, \ldots$) specification and its continuous-time limit, metronomic decision-making entails an exogenously-fixed "decision schedule" in which decisions are evenly spread across time — akin to a practicing musician who uses a clicking metronome to establish a fixed rhythm.

While often an empirical necessity, the rigidity of standard time is a major theoretical limitation in the realm of *habits*.[1] For instance, the development of a habit is typically characterized by simultaneous rises in the consumption frequency and in the level of consumption per occasion. Metronomic decision-making is not amenable to accurate micro-level descriptions because, in a standard interior solution, the fixed time-interval between decisions implies a fixed consumption frequency. Moreover, I claim that standard time is insufficient to capture the defining *incentives* of so-called bad habits, namely the incentive that drives *addiction* — a potentially troublesome habit for utility theory since addictions seem to bring more harm than benefit.

While exploring the themes described above, this paper develops a new framework for bad habits based on "endogenous decision points." The *decision points*, defined as the points in time ($t = t_0, t_1, \ldots$) an individual faces a decision of interest, are endogenous in that they depend on past consumption choices. The basic model is predicated on the role of *cravings*, which are modeled as decision points, i.e. a craving forces the individual to consider consumption. The decision point is a natural formalization because when cravings strike, an addict becomes fixated on the object of dependence: as neuropsychology findings

[1]Habits constitute a substantial portion of our everyday activities, according to conjectures by researchers in psychology. From diary accounts of day-to-day behavior, Verplanken and Wood (2006) estimate 45% of documented actions were habits. Other studies contend *most* behavior is habitual (Louis and Sutton, 1991; Verplanken et al., 2005).

indicate, cravings reorient decision-making faculties towards the craved good.[2] Due to their interruptive nature, each craving involves a fixed *decision opportunity cost*, the loss from the momentary disruption to outside opportunities. With the decision opportunity cost as the only payoff parameter in the basic model, the individual never wants to face the decision.

Two core assumptions relate choices to the timing of future decisions: (i) by reinforcing the habit, consumption increases the long-run frequency of cravings; and (ii) consumption *reduces* the short-run frequency of cravings. From (i), a strong habit is "bad" because it involves frequent unwanted decisions. However, the short-run effect in (ii) embeds a strategic incentive to consume as a means to reduce or delay imminent cravings, allowing outside opportunities to continue uninterrupted in the interim. This, I argue, is the key incentive underlying addiction.

As shown in section 2, the cravings model generates a stable addicted steady-state with a "slippery slope" equilibrium path from an unstable steady-state near zero-consumption. Behavior under addiction is jointly defined by the consumption frequency and the level of consumption per occasion, which matches pharmacological evidence: as Benowitz (1991) describes, addiction involves "certain rates of delivery and certain intervals between doses." Both the frequency and the per-decision level of consumption rise with habit strength. This joint measure of habit strength uniquely captures evidence that cigarette addicts inhale more nicotine per cigarette than occasional smokers, as standard addiction and habit-formation models do not accommodate simultaneously varying levels and frequencies of consumption.

Section 3 establishes "interval-driven adjacent substitution" under addiction. *Adjacent substitution* means demand in the near-term future falls with present consumption — i.e. the good now and in the immediate future are substitutes. Consistent with laboratory evidence on smoking, adjacent substitution is *interval-driven* because the time-interval to the next consumption occasion increases with current use. Adjacent substitution is noteworthy for economic analyses of addiction because its opposite — adjacent complementarity — is at the foundation of the prevailing "rational addiction" model, first developed by Becker and

[2]The phrase "reorients decision-making faculties" refers to what psychologists may describe as enlistment of "cognitive control resources" or as prompting an "attentional switch." It can be seen from neuroimaging data that drug cravings activate working memory systems (Grant et al., 1996; Garavan et al., 2000); as Garavan and Stout (2005) describe, "working memories are occupied with drug craving thoughts and ruminations."

Murphy (1988). Moreover, through its interval-driven feature, adjacent substitution is key to the puzzle of addiction since it embodies the underlying incentive to consume, which in turn (and as seen) carries new implications for *commitment*. Addictive demand also exhibits *distant complementarity*, i.e. the good now and in the distant future are complements, largely because consumption increases the long-run frequency of decisions.

To assess what conventional discrete-time analysis can and cannot tell us when past choices affect the timing of decisions, Section 4 considers measurement and inference when choices generated from endogenous decision points are aggregated to discrete-time. *Measured* adjacent substitution suffices to distinguish the model from prevailing standard-time models, provided the data aren't too coarse; most notably, it contrasts the *adjacent complementarity* inherent in rational addiction theory. Inferring preferences in discrete-time reconciles anomalous discounting patterns — severe impatience, commodity-dependence, and endogenous time preference — that are prominent in both theoretical and empirical research on addiction.[3] The exercise also shows how the predominant, time-inseparable "habit-formation preferences" can be an artifact of discrete-time aggregation and its portrayal as such fits with the neuropsychology conclusion that drugs are increasingly 'wanted' despite not being increasingly 'liked' in the course of addiction.

In Section 5, *external cues* are modeled as random decision points and integrated into the basic framework. Consistent with evidence (and in contrast to prevailing cues addiction models), the model predicts occasional users are the most sensitive to random, external cues, while addicts' consumption patterns are more predictable and predominantly driven by internal cravings. Increasing the cue-arrival rate leads to a rise in consumption frequencies (provided levels are nonzero), yet per-decision levels drop. This latter prediction embeds a novelty effect in that rare cues induce high consumption, as well as a diminishing sensitivity to cues (i.e. induced consumption levels fall) upon repeated exposure. In fact, the model shows how overexposure to cues can lead the individual to become completely desensitized.

While cues undercut the incentive to consume when the incidence of future cues is largely independent of consumption, certain types of endogenous cues (in addition to cravings)— e.g.

[3]For instance, severe impatience helps justify harmfully addictive consumption in rational addiction theory. It is also evident in Becker et al.'s (1994) follow-up empirical analysis of the rational addiction model, which finds implausibly high annual subjective discount rates, with estimates ranging from 56 to 223 percent.

advertisements, peer consumption, or the good itself — can be important in the initiation and sustenance of bad habits. For example, if imminent availability of the good induces frequent decision points, the individual may be motivated to consume all available good simply as a means to get rid of it. Since each type of cue motivates a new decision point model in its own right, the representation of cues as decision points may also prove fruitful beyond the topical focus on addiction.

Throughout this paper, the endogenous decision points framework will be related to the existing addiction literature. The main alternative to the cravings model is Becker and Murphy's (1988) rational addiction theory based on adjacent complementarity and its subsequent adaptations, such as Orphanides and Zervos' relaxation of perfect information (1995) and endogenization of time-preferences (1998), and Gruber and Kőszegi's (2001) use of present-biased discounting to account for addicts' demand for commitment. In a related theory, Gul and Pesendorfer (2007) capture history-dependence and commitment through a utility function that depends on yesterday's choice as well as today's menu. The two benchmark theories for the cues model are Laibson (2001), in which cues affect consumption preferences, and Bernheim and Rangel (2004), in which cues disrupt the alignment of choices and preferences, leading to "mistakes." While the cues-as-decision points model uniquely captures the regimentation of consumption and the diminishing role of external cues with onset of addiction, the welfare implications do not strongly distinguish the model from its two benchmarks. Relevant evidence on cravings and cues will be cited where appropriate. The bulk of cited evidence pertains to tobacco use because smoking offers an intuitive illustration of the model and because cigarette addiction is unrivaled in its scale.[4]

2 BASIC MODEL: CRAVINGS AS DECISION POINTS

An individual faces a repeated decision indexed by $i = 0, 1, 2, \ldots$. The *decision points*, $(t_0, t_1, \ldots)$, are the chronologically-ordered times the decision is faced. When not considering the decision of interest, there is a presumed desirable outside opportunity. Decision points

[4]There are one billion smokers who smoke nearly six trillion cigarettes a year, sustaining an industry that collects nearly a half-trillion dollars in annual revenues from a product projected to kill one billion people during the 21st century (Eriksen et al., 2012).

interrupt the outside opportunity; due to these interruptions, each decision point entails a *decision opportunity cost*. For simplicity, the decision opportunity cost is normalized to -1, so its time-profile looks like this:

At a decision point t_i, the individual chooses consumption $c_i \in [0,1]$ and receives instantaneous utility $u(c_i)$. If the decision point is a known, deterministic function of the consumption history, $((c_{i-1}, t_{i-1}), (c_{i-2}, t_{i-2}), \ldots)$, then the individual chooses the consumption sequence $(c_0, c_1, \ldots)$ to maximize lifetime utility

$$U = \sum_{i=0}^{\infty} \delta^{t_i}(-1 + u(c_i)). \tag{1}$$

Here, lifetime utility is summed over the decision index i and expressed relative to the outside opportunity — i.e. if the individual never faces the decision, lifetime utility would be zero.

To allow recursive computation of decision points, the *interval function*, denoted by τ, is defined as the time-duration from the current decision to the next:

$$\tau(s_i, c_i) = t_{i+1} - t_i,$$

where $s_i \in [0,1]$ is the *habit stock* — a proxy for past consumption that evolves according to

$$s_{i+1} = (1-\sigma)s_i + \sigma c_i, \tag{2}$$

for some $\sigma \in [0,1]$. Thus the habit stock at a given decision point is a weighted average of the habit stock and the consumption level associated with the previous decision (observe $c_i = s_i$ maintains a constant habit stock).[5] The *speed factor* σ captures how quickly the

[5]The form in (2) is adapted from Laibson (2001), in which "red" and "green" stock variables evolve only when a cue of their color is present. Thus the red stock does not decay when the green cue appears even though the red habit is not reinforced by consumption. The transition in (2) is analogously linked to the next decision, as opposed to a future time, so that a deliberate choice is needed for the habit to evolve. Used for mathematical cleanliness, omitting time from the transition is not essential for the results of the paper.

habit changes with consumption.

As a simple benchmark for the basic cravings model, the instantaneous utility function is eliminated:

Assumption ZP [Zero Static Consumption Preferences] $u(c) = 0$ *for all* c.

Assumption ZP abstracts from static consumption preferences in that there are no direct returns to consumption — instead, chosen consumption matters solely through its influence on the timing of future decisions. Thus Assumption ZP allows us to explore behavior driven entirely by the interval function τ with the -1 decision opportunity cost.[6] Since the decision opportunity cost is the only payoff parameter under ZP, it is never desirable to face a decision.

To start, *cravings* are modeled as decision points (i.e. a craving forces the individual to consider consumption). Accordingly, the interval function captures key properties of cravings discussed in the introduction. Letting a subscript denote the associated partial derivative (e.g. $\tau_c = \frac{\partial \tau(s,c)}{\partial c}$), the interval function's basic shape is given by:

Assumption 1 $\tau : [0,1]^2 \to \mathbb{R}_{++}$ *is twice-continuously differentiable and satisfies:*

(i) $\tau_s(s,c) < 0$*, for all* s, c.

(ii) $\tau_c(s,c) > 0$*, for all* s, c.

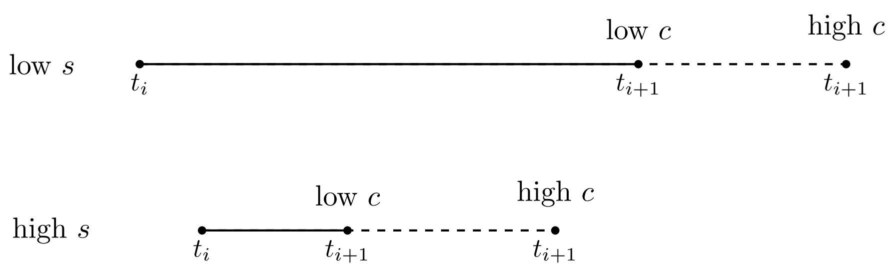
(iii) $s' > s$ *implies* $\tau(s', s') < \tau(s, s)$.

(iv) $-\delta^{\tau(s,c)}$ *is strictly concave with* $\frac{\partial^2}{\partial s \partial c}\left[-\delta^{\tau(s,c)}\right] > 0$ *for all* s, c.

Part (i) says a larger habit stock entails more frequent decisions, ceteris paribus, which captures the long-run reinforcement of past consumption. Part (ii) says, with s fixed, the interval to the next decision increases with consumption, which captures the observation from laboratory research that consumption lessens cravings in the short-run;[7] in light of the decision opportunity cost, $\tau_c > 0$ embodies a short-term incentive to consume, as a means to delay the next decision point. The intervals in the below diagram illustrate the essence of parts (i) and (ii):

[6] To be sure, this assumption is not adopted for its realism, but to elucidate — and later, given the results, to emphasize — the role of endogenous decision points relative to the role of preferences in understanding addiction.

[7] Houtsmuller and Stitzer (1999) show rapid smoking suppresses cravings. Dallery et al. (2003) find the latency to smoke is substantially longer following rapid smoking relative to normal paced smoking. Zacny and Stitzer (1985) similarly demonstrate the latency to smoke decreases after nicotine deprivation.



Part (iii) of Assumption 1 says if $c = s$ (which holds in a steady-state), then simultaneously increasing both by the same amount decreases the time between decisions, i.e. the interval-shortening effect of s outweighs the lengthening effect of c along the $c = s$ frontier. Therefore, a high steady-state associated with a higher consumption level entails more frequent decisions than a low steady-state. Concavity of $-\delta^{\tau(s,c)}$ from part (iv) implies diminishing returns to consumption. To see why, first note $-\delta^{\tau(s,c)}$ is the discounted value of the opportunity cost at the next decision point. Since the sole benefit of consumption under ZP is delaying the next-decision opportunity cost, $-\delta^{\tau}$ can be regarded as the effective return function and its concavity is analogous to diminishing returns through a concave instantaneous utility function — a standard assumption in discrete-time dynamic programming (e.g. Stokey et al., 1989). The positive cross partial derivative of $-\delta^{\tau(s,c)}$ implies that the effective marginal return to consumption rises with habit strength, which captures the notion that the extent to which consumption alleviates cravings is greater for strong habits than for weak habits.

2.1 *Dynamic Optimization*

Under ZP, dynamic optimization is characterized by the Bellman equation:

$$V(s) = -1 + \max_{c} \{\delta^{\tau(s,c)} V((1-\sigma)s + \sigma c)\}. \tag{3}$$

$V(s)$ is the value function at a decision point with habit stock s. At each decision point, the individual pays the decision opportunity cost and chooses consumption to maximize the present value of the next-decision value function. The opportunity cost is placed outside the maximization argument to emphasize its invariance to chosen consumption. Chosen consumption determines the extent of discounting through τ (where large c helps), and determines next decision's habit stock in the argument of the future value function (where large c hurts). The first-order and envelope conditions are:

$$\begin{aligned} 0 &= \sigma V'(s_{i+1}) + \ln(\delta)\tau_c(s_i,c_i)V(s_{i+1}), && (4) \\ \text{and} \qquad V'(s_i) &= \delta^{\tau(s_i,c_i)}[(1-\sigma)V'(s_{i+1}) + \ln(\delta)\tau_s(s_i,c_i)V(s_{i+1})]. && (5) \end{aligned}$$

Let the superscript + denote the variable or function associated with the next decision and ++ to denote the next-after-next decision (e.g. $\tau^+ = \tau(s_{i+1}, c_{i+1})$, $\tau^{++} = \tau(s_{i+2}, c_{i+2})$, etc.). Given s_0, if an interior optimal consumption path exists, it is defined by the Euler equation:[8]

$$\frac{\sigma\tau_s^+ - (1-\sigma)\tau_c^+}{\sigma\tau_s^+ - (1-\sigma)\tau_c^+ + \tau_c} = 1 + \delta^{\tau^+}\left[\frac{\sigma\tau_s^{++} - (1-\sigma)\tau_c^{++}}{\sigma\tau_s^{++} - (1-\sigma)\tau_c^{++} + \tau_c^+}\right]. \tag{6}$$

2.2 *Steady-States*

To characterize potential steady-states, define:

$$\mu(s,c) = -\frac{\partial}{\partial c}\left(\frac{\delta^{\tau(s,c)}}{1-\delta^{\tau(s^+,s^+)}}\right), \tag{7}$$

and let $\bar{\mu}(s) = \mu(s,s)$ define the *movement function* (for ZP). The movement function gives the marginal returns to consumption at $c = s$, provided the individual consumes exactly the next-decision habit stock at all future decisions. Since the optimization problem is Markovian, if $c = s$ is optimal now, then the habit stock permanently remains at s. It follows that if s is an interior steady-state under ZP, then $\bar{\mu}(s) = 0$. The habit stock rises to the next decision if $\bar{\mu}(s) > 0$ because it is then optimal to consume more than s (and falls if $\bar{\mu}(s) < 0$ because it is then optimal to consume less than s). Hence, the sign of the movement function indicates the direction the habit stock moves from the current decision to the next under ZP. Equivalently, letting $\tilde{c}(s)$ denote the optimal consumption level given the habit stock s, the sign of $\bar{\mu}(s)$ and the sign of $(\tilde{c}(s) - s)$ will agree under ZP.

Assumption 2 $\mu : [0,1]^2 \to \mathbb{R}$ *is continuously-differentiable and satisfies:*
(i): $\bar{\mu}(0)=0$, $\bar{\mu}'(0)>0$, *and* $\bar{\mu}(1)<0$.

[8]The derivation of the Euler equation is provided in Appendix A.1.

(ii): *If* $\bar{\mu}(s) \leq 0$ *with* $s > 0$*, then* $s' > s$ *implies* $\bar{\mu}(s') < 0$*.*

(iii): *If* $\bar{\mu}(s) = 0$ *with* $s > 0$*, then* $\mu(s, s)$ *is increasing in its first argument.*

The $\bar{\mu}(0) = 0$ condition of part (i) essentially defines $s = 0$ as the habit such that zero consumption is "exactly" optimal under ZP — i.e. $\tilde{c}(0) = 0$ independent of the fact that zero is the lower bound of c's domain. Thus Assumption 2 ensures a zero-consumption steady-state at $s = 0$. The next condition, $\bar{\mu}'(0) > 0$, implies optimal consumption exceeds the habit stock for sufficiently small $s > 0$. The final condition, $\bar{\mu}(1) < 0$, implies optimal consumption is less than the habit stock at the maximum habit. Since the movement function must cross the horizontal axis from above for some $s \in (0, 1)$, part (i) of Assumption 2 also helps establish an interior steady-state; its uniqueness is assured by part (ii), which implies that there is only one nonzero habit stock for which $\bar{\mu}(s) = 0$.

Part (iii) of Assumption 2 captures the tolerance aspect of addiction in that consumption becomes less "satisfying" as a habit intensifies from a nonzero steady-state; that is, more consumption is required to optimally alleviate cravings in the near-term (when weighed against the long-term costs of habit-reinforcement). Assumptions 1 and 2 are maintained throughout the paper.[9]

Proposition 1 [Addicted Steady-State] *Under ZP, there is a unique* $s^* \in (0, 1)$ *such that* s_i *converges to* s^* *if and only if* $s_0 > 0$*.*

All proofs are in the Appendix. Proposition 1 establishes a stable steady-state of addiction s^*, where the habit stock converges to s^* for any $s_0 > 0$. If $s_0 = 0$, the individual remains at the (unstable) zero-consumption steady-state. The stability of s^* and instability of the zero-consumption steady-state jointly represent a drastic case where addiction becomes inevitable with any small deviation from $c = 0$. This reflects the "slippery slope" nature of addiction in that an individual can readily fall into its trap, but escape is difficult. Behavior of an addict is defined by the steady-state consumption level $c^* = s^*$ and by the intervals between consumption occasions, $\tau^* = \tau(s^*, c^*)$, which fits with the previously-cited pharmacological evidence that addiction involves consistent doses separated by consistent time-intervals.

[9] A parametric example that satisfies Assumptions 1 and 2 and accompanying discussion are provided in the appendix of Landry (2012a).

Corollary 1 [Observable Measures of Habit Strength] *Under ZP:*

(i) $\tilde{c}(s)$ *is increasing at* s^**. If* σ *is sufficiently close to zero,* $\tilde{c}(s)$ *is increasing for all* s*.*

(ii) $s < s^*$ *implies* $\tau(s, \tilde{c}(s)) > \tau^*$*;* $s > s^*$ *implies* $\tau(s, \tilde{c}(s)) < \tau^*$*.*

Corollary 1 characterizes the relationship between habit strength and behavior around the interior steady-state, s^*. Part (i) establishes that the per-decision consumption level rises with the habit stock at s^*. If the speed factor is sufficiently small, this monotonic relationship holds over the entire spectrum of habits. It follows from part (ii) that consumption is more frequent at s^* than for weaker habits and less frequent at s^* than for stronger habits, where the frequency is the reciprocal of the time-interval between consecutive consumption occasions. This joint level-and-frequency characterization of habit strength captures the finding that regular cigarette smokers inhale more nicotine per cigarette than occasional smokers (Shiffman, 1989; Shiffman et al., 1994). As mentioned in the introduction, standard habit-formation and addiction models, which are cast in metronomic time, account for the level but not the frequency aspect of habit strength.[10] Notions outside economics likewise capture one out of two aspects: the standard measure of habit strength in other behavioral disciplines is based on frequency, but does not include variation in per-occasion levels (Ouellette and Wood, 1998; Verplanken, 2006).[11]

2.3 *Harmful Consumption and "Chippers"*

Unaccounted for by ZP, the direct costs of tobacco consumption have grown.[12] The rise in direct costs has coincided with the rise of *chippers*, a class of low frequency users who

[10]Discrete-time models with stochastic influences, e.g. stochastic "cues," permit consumption frequencies that vary with habit strength. However, such models do not accommodate the stable and predictable behavior of addicts that is characterized by consistent does separated by consistent intervals. Refer to Section 5 for a treatment of stochastic cues.

[11]Still, these studies suggest that the standard frequency measure is an incomplete psychological representation since behavior often becomes *automatized* as habits develop. The automatization of choices, which reduces (but does not eliminate) their toll on decision-making faculties, suggests there is gray area in classifying a "decision." (If a "choice" is performed automatically without deliberation, is it preceded by a decision?) Automatization could be accommodated in the current setup by assuming the decision opportunity cost decreases with s (given $c > 0$), yet its relevance for explaining observable consumption patterns is unclear. As Baker et al. (2004) argue, automatization may not be particularly significant for understanding the motivations of addiction and that, more often than not, addicts are largely aware of "deciding" to use drugs during use.

[12]Since the 1960s, several costs and restrictions have proliferated — e.g. new taxes, better information regarding health risks, the emergence of a social stigma, and bans on smoking at work or in public areas. See Becker et al. (1994), or Chaloupka and Warner (2000).

comprise nearly 40 percent of U.S. smokers.[13] To account for direct costs, let $\theta \geq 0$ denote a direct cost parameter. Express instantaneous utility as $u(c|\theta)$ with the normalization $u(0|\theta) = 0$, for all θ, where it is presumed $\theta = 0$ corresponds to ZP so that $u(c|0) = 0$, for all c. Now consider the alternative to ZP:

Assumption NP [Negative Static Consumption Preferences] *Direct costs are nonzero, $\theta > 0$, where the instantaneous utility function $u : [0,1] \times \mathbb{R}_+ \to \mathbb{R}$ is twice continuously differentiable and strictly concave, with $u_c < 0$ (provided $\theta > 0$) and $u_{c\theta} < 0$.*

With NP, consumption is directly harmful in that the instantaneous utility function is negative and decreasing.[14] Throughout the paper, results for NP will generally hold as long as consumption preferences aren't "too negative," i.e. for a range of small $\theta > 0$. Therefore, in subsequent results, the phrase "under NP" is used as shorthand for "there is a $\bar{\theta} > 0$ such that $\theta \in (0, \bar{\theta})$ implies the following holds under NP." This implicit qualifier reflects the notion that if direct costs are too large, the individual will never consume (and analyzing "behavior" in this scenario is an empty endeavor).

Proposition 2 [Trimodality] *Under NP there are three steady-states, $\{0, s_L^*, s_H^*\}$, where s_i converges to zero iff $s_0 < s_L^*$, and s_i converges to s_H^* iff $s_0 > s_L^*$.*

Thus integrating a small direct cost generates a third "ambivalent chipper" steady-state, s_L^*, illustrating the emergence of *trimodality*, a distribution of consumption with three modes.[15] The instability of this intermediate steady-state qualitatively captures evidence, as nonsmokers' and heavy smokers' positions are highly stable compared to that of moderate smokers (Zhu et al., 2003). Now real-life chippers likely do not exist exactly at s_L^*, but instead in its

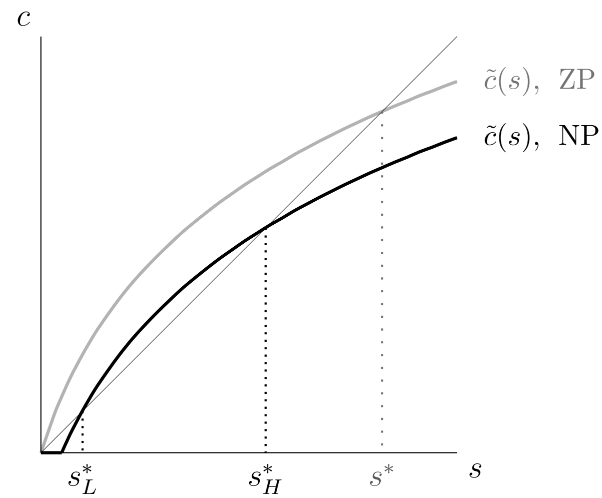
[13]See Shiffman (2009) for a helpful primer on chippers. The 40 percent figure is based on a recent Health and Human Services survey (Substance Abuse and Mental Health Services Administration, 2010). While the survey does not use the term "chipper," the statistic holds for the usual definition of chippers as nondaily smokers.

[14]Since NP consolidates the *direct* returns from consumption to $u(c)$, it is still an idealization in that actual direct returns likely involve an immediate benefit and a larger, future cost. While offering a step towards realism relative to ZP, Assumption NP "handicaps" the decision points model relative to standard addiction theories in two ways: (i) bad habits must be motivated despite a "dislike" for consumption; and (ii) because consolidation of present and future returns with $u'(c) < 0$ means direct costs must outweigh consumption's benefits, future costs cannot be diluted by sufficiently steep impatience (low δ) to "rationalize" consumption. Also note that with constant discounting and time-separable utility this consolidation has no effect on optimizing behavior.

[15]The notion that the prominence of chippers rises with θ is clear when direct costs increase from $\theta = 0$ because chippers do not exist under ZP. While not as obvious, the interpretation remains valid for $\theta > 0$. First, as θ continues to rise, so does s_L^*, making it harder to justify a bimodal characterization that implicitly lumps chippers with abstainers at a steady-state in the vicinity of zero. Second, the range of s_0's such that s converges to zero in the long-run widens; hence, we would expect the prevalence of users to fall, and consequently the prominence of chippers to rise relative to addicts.

vicinity, where the ambivalent chipper represents an occasional user who sits perfectly on the fence between quitting and becoming addicted in the long-run.[16]

The figure below shows how optimal consumption may look before and after integrating direct costs:

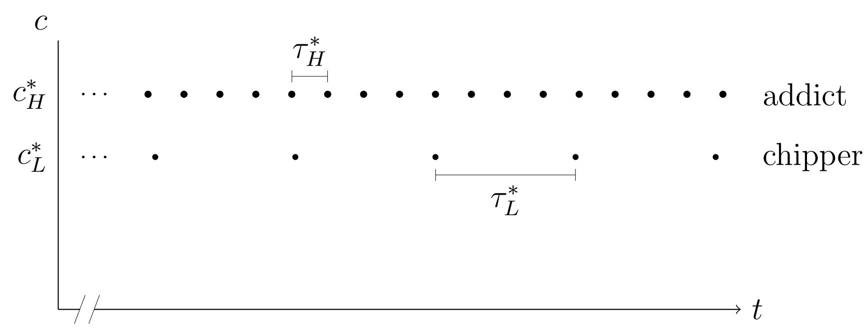


As before, NP gives a zero-consumption steady-state at $s = 0$, but it is now stable so small deviations no longer lead to addiction.[17] The high steady-state, s_H^*, is the addicted steady-state under NP, analogous to s^* under ZP. The position of the low steady-state, s_L^*, suggests chippers may signify a rough "threshold" for addiction — an idea proposed by medical researchers (Benowitz and Henningfield, 1994).

The (ambivalent) chipper's behavior is characterized by the consumption level $c_L^* = s_L^*$ and the intervals $\tau_L^* = \tau(s_L^*, s_L^*)$, while the addict is described by c_H^* and τ_H^*. The contrast between the consumption patterns of chippers and addicts highlights the joint level-and-frequency characterization of habit strength for stable habits, as illustrated below:

[16]Although s_L^* does not attract a significant population share in the long-run, an individual who starts near (but not at) s_L^* may remain nearby for a long time because habits move slowly when close to a steady-state — if many chippers are only "approximate" chippers, then the likelihood a smoker is classified as such will decrease with age, which matches evidence, as a smaller share of older smokers are chippers than younger smokers (Hennrikus et al. 1996; Wortley et al., 2003).

[17]Stability of $s = 0$ under NP follows because while assumption 2 is retained, the interpretation of $\bar{\mu}$ holds only for $\theta = 0$; $\bar{\mu}(0) = 0$ with $\theta > 0$ overestimates the marginal return from $c = 0$ at zero habit stock.



Each dot here represents a single instance of consumption. The lower height of chippers' dots indicates they consume less per occasion than addicts, and the longer intervals between neighboring dots indicate chippers consume less frequently than addicts.

2.4 *Principal "Macroscopic" Features of Addiction*

Drawing on evidence from disparate fields, Landry (2012b) highlights four principal *macroscopic* features of addiction through an economic lens: (i) addiction is "bad," (ii) addiction involves forward-looking optimization, (iii) opportunity costs are a main driver of addiction, and (iv) addictive demand exhibits adjacent substitution (with distant complementarity). "Macroscopic" in that they are *not* contingent on knowing the timing of decisions, the four features facilitate comparisons to prevailing representations of bad habits, which are cast in standard time.

In the current setup, addiction is bad because it entails frequent payments of the decision opportunity cost, where the notion that addiction can be bad simply by being a "waste of time" is a unique feature of the model. While this mechanism is novel, the model under ZP captures a *harmful* addiction in the traditional sense of Stigler and Becker (1977), as well as Becker and Murphy (1988), in that a higher stock of past consumption implies lower future utility, i.e. $V'(s) < 0$. Under NP, the model motivates addiction under a stronger concept of "harmful" than previous treatments in that consumption is directly costly too, i.e. $u'(c) < 0$ and $V'(s) < 0$. The next two properties are also are inherent in the model's specification. That is, forward-looking optimization and opportunity costs as the key driver hold by construction, where the emphasis on opportunity costs is also a unique feature of the model. The fourth property, adjacent substitution (with distant complementarity), requires elaboration.

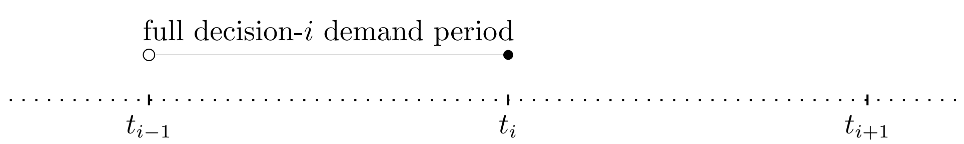
3 INTERTEMPORAL SUBSTITUTION

3.1 *Demand: Frequency and Level of Consumption*

Adjacent substitution means demand in the "adjacent" future decreases with current consumption.[18] To formally define adjacent substitution in a standard, discrete-time setting, the relevant demand measure is consumption in the next decision period. However, next decision's consumption level is an inconsistent standard in the current framework because the intervals between decisions vary endogenously. Since demand ought to reflect how much and how often one consumes, a time-averaged consumption rate is a natural measure. *Decision-i demand* is thus denoted by $x(i)$ and defined as the mean consumption rate during the union of decision i's "active" and "latent" periods (i.e. the union of the decision point and the waiting period that immediately preceded it):[19]

$$x(i) = \frac{c_i}{\tau(s_{i-1}, c_{i-1})}.$$

Inspecting the diagram below, it's seen $\tau(s_{i-1}, c_{i-1})$ is the appropriate time-window, which follows because the full demand period for decision i is $(t_{i-1}, t_i]$.



Adjacent substitution holds if next-decision demand falls with current consumption: $-\frac{\partial x(i+1)}{\partial c_i} > 0$, where the left-side of the inequality is the *marginal rate of adjacent substitution* (MRAS). MRAS reflects the degree of substitutability between the good now and the good in the

[18]Adjacent substitution has been demonstrated in many settings. For instance, Rose et al. (1984) find that smokers prefer higher nicotine intake following two hours of nicotine deprivation. In a laboratory setting, Bickel et al. (1998) show that price increases trigger "drug seeking" behavior, in which an addict continues to crave a good until it is consumed, as addicts substitute to future (and presumably cheaper) consumption. Erskine et al. (2010) report that smokers attempting to abstain for a week increase consumption during the following week, relative to a control group. See Landry (2012b) for additional background.

[19]That is, decision-i demand is decomposed as the active demand at the decision point t_i and the latent demand during the latency period ending at t_i. The term "latent demand" is borrowed from Morgenstern's (1948) description of interim demand as "latent" for a consumer who must wait until a particular future time to purchase goods.

immediate future. *Adjacent complementarity* holds if MRAS is negative (i.e. the good now and in the immediate future are complements). MRAS' sign is ambiguous at the outset — consumption extends the interval, but may also increase the next-decision consumption level. That said, as follows from $x(i+1) = \frac{\tilde{c}((1-\sigma)s_i+\sigma c_i)}{\tau(s_i,c_i)}$, the interval-extending effect dominates if the speed factor σ is sufficiently small, which would guarantee adjacent substitution.

3.2 *Interval-Driven Adjacent Substitution*

The next result shows how addicts in behaviorally identical steady-states (i.e. same c^* and τ^*) with the same interval function can be parametrically different:

Proposition 3 [Comparing Addicts] *Under ZP, consider the addicted steady-state described by (c^*, τ^*) that exists given the interval function τ with discount and speed factors δ and σ. Take any $\sigma' \in (0,1)$ and define:*

$$\delta' = \left[1 - \sigma' \left(\frac{\tau_s(s^*, c^*)}{\tau_c(s^*, c^*)} + 1\right)\right]^{-1/\tau(s^*,c^*)}. \tag{8}$$

Then behavior in the addicted steady-state given τ, δ', and σ' is also described by (c^*, τ^*).

"Different" addicts with the same interval function can be in the same steady-state because steady-state behavior does not pin down all of the model's parameters. Equation (8) allows us to compare two such addicts. Observe that a more patient (higher δ) addict has a habit that adjusts slower to consumption (lower σ), which follows because both the discount and speed factors dampen the long-term costs of consumption. Accommodating realistic and "rational" parameterizations of patience, Proposition 3 implies that the addicted steady-state exists for δ arbitrarily close to one.[20] Further, since MRAS > 0 for sufficiently small σ, adjacent substitution is assured for a range of δ that includes the most patient addicts:

Corollary 2 [Interval-Driven Adjacent Substitution] *Under ZP, given the same (c^*, τ^*) and τ from Proposition 3, there is a $\bar{\delta} < 1$ such that $\delta \in (\bar{\delta}, 1)$ implies there is a corresponding $\sigma \in (0,1)$ for which the steady-state (c^*, τ^*) exists and adjacent substitution holds.*

[20]A caveat: near-perfect patience comes hand-in-hand with a colossally slow habit stock. A caveat to the caveat: in the present construction, consumption has no persistent, positive effect beyond the next decision point. This was a simplification to obviate the need for multiple state variables. By incorporating persistence to the short-term effect of consumption, a given δ could coexist with a faster habit stock, all else equal.

Corollary 2 establishes *interval-driven* adjacent substitution in that the interval-extending effect of consumption is the basis for adjacent substitution; this particular form of adjacent substitution matches laboratory evidence that the latency period to the next instance of consumption rises with the present consumption level (Zacny and Stitzer, 1985; Dallery et al., 2003). Thus, through its interval-driven feature, adjacent substitution in the decision points model is a manifestation of the incentive for addictive consumption. Since MRAS is increasing in the magnitude of $\tau_c > 0$, which in turn proxies for the strength of this incentive, a greater degree of adjacent substitution reflects a more powerful short-term incentive to consume, ceteris paribus.

In addition to capturing the incentive to consume, the interval-driven aspect of adjacent substitution embeds an unusual depiction of *commitment*: by delaying the next opportunity to consume, *consumption* is a valuable short-term commitment strategy to restrict future consumption.[21] Because avoiding a decision point allows the individual to engage outside opportunities, commitment and flexibility arrive in tandem — a contrast to the usual treatment in which they are opposites, characterized by constricted or expanded choice sets.[22] This *decision*-level characterization of commitment reflects the notion that considering the primary decision generally precludes (at that moment) considering the decision to consume an unrelated good, thereby precluding its consumption. As it pertains to cravings, decision-level commitment arises because a neglected craving is an ongoing drain on decision-making faculties, and is inherent in any approach that postpones or eliminates cravings— such as wearing a nicotine patch to facilitate quitting.[23]

Apart from the interval-driven aspect (and its implications for commitment), adjacent substitution still bucks convention, as adjacent complementarity is the definition of addiction in Becker and Murphy's (1988) preeminent rational addiction theory based on *habit-*

[21]Here, consumption is analogous to the canonical representation of illiquidity as a commitment device in Laibson's (1997) hyperbolic discounting model, in which, upon the sale of an asset, illiquidity postpones the opportunity to consume from its proceeds.

[22]Prevailing treatments of commitment in the addiction literature include Gruber and Kőszegi's (2001) rational addiction model with quasi-hyperbolic discounting and Gul and Pesendorfer's (2007) temptation-based preference approach. For a discussion of commitment in the context of external cues, refer to section 5.4.

[23]Since it reduces an addict's frequency of cravings to that of a less addicted individual, a nicotine patch could be modeled as a device that lowers the "effective" habit stock by some $\phi > 0$. In this case, the interval function would become $\tau(s - \phi, c)$, so that the decision points and consumption choices of a patch-wearing individual would be equivalent to a patchless scenario with a lower habit stock (abstracting from potential boundary issues with τ undefined for $s < 0$).

formation preferences. The standard tool in economics for modeling habits, habit-formation preferences are represented by a time-inseparable utility function in which past consumption enters today's return, e.g. $u(c, s)$ with $u_c > 0$ and $u_{sc} > 0$ presumed.[24] Adjacent complementarity is manifest in habit-formation preferences because the marginal utility of consumption rises with past consumption. Although many alternatives to rational addiction have been proposed, there have been no serious objections to adjacent complementarity.

4 MEASUREMENT AND INFERENCE IN DISCRETE-TIME

This section considers a simple discrete-time empirical analysis of behavior from endogenous decision points, allowing us to compare the model to prevailing treatments of bad habits in a common temporal framework. As choices are typically aggregated into metronomic bins in empirical work, the exercise will also help to distinguish what traditional discrete-time inference can and cannot tell us when the timing of decisions varies endogenously.

4.1 *Detecting Adjacent Substitution*

Consider a discrete-time setup (presuming the decision points model is the data generating process), where ℓ is the fixed measurement period length T_n is the end point of measurement period n. Then *measured demand* for measurement period n, denoted as C_n, is its average demand level:[25]

$$C_n = \frac{1}{\ell} \int_{T_n-\ell}^{T_n} x(i : t_{i-1} < t \leq t_i) dt.$$

Accordingly, *measured adjacent substitution* is defined in a typical discrete-time manner: $-\frac{\partial C_{n+1}}{\partial C_n} > 0$, which implies substitutability between consecutive measurement periods, i.e.

[24] Habit-formation preferences are the prototype of *time-inseparability* (history-dependence). As Pollak (1970) describes his seminal habit hypothesis: "(i) that past consumption influences current preferences and hence, current demand and (ii) that a higher level of past consumption of a good implies, ceteris paribus, a higher level of present consumption." Time-inseparable preferences continue to be central in the extensive habit-formation literature that followed — including adaptations to Becker and Murphy's rational addiction theory (Orphanides and Zervos, 1995; Orphanides and Zervos, 1998; Gruber and Kőszegi, 2001; Laibson, 2001) as well as recent treatments not focused on addiction, such as Rozen's (2010) axiomatization and Crawford's (2010) revealed-preference empirical treatment of time-inseparability.

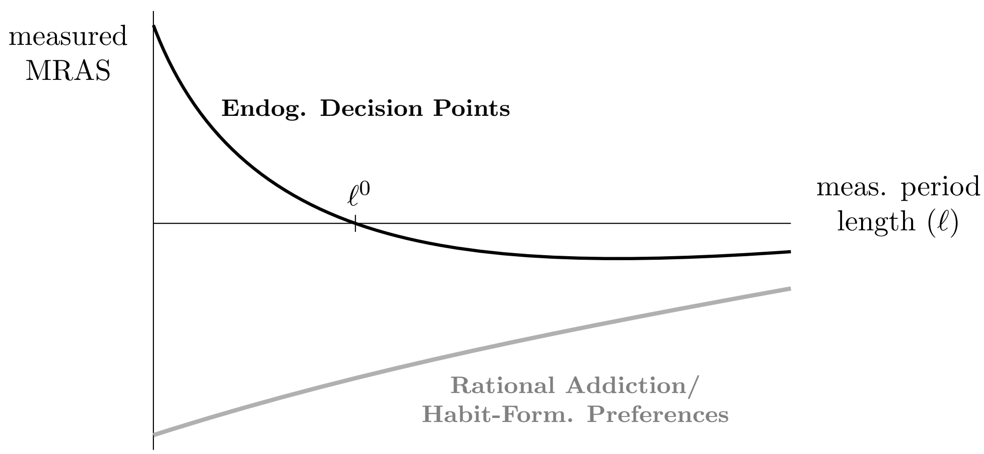
[25] Implicit in this formulation is that the flow demand is constant over each decision's demand period. This "flattening" allows a continuous measure of C. If the relevant instant associated with decision-i demand is the time of the purchase for consumption at t_i, the specification can be motivated by assuming the purchase is equally likely to occur at any time in $(t_{i-1}, t_i]$.

the *measured* MRAS is positive.[26] Per usual, *measured adjacent complementarity* holds if the inequality is reversed.

Proposition 4 [Measured Substitution Threshold]
Given adjacent substitution holds, there is a $\ell^0 > 0$ such that an addict's demand exhibits measured adjacent substitution if $\ell < \ell^0$ (and measured adjacent complementarity if $\ell > \ell^0$).

Thus if the measurement period length exceeds a threshold, addictive behavior falsely appears to satisfy adjacent complementarity — a reflection of *distant* complementarity. Below the threshold, adjacent substitution is detected. The result shows how the decision points model is distinguishable from rational addiction and from habit-formation preferences even in standard time, with sufficiently high-resolution data.

The qualitative relationship between measured intertemporal substitution and data resolution is shown below:



The substitution threshold ℓ^0 from Proposition 4 may serve as a crude measure for the duration of withdrawal because once withdrawal ends, so does the barrage of cravings that deters abstinence. Addictive substances are characterized by relatively long withdrawal — three to four weeks for nicotine and up to ten weeks for cocaine (Hughes et al., 1994). These lengthy durations fit with (but do not directly reveal) the strong incentive inherent in the

[26] As is, measured MRAS' denominator is not well defined because there are multiple ways to perturb demand in n if the measurement period contains multiple decisions. Qualitatively, it will not matter for the results whether the perturbed demand is at the beginning of the measurement period, at the end, or at some fixed fraction in between. For simplicity and without loss of (qualitative) generality, perturbed consumption is assumed to be at the end of the measurement period, so that measured adjacent substitution can be expressed as $-\frac{\partial C_{n+1}}{\partial x(i)}$ where $t_i = T_n$.

underlying interval-driven adjacent substitution because there is less reason to consume if withdrawal is short-lived. The length of nicotine withdrawal is also compatible with evidence from Erskine et al. (2010) that substitution persists at least one week into the future, as smokers increase consumption following a week of attempted abstinence relative to a control group.[27]

The substitution threshold may also have policy relevance in that ℓ^0 represents the minimum duration of a temporary consumption ban such that the ban does not lead to an increase in demand immediately *after* it is in effect, relative to demand in the absence of a ban. Thus, if a policy-maker's objective is to reduce consumption, bans longer than ℓ^0 will provide continued benefits after they expire, while bans shorter than ℓ^0 are undermined by post-ban increases in consumption. This latter prediction is not shared by the standard model based on adjacent complementarity, which predicts that any temporary ban would cause post-ban demand to drop, regardless of its duration. Consistent with the decision points model, Evans et al. (1999) find that daily consumption falls by less than the share of the time during the workday when a workplace smoking ban is instituted, implying that consumption increases outside working hours.

While a helpful start, measured adjacent substitution masks the richer description of interval-driven adjacent substitution. Further, because the endogenous intervals (and decision opportunity costs) are undetected, discrete-time measurement conceals the incentive to consume — regardless of dataset resolution. This is not a trivial omission considering theoretical interest in addiction largely stems from the challenge of explaining *why* a rational agent would consume harmful addictive products. As the agent's motivation is invariably hidden in a metronomic world, the next subsection examines how, in order to rationalize behavior, preferences are molded as they are revealed in discrete-time.

[27] Although adjacent complementarity is the centerpiece of Becker and Murphy's (1988) rational addiction theory, Becker (1992) informally provides the strongest acknowledgment of adjacent substitution in the microeconomic habit-formation literature: "if I just ate a filling dinner, I do not want to eat another dinner in the near future ... essentially all goods are substitutes if the time intervals are sufficiently close and the quantities consumed are big enough." While predominantly considered in the realm of eating, Becker's observation reflects the essence of Proposition 4 — that sufficiently small intervals will "measure" adjacent substitution.

4.2 *Inferring Preferences with "Omitted Decision Point" Bias*

Empirical analyses generally seek to understand observed behavior in terms of economic primitives. Hence, as a natural next step, preferences are inferred using the misspecified measurement framework. Given that the incentive remains concealed, the inferences will help us understand how harmful addictions are rationalized in models that presume metronomic decision-making. The procedure will "reveal" both static consumption preferences and time preferences, i.e. discounting. As will be addressed, Landry (2012b) documents two departures from the standard constant discounting assumption that are especially prominent in research on addiction: (i) *commodity-dependence*, as addicts appear exceedingly impatient to consume drugs, discounting future drugs much steeper than future money; and (ii) *endogenous time-preference*, as drug use appears to improve short-run patience and lessen patience in the long-run — this latter effect is inherent in theories of endogenous time preference in which addictive consumption steepens impatience (Becker and Mulligan, 1997; Orphanides and Zervos, 1998).[28]

As a conventional approach to infer preferences, consider a contemporaneous payoff function $U^+(C)$ and a decreasing future loss function $U^-(C)$ where C is demand in the current measurement period. For ease of exposition (and without loss of generality), the future loss occurs one time-unit after the payoff. Thus the composite return is:

$$U(C|\delta) = U^+(C) + \delta U^-(C).$$

This form reflects the usual contention that addictive consumption entails present benefits and future costs (beyond the indirect costs of habit reinforcement). Now suppose, with the true discount factor δ, the composite return accurately represents time-aggregated static

[28] A third and well-known constant discounting departure, time-inconsistency will not be formally addressed. Typically motivated by the demand for commitment, as in Gruber and Kőszegi's (2001) integration of quasi-hyperbolic discounting into rational addiction theory, time-inconsistent discounting is not covered for two reasons. First, as in Gruber and Kőszegi's framework, constant discounting and quasi-hyperbolic discounting are indistinguishable in the current estimation procedure. Second, commitment value has already been motivated from endogenous decision points without time-inconsistency.

consumption preferences.[29] Then $U(C_n|\delta)$ is any positive affine transformation of

$$\int_{T_n-\ell}^{T_n} \left[\frac{\delta^{t_i} u(c_i)}{t_i - t_{i-1}} : t_{i-1} < t \leq t_i \right] dt.$$

That is, with the correct δ, the composite return over time-aggregated demand is equivalent to the true time-aggregated direct returns from demand in the measurement period. Based on the known payoff and future loss functions, the *measured discount factor* for period-n, denoted by $\hat{\delta}_n$, is calculated from the empirical utility maximization problem:

$$\hat{\delta}_n = \{\delta_n : C_n = \arg\max_C \ U(C|\delta_n)\}.$$

Thus the measured discount factor is the discount factor for which observed demand appears to maximize utility. In turn, the *measured marginal utility of consumption* can be computed at any demand level from

$$U'(C|\hat{\delta}_n) = U^{(+)'}(C|\hat{\delta}_n) + \hat{\delta}_n U^{(-)'}(C|\hat{\delta}_n),$$

which characterizes the shape of the individual's inferred consumption preferences under time-aggregation.

The next result shows how ignoring decision points can account for apparent constant discounting departures, while shedding light on the inference of consumption preferences when "time" is misspecified.

Proposition 5 *Under NP, assume U^+ and U^- are both weakly concave.*
(i-a) [Impatience for Good] $\hat{\delta}_n < \delta$, *provided* $C_n > 0$.
(i-b) ["False Positive" Preferences] $U'(C|\hat{\delta}_n) > 0$ *for all* $C \in [0, C_n]$.
Given adjacent substitution holds for an addict:
(ii-a) [Endogenous Discounting] $\hat{\delta}_{n+1}$ *falls with* C_n *if* $\ell > \ell^0$, *and rises with* C_n *if* $\ell < \ell^0$, *where* ℓ^0 *is the substitution threshold in Proposition 4.*

[29] As used here, *static* consumption preferences means the choice is considered in isolation from future choices and thus reflects only the direct costs of consumption. The results derived from this specification are robust to inclusion of a future value term (along with $U^-(C)$) to account for indirect costs. A future value term is omitted for simplicity and also to adhere to common practice, as measured discount rates typically do not account for habit reinforcement (Frederick et al., 2002).

(ii-b) [Time-Inseparability] *For any* $C \geq 0$*:* $U'(C|\hat{\hat{\delta}}_{n+1})$ *increases with* C_n *if* $\ell > \ell^0$*, and decreases with* C_n *if* $\ell < \ell^0$*.*

Proposition 5 highlights four *omitted decision-point biases* arising in discrete-time; that is, to compensate for the measurement framework's exogenously-fixed intervals, the estimation misattributes decision-point influences to the discount and utility functions. Part (i-a) shows how consumption is justified by excessive impatience for the good, which reconciles commodity-dependent discounting since the estimate is less than the true δ (which is presumably measurable from outside choices). Consequently, positive consumption preferences are inferred in part (i-b), as future costs are seemingly neglected. Part (ii-a) captures both long- and short-run forms of endogenous discounting. Estimated patience falls with "yesterday's" demand if the period length is too large to detect adjacent substitution (otherwise, estimated patience rises). Because the discount factor enters the composite return, time-inseparable consumption preferences follow in part (ii-b).[30]

While matching regularities from empirical research, the inferences from Proposition 5 also relate to economic theory, as they encompass the default tools to explain bad habits in standard time. To start, the impatience-based rationalization of positive consumption preferences in part (i) — a reversal of the underlying NP assumption — resembles a key ingredient of rational addiction theory, which employs steep discounting to dilute the future harmful effects of consumption.[31] The long-run form of time-inseparability in part (ii-b) captures the second key ingredient: habit-formation preferences. This depiction of habit-formation preferences as an artifact has neuropsychological backing, as researchers find drugs are increasingly 'wanted' despite not being increasingly 'liked' as addiction develops.[32] The long-run form of endogenous discounting in (ii-a) reflects the history-dependent discount

[30]Apparent time-inseparability can also arise if, instead of taking U^+ as known and estimating δ, any $\delta > 0$ is presumed (whether correct or incorrect) and the form of U^+ is inferred.

[31]As Becker and Murphy (1988) explain: "this paper relies on a weak concept of rationality that does not rule out strong discounts of future events." This reliance is naturally motivated in light of standard time's exogenous decision schedule, as metronomic decision-making imposes a bound of sorts on rationality in that it grants agents no control over the timing of their own decisions. In this vein, endogenous decision points provides an added channel for optimization, which (as seen) permits a representation of harmful addiction with negative consumption preferences and a discount factor arbitrarily close to one (Proposition 4).

[32]In economic parlance, 'liking' naturally maps to the true consumption preference and 'wanting' to demand. The liking-wanting gap is a centerpiece of the incentive-sensitization addiction theory of Robinson and Berridge (1993). See Landry (2012b) for additional background and discussion.

functions used by Orphanides and Zervos (1998) and by Becker and Mulligan (1997).

Since discrete-time inferences from endogenous decision points resemble fundamentally different theoretical models, the exercise points back to the empirical limits of metronomic time. Hence, to accurately infer preferences while accounting for decision-point effects, it may be fruitful to collect real time data, to develop econometric techniques to tease out micro time structures, or to look more at time use surveys.

4.3 *Implications for Welfare*

As Proposition 5 helps convey, the decision points model has several implications for empirical welfare analysis. The general notion that measured preferences in discrete-time are not aligned with true preferences — as underscored by the inference of "false positive" preferences under NP — points to a potential complication for conventional static welfare analysis. Namely, it implies that preferences inferred from time-aggregated demand cannot be taken as a valid indicator of static well-being.[33] This complication is expected because the analyst can't "see" the welfare benefits of consumption in discrete-time. While it poses new challenges (i.e. data burdens) for empirical welfare calculations, the model also retains the classical link between choice and well-being, thus alleviating a common welfare concern in the addiction literature.[34] Namely, the model has an unambiguous welfare standard: the present value of lifetime utility, as given in (1).

As alluded to, the normative coherence of the decision points model is not necessarily compatible with the aforementioned "default" modeling tools. First, commodity-dependent discounting violates unitary time-preference, which precludes an objective standard to aggregate utilities over time.[35] The validity of welfare with habit-formation preferences has

[33] While they attribute this misalignment to "mistakes," Bernheim and Rangel (2004) also argue that preferences revealed from behavior can systematically diverge from true preferences.

[34] In an externality-free environment, there would be no role for taxation or other restrictions on consumption. However, if decision points arise due to phenomena other than cravings, policies that deter consumption can improve consumer welfare. For instance, if advertisements induce unwanted decision points, an advertising ban will benefit consumers. If peer consumption induces a decision point, consumption bans may similarly benefit consumers, especially if peer groups are large and heterogeneous with respect to habit strength — see Landry (2013) for details.

[35] That is, should utilities be aggregated according to the discount rate for cigarettes or the discount rate for money? Although commodity-dependence is not explicitly a feature of rational addiction theory, it is not unrelated either in light of estimated discount rates from empirical rational addiction analyses — 56 to 223 percent in Becker et al. (1994) — that dwarf "plausible" values, as implied by market rates of return on financial investments. Quasi-hyperbolic discounting models suffer from a similar problem in that it is unclear whether future utilities should be weighted by the "present bias" factor, which reflects the time-preferences of the "current self" but not the "future self."

also been questioned. For example, Pollak (1978) argues that the fundamental theorem of welfare economics — "that in competitive equilibrium everyone gets what he wants" — loses its normative significance under endogenous preferences, such as in his canonical habit-formation preferences model (Pollak, 1970), because the theorem may then be "no more than a corollary of the more general proposition that people come to want what they get."

5 EXTERNAL CUES

Exposure to an item or context associated with a behavior can act as a powerful impetus to do the behavior. For addiction, the significance of such external *cues*, e.g. an offer of a cigarette or the sight of an ashtray, is widely documented in psychology — see Caggiula et al. (2001) or Carpenter et al. (2009). This line of research has motivated economic cues models by Laibson (2001) and Bernheim and Rangel (2004). While the precise economic representation of a cue varies from model to model, stochasticness is a shared feature because cues introduce variance in consumption patterns (and long-term outcomes), as use is linked to seemingly random environmental factors.

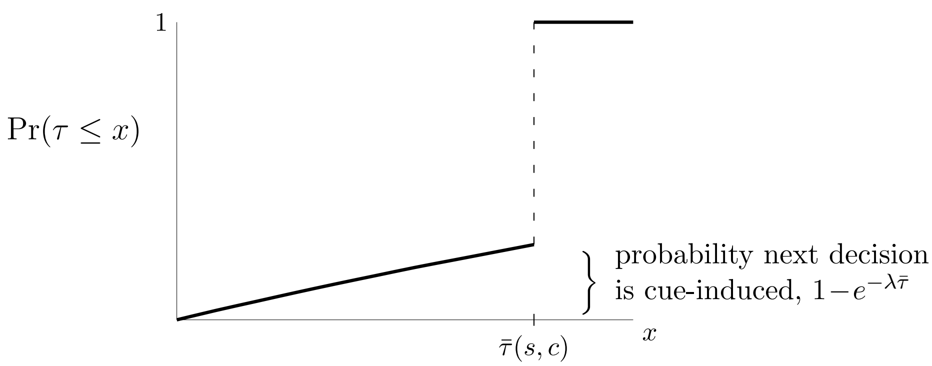
Although it can be difficult to differentiate a cue from a craving in isolation, a clear contrast emerges when comparing their roles across the habit spectrum.[36] That is, stochastic factors (i.e. external cues) are germane at low levels of dependence, yet deterministic forces appear to dominate in the realm of heavy addiction. A trademark of strong nicotine dependence is inflexible smoking patterns largely *uninfluenced* by environmental cues (Shiffman et al., 2004). Accordingly, consumption is more strongly associated with external cues for chippers than for addicts (Shiffman and Paty, 2006); this pattern "significantly distinguishes" addicts from chippers (Shiffman and Sayette, 2005).[37]

[36] Since external cues can elicit internal cravings, to avoid confusion, I use "craving" to refer to an urge with an internal origin and "cue" to refer to an urge with an external origin.

[37] The diminishing influence of external cues in the onset of addiction is also evident in the disproportionate effect of advertisements on younger, newer smokers. Pollay et al. (1996) estimate teenagers' sensitivity to cigarette advertisements is roughly triple that of adults. Furthermore, Cummings et al. (1997) find that over 90 percent of adolescent smokers (versus 35-40 percent of adults) smoke one of the top-three selling brands — Marlboro, Camel, and Newport, which are also the most heavily advertised — while generic brands, which use minimal advertising, capture a five-fold greater share of adult than adolescent demand.

5.1 *Cues as Decision Points*

The influence of a single cue is reminiscent of an internal craving: when a cue arises, the urge to consume suddenly materializes. In light of the similarities, external cues are modeled as (stochastic) decision points. As a simple baseline, assume cues have a fixed arrival rate $\lambda > 0$.[38] The deterministic element (cravings) is retained from the original model with the "natural" interval function $\bar{\tau}$, which is the time until the next decision if no cues arise in the interim. The true τ is now an exponential random variable parameterized by λ and right-censored at $\bar{\tau}$. Its cumulative distribution function is shown below:



The next lemma establishes an equivalence from the original, deterministic model to the new setup that combines stochastic cues with internal cravings.

Lemma 1 *Consider the stochastic cues model described above with arrival rate λ and natural interval function $\bar{\tau}$. Define*

$$\tau^0 = \frac{\ln\left[\left(\lambda - e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}}\right)/(\lambda - \ln(\delta))\right]}{\ln(\delta)}.$$

Then, given s_0, the optimal consumption sequence $(c_0, c_1, \ldots)$ with stochastic cues is the same as in the deterministic setting with the interval function τ^0.

Lemma 1 defines τ^0 as a "certainty equivalent" for the random interval function τ, in that the optimization problem with stochastic cues is the same as in the cravings-only model

[38]Two notes on fixed λ: first, the fixed arrival rate treats the duration of the interruption as negligible. Second, there are reasons to expect the true cue-arrival rate varies with s and c, e.g. smokers are likely exposed to smoking situations more often than nonsmokers. The results of the section are robust to an endogenous cue-arrival rate, provided its curvature is weak relative to the interval function's.

using τ^0. That is, at a decision point, the expected future value with cue-arrival rate λ and natural interval $\bar{\tau}(s,c)$ equals the known future value with $\tau^0(s,c)$, for all s,c. The lemma allows us to carry over previously-derived steady-states to the cues setting.[39] Hence steady-state terminology ("addicts" and "chippers") is maintained with the understanding that the corresponding habit stocks are those that would exist in the original model using τ^0.

5.2 *Random External Cues: Diminished Role under Addiction*

The next result compares the importance of stochastic cues between addicts and chippers:

Proposition 6 *The following are smaller for addicts than for chippers, ceteris paribus:*
(i) *the share of consumption that coincides with a stochastic cue.*
(ii) *the variance of τ.*

Proposition 6 implies that consumption schedules are less random and less associated with stochastic cues for addicts than for chippers, which holds because internal cravings are more frequent for stronger habits. The result matches the evidence that addicts have consistent, regimented patterns of drug use, while the influence of cues is more pronounced for occasional users, who have less predictable consumption routines.[40] Proposition 6 is robust to a degree of habit stock dependence in the cue-arrival rate — e.g. the addict may have a smaller share of consumption coinciding with a cue even if the addict's arrival rate exceeds the chipper's.[41]

The current treatment contrasts the emphasis on random external factors in recent cue-based economic theories. In Laibson's (2001) and Bernheim and Rangel's (2004) models, the path to addiction is marked by an escalating vulnerability to stochastic environmental cues. This runs counter to the evidence that consumption becomes predominantly driven by internal cravings as addiction develops, as the intervals between doses become shorter and

[39]As before, $s_{i+1} = (1-\sigma)s_i + \sigma c_i$ regardless of whether t_{i+1} is craving-induced or cue-induced (without this simplifying assumption, the deterministic equivalence is lost). In the new cues setting, Assumptions 1 and 2 are maintained for $\bar{\tau}$. Increasing λ from zero will have (qualitatively) the same effect on steady-states as increasing θ from zero, so that the existence of a chipper steady-state no longer requires Assumption NP.

[40]The variance of the consumption frequency, $\mathrm{Var}[\tau^{-1}]$ is not defined, but it would also be negatively correlated with s in the continuous limit under a discretization of time units. By contrast, for a cues-only model in which λ is an increasing function of the habit stock, $\mathrm{Var}[\tau^{-1}]$ is positively correlated with s for realistic values of λ. Further details are provided in the appendix of Landry (2012a).

[41]We can use the formula in Lemma 1 to define τ^0 from an endogenous cue-arrival rate, $\lambda(s,c)$, and τ^0 will still be a function of s and c only. Lemma 1's proof does not require fixed λ, hence the "certainty equivalent" interpretation of τ^0 remains valid and analysis can proceed as it would with fixed λ.

more predictable.

5.3 *Exogenous Cues as Deterrents to Consumption*

The next result shows that, for low-frequency cues, increasing the cue-arrival rate has polar effects on the two observable measures of habit strength:

Proposition 7 *There is a $\bar{\lambda} > 0$ such that, increasing λ with $\lambda \in [0, \bar{\lambda}]$ has the following effects (for both addicts and chippers):*
(i) *the expected consumption frequency rises,*
(ii) *the per-decision consumption level falls.*

From part (i), the consumption frequency rises with the cue-arrival rate, which holds mainly because more cues implies more decision points. However, consumption levels shrink from part (ii), which follows from the fact that, by competing with cravings, cues reduce the incentive to consume. For instance, raising c to some $c' > c$ elongates the natural interval to $\bar{\tau}(s, c') > \bar{\tau}(s, c)$, but a cue's arrival prior to $\bar{\tau}(s, c)$ negates the benefit of increasing c to c'.

When isolating the response to a single cue, part (ii) of Proposition 7 implies a "novelty effect" in that exposure to a rare cue induces a higher consumption level than a common cue. While the hypothesis has not been directly tested, Niaura et al. (1992) provide evidence that supports the basic prediction that "more" cues can reduce the propensity to consume, as exposure to an olfactory smoking cue reduces the urge to smoke when a visual cue is already present.[42] The following corollary predicts a related diminishing sensitivity effect in that, upon increasing the cue-arrival rate, subsequent per-occasion consumption levels fall over time.

Corollary 3 [Diminishing Sensitivity] *Given the conditions of Proposition 7, upon increasing λ, subsequent cue-induced consumption levels are strictly decreasing in their chronological order.*

[42] In this study, olfactory and visual cues refer, respectively, to the smell and sight of someone smoking. A laboratory subject would have less incentive to smoke when both cues are present if seeing precedes smelling or if the smell of smoke lingers beyond initial exposure because, when the visual cue arrives, the presence of the olfactory cue means it is unlikely that the next decision point will be craving-induced.

Hence, the first cue induces higher consumption than the second cue, which induces higher consumption than the third cue, and so on. This diminishing sensitivity occurs because the reduction in consumption levels with higher λ causes the habit stock to fall, which further reduces the next decision's consumption level, and matches experimental evidence that the responsiveness to smoking cues decreases with repeated exposure (LaRowe et al., 2007).

The capacity of frequent cues to deter consumption (conditional on the decision point) alludes to the reason Proposition 7 only applies for sufficiently low arrival rates. That is, as λ continues to rise, consumption levels tend to zero, implying that the consumption frequency (which initially rises with λ) tends to zero too:

Proposition 8 [Overexposure] *Fix $\theta > 0$ given NP. There is a $\bar{\bar{\lambda}} > 0$ such that $\lambda > \bar{\bar{\lambda}}$ implies $\tilde{c}(s) = 0$ for all s.*

Overexposure to cues can fully desensitize the individual in that the per-decision consumption level is zero when the cue-arrival rate is sufficiently large. Abstinence becomes optimal because, extending the logic from part (ii) of Proposition 7, sufficiently rapid cues can fully wipe out the incentive to consume by ensuring that the next decision will be cue-induced.[43] As with Proposition 6, the result deemphasizes the importance of cues for understanding behavior under addiction. That said, the result pertains specifically to *exogenous* cues, as abstinence is justified by the individual's helplessness against the barrage of cues. While some cues in reality may come and go regardless of the individual's choice, the next subsection describes how a special type of cue can feature a strong dependence on past choices, which gives rise to starkly different implications than exogenous cues for behavior and for long-run outcomes.

5.4 *The Good as a Persistent Cue*

The motivational force of a cue is commonly attributed to the notion that cues signal the *availability* of the good.[44] Therefore, the *good* itself ought to be a cue. Presuming uncon-

[43]Cues can also reduce and even eliminate (as $\lambda \to \infty$) the indirect disincentive to consume due to $\tau_s < 0$. Since choices only matter through their effect on future cravings under ZP, consumption choices cease to affect utility as $\lambda \to \infty$, so that any $c \in [0, 1]$ is a solution. This indeterminacy is why Proposition 8 only applies to NP (in which case the direct disincentive due to $u'(c) < 0$ is preserved even as $\lambda \to \infty$).

[44]The importance of availability in cue effectiveness is addressed by Droungas et al. (1995), Juliano and Brandon (1998), and Carter and Tiffany (2001).

sumed quantities do not perish, a modification is needed to represent the good as a cue because unlike the good, cues come and go regardless of chosen consumption in the existing setup. To incorporate its persistence, suppose $a(t)$ is the amount of the good that is immediately accessible at t and $\lambda^a > \lambda$ is the cue-arrival rate at all t with $a(t) > 0$, where λ now denotes the arrival rate when $a(t) = 0$. If the amount of the good at some decision point is positive and slightly greater than the "usual" optimal consumption level (without the good as a cue), then it is optimal to consume all of the good: $c_i = a(t_i) > \tilde{c}(s_i)$, where $\tilde{c}$ is maintained as the optimal consumption function without cue-persistence. Access to the good creates an imperative to raise consumption because the unconsumed good invites a heightened arrival rate, from λ to λ^a.[45]

Because its persistence motivates higher than usual consumption, access to the good can precipitate undesirable long-run outcomes. For instance, addiction becomes inevitable for an otherwise ambivalent chipper who consumes $a > s_L^*$, or even for a "recovering" user on the path to abstention with $s < s_L^*$, provided $(1-\sigma)s + \sigma a > s_L^*$. These observations fit with evidence that the physical presence of the good often drives smoking and alcohol relapses (Niaura et al., 1988). Furthermore, the incentive to consume no longer relies on the "soft persistence" of internal cravings, which is consistent with the finding that cigarette cues undercut the effectiveness of quitting aids that inhibit internal cravings, such as the nicotine patch.[46] Because immediate access to large quantities is especially burdensome, the good as a decision point also offers a rationale for why, despite a price premium, smokers commonly buy packs of cigarettes instead of cartons (Khwaja et al., 2007).

As mentioned in Section 3.2, since a decision point is a requisite for consumption, commitment is inherent in any method to prevent decision points. It follows that cue avoidance represents a valuable form of commitment.[47] Moreover, the commitment value associated with avoiding a cue is largely commensurate to the cue's tendency to persist in the face of

[45]The concept parallels Fudenberg and Levine's (2012) consideration of persistent temptations. In their model, an agent suffers a continual cost from the availability of a persistently tempting good (until it is gone). Consequently, it is "easier to resist" a fleeting temptation than a persistent temptation.

[46]In Waters et al. (2004), abstinent smokers randomized to a nicotine patch or placebo were given a cigarette and instructed to hold it as if they were between puffs. The patch lowered baseline urge to smoke, but it did not attenuate the spike in the urge from holding a cigarette. As the authors write, "abstinence-related urges and cue-provoked urges may have different origins and might be treated differently."

[47]Commitment is likewise valuable when it reduces undesirable cues in the prevailing cue theories, as cues can be hedonically aversive in Laibson (2001), while cues trigger mistaken consumption in Bernheim and Rangel (2004).

abstinence. With the good as a persistent cue, eliminating access can be a viable commitment strategy to reduce the frequency of decision points. This example also illustrates how the two main requisites for consumption — the availability of the good and a decision point — can be intertwined. Since availability is desirable conditional on the sequence of decision points, yet the decision point sequence can be worsened by availability, it is not clear cut whether availability helps more than it hurts.

6 CONCLUSIONS

The *decision* is arguably the single greatest restriction on a choice — when a decision presents itself, an incomprehensible universe of possibilities has already been whittled down to some "manageable set." This paper departs from the practice that takes decisions as given, proposing a few ideas to explain where decisions for bad habits may come from, why decisions arise when they do, and how choices can influence the timing of future decisions. The framework provides an alternative to standard time's inherent "metronomism," which, as argued, is an overlooked imposition that limits the range and explanatory power of economic models.

From the general notion of a "cue" — exposure to an item or context associated with a behavior — new decision point models can be readily motivated. For instance, *advertisements* can be modeled as decision points. Advertisements and other promotional strategies appear to be especially important in explaining where individuals' first decision points often come from. Consistent with the tobacco industry's youth-targeting strategies, advertising to a child who has never actively considered smoking (even if aware that cigarettes exist) can rouse a profitable new habit, simply by inducing the initial decision point t_0.[48] The use of decision points to recruit new customers similarly fits with DiFranza and McAfee's (1992) observation that the tobacco industry "repeats the word 'decision' like a mantra." Even industry "prevention" programs appear to be a sly method of propagating decision points among susceptible youth, as they consistently draw attention to the *decision* to smoke.[49] For

[48]Marketers of Camel cigarettes have proven particularly adept at making inroads with the very young, as over 90 percent of six-year olds knew the smoking cartoon "Joe Camel" (Camel's ex-mascot) — a recognition level on par with Mickey Mouse — in a study by Fischer et al. (1991).

[49]Landman et al. (2002) classify the portrayal of smoking as an "adult decision" as the overarching theme of youth-directed industry programs. The authors also report that Philip Morris (sellers of Marlboro's) conducted over 130

instance, the Tobacco Institute's first educational program, *Helping Youth Decide*, purports to help "young teenagers learn to make more of their own decisions."

A follow-up to this paper, Landry (2013), considers endogenous decision points in a multi-agent setting in which *peer consumption* is a decision point. The group model predicts three commonly-observed aspects of conformity that appear to underly the standard propensity measure of peer effects: (i) herd-behavior within groups, e.g. one individual's idiosyncratic choice to try an addictive good can lead her peers to likewise consume for the first time; (ii) self-sorting into homogeneous groups, driven by the desire of infrequent users to avoid frequent users due to the frequent, unwanted decision points they inflict on their peers; and (iii) synchronization of consumption, as exemplified by the prevalence of social smokers who predominantly smoke in unison with others. This decision point approach to social interactions also motivates insistent *peer pressure* and shows how, by relenting only when its target agrees to consume, peer pressure incentivizes consumption in a similar manner as cravings (or, for that matter, the unconsumed good as a cue).

The decision point appears to be a versatile modeling device, capable of unifying a wide range of phenomena that are important in the realm of bad habits. Surveying the existing literatures in economics on habits, addiction, advertising, and social interactions, a consistent pattern is revealed, as the prevailing approaches fall into one of two categories: (i) models that are based on endogenous (or otherwise nonstandard) preferences, and (ii) models that work through information or beliefs. While its usefulness in contexts besides "bad habits" remains unexplored, the decision point therefore represents an alternate tool that may offer a new understanding of behaviors that are currently captured through preference- or information-based models.

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youth "prevention" campaigns in over 70 countries, as of 2001. Unsurprisingly, Farrelly et al. (2002) find intentions to smoke rise after exposure to a Philip Morris youth anti-smoking campaign.

A APPENDIX

A.1 *Derivation of the Euler Equation*

The Euler equation (6) is derived from the Bellman equation (3), the first-order condition (4), and the envelope condition (5) as follows: First, substitute out V'^{+} in (5) using (4). Second, in the new expression for (5), iterate every term forward one decision. Again, substitute out V'^{+} (after the iteration) using (4). Third, substitute out V^{++} using (3) once-iterated — i.e. using the Bellman with the left-side set to V^{+}. After solving for V^{+}, insert the expression and its once-iterated variant for V^{++} into the left- and right-sides, respectively, of (3) to get the Euler equation (6). Note, the left-side of the Euler equation is the absolute value of the next-decision value function $-V^{+} > 0$.

A.2 *Proof of Proposition* 1

It will help to work with the following change-of-variables, substituting out consumption, and instead allowing consecutive habit stock variables enter as the arguments of the interval function:

$$\check{\tau}(s_i, s_{i+1}) = \tau(s_i, c_i) = \tau\big(s_i, \tfrac{s_{i+1}-(1-\sigma)s_i}{\sigma}\big)$$

To denote the partial derivatives of the newly-expressed interval function, the subscripts 1 and 2 are used for the current and the next-decision habit stocks, respectively:

$$\begin{aligned}
\check{\tau}_1(s_i, s_{i+1}) &= \frac{\partial\check{\tau}(s_i, s_{i+1})}{\partial s_i} = \tau_s(s_i, c_i) - \frac{(1-\sigma)\tau_c(s_i, c_i)}{\sigma} \\
\check{\tau}_2(s_i, s_{i+1}) &= \frac{\partial\check{\tau}(s_i, s_{i+1})}{\partial s_{i+1}} = \frac{\tau_c(s_i, c_i)}{\sigma}.
\end{aligned}$$

Expressing the problem in terms of the habit stock sequence only, the Bellman (under ZP) is

$$V(s_i) = -1 + \max_{s_{i+1}}\{\delta^{\check{\tau}(s_i, s_{i+1})} V(s_{i+1})\},$$

where $s_{i+1} \in [(1-\sigma)s_i, (1-\sigma)s_i + \sigma]$. The corresponding first-order and envelope conditions are, in order:

$$\begin{aligned} 0 &= V'(s_{i+1}) + \ln(\delta)\check{\tau}_2(s_i, s_{i+1})V(s_{i+1}) \\ V'(s_i) &= \ln(\delta)\check{\tau}_1(s_i, s_{i+1})\delta^{\check{\tau}(s_i, s_{i+1})}V(s_{i+1}) \end{aligned}$$

Plugging the once-iterated envelope condition into the first-order condition (to eliminate $V'(s_{i+1})$), then substituting out $V(s_{i+2})$ using the once-iterated Bellman, and rearranging gives

$$V(s_{i+1}) = \frac{-\check{\tau}_1(s_{i+1}, s_{i+2})}{\check{\tau}_1(s_{i+1}, s_{i+2}) + \check{\tau}_2(s_i, s_{i+1})}.$$

Plugging the above expression and its once-iterated version into the once-iterated Bellman gives the Euler equation:

$$\frac{\check{\tau}_1(s_{i+1}, s_{i+2})}{\check{\tau}_1(s_{i+1}, s_{i+2}) + \check{\tau}_2(s_i, s_{i+1})} = 1 + \frac{\delta^{\check{\tau}(s_{i+1}, s_{i+2})}\check{\tau}_1(s_{i+2}, s_{i+3})}{\check{\tau}_1(s_{i+2}, s_{i+3}) + \check{\tau}_2(s_{i+1}, s_{i+2})} \tag{9}$$

By undoing the change-of-variables so that the above is expressed in terms of τ, τ_s, and τ_c instead of $\check{\tau}$, $\check{\tau}_1$, $\check{\tau}_2$, etc., it is readily verifiable that equation (9) is equivalent to the original Euler equation (6).

Let $\{s_i^*\} = (s_0^*, s_1^*, \ldots)$ denote the sequence that satisfies equation (9) given $s_0^* = s_0$, and let $\{s_i\}_{i=0}^{\infty} = (s_0, s_1, \ldots)$ be any other feasible sequence of habit stocks (in which $s_{i+1} \in [(1-\sigma)s_i, (1-\sigma)s_i + \sigma]$ for all $i = 0, 1, \ldots$) given s_0. Now let D define the difference between the lifetime utilities with $\{s_i^*\}$ and with $\{s_i\}$:

$$D = \sum_{i=0}^{I} \delta^{t_i} - \delta^{t_i^*}$$

To show that the sequence that satisfies the Euler equation, $\{s_i^*\}$, is optimal, it suffices to show that $D \geq 0$. By concavity of $-\delta^{\check{\tau}}$, and with $s_0^* - s_0 = 0$, we have

$$D \geq \lim_{I\to\infty} \sum_{i=1}^{I} \left[\sum_{k=0}^{i} -\frac{\partial \delta^{t_i^*}}{\partial s_k^*} \cdot (s_k^* - s_k) \right]$$

$$= \lim_{I\to\infty} \sum_{i=1}^{I} \ln(\delta)\delta^{t_i^*} \left[\check{\tau}_1(s_i^*, s_{i+1}^*)(s_i^* - s_i) - \sum_{k=1}^{i} (\check{\tau}_1(s_k^*, s_{k+1}^*) + \check{\tau}_2(s_{k-1}^*, s_k^*))(s_k^* - s_k) \right]$$

Factoring out $-\ln(\delta)$ and collecting each $s_i^* - s_i$ term, we get

$$D \propto \lim_{I\to\infty} \sum_{i=1}^{I} \delta^{t_i^*} \left[\check{\tau}_1(s_i^*, s_{i+1}^*) \delta^{\check{\tau}(s_i^*, s_{i+1}^*)} \left(\sum_{j=i+1}^{I} \delta^{t_j^* - t_{i+1}^*} \right) \right.$$

$$\left. + \check{\tau}_2(s_{i-1}^*, s_i^*) \left(\sum_{j=i}^{I} \delta^{t_j^* - t_i^*} \right) \right] (s_i^* - s_i)$$

$$= \lim_{I\to\infty} \sum_{i=1}^{I} \delta^{t_i^*} \left[\check{\tau}_1(s_i^*, s_{i+1}^*) \left(\sum_{j=i+1}^{I} \delta^{t_j^* - t_i^*} \right) + \check{\tau}_2(s_{i-1}^*, s_i^*) \left(\sum_{j=i}^{I} \delta^{t_j^* - t_i^*} \right) \right] (s_i^* - s_i)$$

$$= \lim_{I\to\infty} \sum_{i=1}^{I} \delta^{t_i^*} \left[\check{\tau}_1(s_i^*, s_{i+1}^*) \left(-1 + \sum_{j=i}^{I} \delta^{t_j^* - t_i^*} \right) + \check{\tau}_2(s_{i-1}^*, s_i^*) \sum_{j=i}^{I} \delta^{t_j^* - t_i^*} \right] (s_i^* - s_i).$$

Now if we define

$$X_i = \sum_{j=I+1}^{\infty} \delta^{t_j^* - t_i^*}, \qquad \text{so that} \quad \lim_{I\to\infty} X_i = 0, \quad \text{for all } i.$$

Then we can use:

$$\sum_{j=i}^{\infty} \delta^{t_j^* - t_i^*} = \frac{\check{\tau}_1(s_i^*, s_{i+1}^*)}{\check{\tau}_1(s_i^*, s_{i+1}^*) + \check{\tau}_2(s_{i-1}^*, s_i^*)}$$

which gives

$$D \geq \lim_{I\to\infty} \sum_{i=1}^{I} \delta^{t_i^*} \left[\check{\tau}_1(s_i^*, s_{i+1}^*) \left(-\frac{\check{\tau}_2(s_{i-1}^*, s_i^*)}{\check{\tau}_1(s_i^*, s_{i+1}^*) + \check{\tau}_2(s_{i-1}^*, s_i^*)} - X_i \right) \right.$$

$$\left. + \check{\tau}_2(s_{i-1}^*, s_i^*) \left(\frac{\check{\tau}_1(s_i^*, s_{i+1}^*)}{\check{\tau}_1(s_i^*, s_{i+1}^*) + \check{\tau}_2(s_{i-1}^*, s_i^*)} - X_i \right) \right] (s_i^* - s_i)$$

$$= \lim_{I\to\infty} \left\{ -\sum_{i=1}^{I} \delta^{t_i^*} \left[\check{\tau}_1(s_i^*, s_{i+1}^*) + \check{\tau}_2(s_{i-1}^*, s_i^*) \right] X_i (s_i^* - s_i) \right\} = 0$$

Hence the Euler equation (6) is sufficient for the optimal consumption sequence. Thus, the steady-state condition derived from the Euler equation, $\bar{\mu}(s) = 0$, is sufficient for an interior steady-state. It follows that $\bar{\mu}(0) = 0$ guarantees $s = 0$ is a steady-state and $\bar{\mu}'(0) > 0$ guarantees its instability. From continuity of $\bar{\mu}$ (along with $\bar{\mu}(0) = 0$, $\bar{\mu}'(0) > 0$, and $\bar{\mu}(1) > 0$) an interior steady-state is guaranteed since $\bar{\mu}(s)$ must equal zero for some $s \in (0,1)$. Its uniqueness is guaranteed from $\bar{\mu}(s') < 0$ for $s' > s > 0$ given $\bar{\mu}(s) = 0$. Since $\bar{\mu}(s)$ crosses zero from above, the unique interior steady-state is stable. ■

A.3 *Proof of Corollary* 1

A.3.1 *Proof of Corollary* 1*, part (i)*

The fact that $\tilde{c}(s)$ is increasing at s^* follows from $\mu_s(s^*, c^*) > 0$. That is, since marginal returns to consumption are zero at $s^* = c^*$, $\mu_s(s^*, c^*) > 0$ implies marginal returns rise above zero as s increases from s^* (and marginal returns fall below zero as s decreases from s^*).

For $\tilde{c}(s)$ to be increasing in s for all s, we would need the Bellman's maximization argument, $\delta^{\tau(s,c)}V((1-\sigma)s + \sigma c)$, to be supermodular, i.e. satisfying the property of increasing differences. That is, for any $c' > c$, if

$$\delta^{\tau(s,c')}V((1-\sigma)s + \sigma c') - \delta^{\tau(s,c)}V((1-\sigma)s + \sigma c)$$

is increasing in s, Topkis' Theorem (Topkis, 1978) establishes the desired monotonicity in $\tilde{c}(s)$. Hence, we need

$$\delta^{\tau(s,c')}V[(1-\sigma)s + \sigma c'] - \delta^{\tau(s,c)}V[(1-\sigma)s + \sigma c]$$

to be increasing in s, i.e.

$$\begin{aligned} &(1-\sigma)\delta^{\tau(s,c')}V'[(1-\sigma)s + \sigma c'] + \tfrac{\partial}{\partial s}[\delta^{\tau(s,c')}]V[(1-\sigma)s + \sigma c'] \\ &- (1-\sigma)\delta^{\tau(s,c)}V'[(1-\sigma)s + \sigma c] - \tfrac{\partial}{\partial s}[\delta^{\tau(s,c)}]V[(1-\sigma)s + \sigma c] \ > \ 0. \end{aligned} \tag{10}$$

If we define:

$$\Delta V(y,e) = V(y+e) - V(y)$$

$$\Delta V'(y,e) = V'(y+e) - V'(y),$$

Then rearranging terms in (10) gives:

$$\begin{aligned} &(1-\sigma)\big(\delta^{\tau(s,c')}-\delta^{\tau(s,c)}\big)V'[(1-\sigma)s+\sigma c']+\big(\tfrac{\partial}{\partial s}[\delta^{\tau(s,c')}-\delta^{\tau(s,c)}]\big)V[(1-\sigma)s+\sigma c'] \\ &\quad + \tfrac{\partial \delta^{\tau(s,c)}}{\partial s}\big[(1-\sigma)\Delta V'[(1-\sigma)s+\sigma c, \sigma(c'-c)]+\Delta V[(1-\sigma)s+\sigma c, \sigma(c'-c)]\big] > 0 \end{aligned} \tag{11}$$

as the condition for supermodularity. The limit of the left-side of (11) as σ tends to zero is

$$(\delta^{\tau(s,c')} - \delta^{\tau(s,c)})V'(s) + \tfrac{\partial}{\partial s}[\delta^{\tau(s,c')} - \delta^{\tau(s,c)}]V(s),$$

where ΔV and $\Delta V'$ both converged to zero with σ.

We know $\tau_c > 0$, which implies $\delta^{\tau(s,c')} - \delta^{\tau(s,c)} < 0$. Therefore $(\delta^{\tau(s,c')} - \delta^{\tau(s,c)})V'(s) > 0$. We know $\frac{\partial^2}{\partial s \partial c}[-\delta^{\tau}] > 0$, which implies $\frac{\partial}{\partial s}[\delta^{\tau(s,c')} - \delta^{\tau(s,c)}] < 0$. Therefore $\frac{\partial}{\partial s}[\delta^{\tau(s,c')} - \delta^{\tau(s,c)}]V(s) > 0$. Since both terms are positive, supermodularity holds and from Topkis' Theorem, $\tilde{c}(s)$ must be increasing at all s for sufficiently small σ. ■

A.3.2 *Proof of Corollary* 1*, part (ii)*

Take $s \in (0, s^*)$. Since $\bar{\mu}(s^*) = 0$, $\bar{\mu}(s) > 0$. It follows that $\tilde{c}(s) > s$, which implies $\tau(s,s) < \tau(s, \tilde{c}(s))$ because $\tau_c > 0$. Since $\tau(s^*, s^*) < \tau(s,s)$ given $s^* > s$, this gives $\tau(s, \tilde{c}(s)) > \tau(s^*, s^*)$.

Alternatively, take $s' \in (s^*, 1]$. Since $\bar{\mu}(s^*) = 0$ with $s' > s^* > 0$, $\bar{\mu}(s') < 0$. Therefore $\tilde{c}(s') < s'$, which implies $\tau(s', s') > \tau(s', \tilde{c}(s'))$ (again because $\tau_c > 0$). Since $\tau(s^*, s^*) > \tau(s', s')$ given $s^* < s'$, this gives $\tau(s^*, s^*) > \tau(s', \tilde{c}(s'))$. ■

A.4 *Proof of Proposition* 2

Note NP holds for any result, provided it holds in the limit as $\theta \to 0^+$. Thus if a result holds for ZP, it also holds for NP, unless there is a discontinuity — whether mathematical or in a qualitative property — at $\theta = 0$.

From the NP Bellman, given by $V(s) = -1 + \max_c \{u(c|\theta) + \delta^{\tau(s,c)}V((1-\sigma)s + \sigma c)\}$, we can derive the first-order and envelope conditions:

$$\begin{aligned} 0 &= u'(c_i|\theta) + \delta^{\tau(s_i,c_i)}[\sigma V'(s_{i+1}) + \ln(\delta)\tau_c(s_i,c_i)V(s_{i+1})], \\ \text{and} \qquad V'(s_i) &= \delta^{\tau(s_i,c_i)}[(1-\sigma)V'(s_{i+1}) + \ln(\delta)\tau_s(s_i,c_i)V(s_{i+1})]. \end{aligned}$$

Setting $c = s$ throughout, we can derive the steady-state condition. Define

$$\bar{\mu}^{\theta}(s) = \bar{\mu}(s) + \frac{u'(s|\theta)[1-(1-\sigma)\delta^{\tau(s,s)}]}{(1-\delta^{\tau(s,s)})(1-u(s|\theta))} < \bar{\mu}(s)$$

It is readily verifiable that $\bar{\mu}^{\theta}(s)$ is the NP movement function analog so that $\bar{\mu}^{\theta}(s) = 0$ implies s is a steady-state under NP. Its derivative is

$$\bar{\mu}^{\theta'}(s) = \bar{\mu}'(s) + \frac{\sigma(\tau_s+\tau_c)\ln(\delta)\delta^{\tau}u'}{(1-\delta^{\tau})^2(1-u)} + \frac{(1-(1-\sigma)\delta^{\tau})[(u')^2+(1-u)u'']}{(1-\delta^{\tau})(1-u)^2,}$$

where τ and its partial derivatives are all evaluated at $c = s$. Taking the small θ limit, all u terms (including derivatives) converge to zero since u is twice continuously differentiable in both arguments with $u(c|0) = u'(c|0) = 0$.

Therefore $\lim_{\theta\to 0^+}\bar{\mu}^{\theta}(s) = \bar{\mu}(s)$ and $\lim_{\theta\to 0^+}\bar{\mu}^{\theta'}(s) = \bar{\mu}'(s)$, i.e. the NP movement function converges to the ZP movement function in the small θ limit. Since $\bar{\mu}^{\theta'}(0) < 0$ for any $\theta > 0$, the marginal returns to consumption from $c = 0$ at zero-habit with $\theta > 0$ is strictly less than the marginal returns with $\theta = 0$. Therefore, at zero-habit optimal consumption is zero (now $c \in [0, 1]$ binds), so $s = 0$ remains a steady-state.

By continuous differentiability and convergence of $\bar{\mu}^{\theta}(s)$ to $\bar{\mu}(s)$ as $\theta \to 0^+$ with $\bar{\mu}'(0) > 0$ and $\bar{\mu}$'s single-crossing property for all $s > 0$: there is a $\theta_1 > 0$ such that $\theta < \theta_1$ implies $\max_s\{\bar{\mu}^{\theta}(s)\} > 0$; and there is a $\theta_2 > 0$ such that $\theta < \theta_2$ implies $\max_s\{\bar{\mu}^{\theta'}(0)\} > 0$. With $\bar{\mu}^{\theta}(s) < \bar{\mu}(s)$, it follows that for sufficiently small θ, $\theta < \min\{\theta_1, \theta_2\}$, there is an interval $[a, b]$ with $0 < a < b < s^* < 1$ such that $\bar{\mu}^{\theta}(s) \geq 0$ if and only if $s \in [a, b]$, where $\bar{\mu}^{\theta}(s) = 0$ if and only if $s \in \{a, b\}$. In turn, given small $\theta > 0$, a must be the unique unstable steady-state since $\bar{\mu}^{\theta'}(a) > 0$ and b must be the unique stable interior steady-state since $\bar{\mu}^{\theta'}(b) < 0$ by convergence to $\bar{\mu}$. ■

A.5 *Proof of Proposition 3*

Rearranging the ZP steady-state expression, $\bar{\mu} = 0$, gives:

$$\delta = [1 - \sigma(\tau_s/\tau_c + 1)]^{-1/\tau}, \tag{12}$$

where all terms are evaluated at the addicted steady-state. Since $\tau_s + \tau_c < 0$ at a steady-state where $\tau_c > 0$ (Assumption 1), it follows that $\delta \in (0,1)$ for $\sigma \in (0,1)$. It also follows that higher σ implies lower δ, ceteris paribus, as can be seen from differentiating the right-side of (12) with respect to σ, i.e. $[1 - \sigma(\tau_s/\tau_c + 1)]^{-\frac{1+\tau}{\tau}} \tau^{-1}(\tau_s/\tau_c + 1) < 0$. ■

A.6 *Proof of Corollary 2*

MRAS in a steady-state is $(\tau^*)^{-2}[-\sigma\tau^*\tilde{c}'(s^*) + s^*\tau_c^*]$.[50] Observe MRAS is monotonic in σ and its limit is positive as $\sigma \to 0$. Consider two cases:

Case 1. $\tilde{c}'(s^*) \leq \frac{s^*\tau_c^*}{\tau^*}$. In this case, MRAS is positive for all $\sigma \in (0,1)$. Then let $\bar{\delta} = \left(\frac{-\tau_c^*}{\tau_s^*}\right)^{1/\tau^*}$, which is the δ that satisfies the steady-state equation for $\sigma = 1$. It follows that the steady-state exists and adjacent substitution holds for all $\delta \in (\bar{\delta}, 1)$, as desired.

Case 2. $\tilde{c}'(s^*) > \frac{s^*\tau_c^*}{\tau^*}$. In this case, the MRAS is negative for $\sigma = 1$. Since MRAS is linearly decreasing in σ and is positive for $\sigma = 0$, there must be a $\sigma \in (0,1)$ such that MRAS is zero. Observe MRAS is zero for $\sigma = \frac{s^*\tau_c^*}{\tau^*\tilde{c}'(s^*)}$. Let the threshold discount factor be that which corresponds to zero MRAS, i.e. $\bar{\delta} = \left(1 - \frac{s^*(\tau_s^*+\tau_c^*)}{\tau^*\tilde{c}'(s^*)}\right)^{-1/\tau^*}$. Then the steady-state exists and adjacent substitution holds for all $\delta \in (\bar{\delta}, 1)$, as desired. ■

A.7 *Proof of Proposition 4*

Without loss of generality, suppose $n = i = 0$ and $T_0 = t_0 = 0$. Let $I = \max i : t_i < \ell$, i.e. t_I is the last decision point in the interior of the measured demand period. For notational

[50] As in this proof, comparative statics are expressed using (partial) derivatives for clarity. However, all proofs can be worked out without drawing on differentiability in the same way except replacing any partial derivative $\partial f(c,\cdot)/\partial c$ with $(f(c',\cdot) - f(c,\cdot))/(c' - c)$ for c' sufficiently close to c (where the signs are the same if $c' > c$ and reversed if $c' < c$), and $\tilde{c}'(s)$ by $(\tilde{c}(s') - \tilde{c}(s))/(s' - s)$, where s' is the habit stock associated with c'. In this proof, for instance, the condition for adjacent substitution would become $c^*/\tau^* < \tilde{c}((1-\sigma)s^* + \sigma c)/\tau(s^*, c)$ for $c < c^*$ (and the reverse for $c > c^*$).

ease, first consider the ZP case. Then

$$C_1 \;=\; \frac{1}{\ell}\int_0^\ell x(i: t_{i-1} < t \leq t_i)dt \quad = \frac{1}{\ell}\left(\sum_{i=1}^{I} c_i\right) + \frac{(\ell - t_I)c_{I+1}}{\ell\tau(s_I, c_I)}.$$

Now measured adjacent substitution (complementarity) holds if the measured MRAS is positive (negative). Since only sign matters, these conditions are equivalent if the measured MRAS is multiplied by the constant $\ell > 0$ (replacing mean with total demand in the numerator). That is, measured adjacent substitution holds if $-\frac{\partial[\ell \cdot C_1]}{\partial c_0} > 0$. For any $\ell < \tau^*$, measured adjacent substitution is satisfied because $-\frac{\partial[\ell \cdot C_1]}{\partial c_0} > 0$ iff $-\frac{\partial[\ell \cdot x(1)\tau^*]}{\partial c_0} > 0$ iff $-\frac{\partial x(1)}{\partial c_0} > 0$, which holds by assumption.

Since $\frac{\partial c_k}{\partial c_0} = \tilde{c}'(s^*)\frac{\partial s_k}{\partial c_0}$ and $\frac{\partial s_1}{\partial c_0} = \sigma$, it follows from the stock transitions that the marginal effect of c_0 on future variables is:

$$\begin{aligned}
\frac{\partial s_k}{\partial c_0} &= \sigma[(1-\sigma) + \sigma\tilde{c}'(s^*)]^{k-1} \\
\frac{\partial c_k}{\partial c_0} &= \sigma\tilde{c}'(s^*)[(1-\sigma) + \sigma\tilde{c}'(s^*)]^{k-1}.
\end{aligned}$$

With $\frac{\partial t_1}{\partial c_0} = \tau_c^*$, the effect on future decision points is:

$$\frac{\partial t_{k+1}}{\partial c_0} \;=\; \frac{\partial t_k}{\partial c_0} + \frac{\partial \tau(s_k, c_k)}{\partial c_0} \;=\; \frac{\partial t_k}{\partial c_0} + \tau_s^*\frac{\partial s_k}{\partial c_0} + \tau_c^*\frac{\partial c_k}{\partial c_0}$$

which, for all $k \geq 2$, can alternatively be expressed as

$$\frac{\partial t_k}{\partial c_0} \;=\; \tau_c^* + (\tau_s^* + \tilde{c}'(s^*)\tau_c^*)\frac{1 - [(1-\sigma) + \sigma\tilde{c}'(s^*)]^{k-1}}{1 - \tilde{c}'(s^*)}$$

Now $\bar{\mu}'(s^*) < 0$, which follows from $\bar{\mu}(s) < 0$ for $s > s^*$ ($\bar{\mu}$'s single crossing property above $s = 0$). It follows that $\tilde{c}'(s^*) < 1$ since $\tilde{c}(s^* + \epsilon) < s^* + \epsilon$ for $\epsilon > 0$. Therefore, since $\tilde{c}(s^*)$ is increasing in s, $[(1-\sigma) + \sigma\tilde{c}'(s^*)] \in (0, 1)$, so that

$$0 < \frac{\partial s_{k+1}}{\partial c_0} < \frac{\partial s_k}{\partial c_0} \quad \text{and} \quad 0 < \frac{\partial c_{k+1}}{\partial c_0} < \frac{\partial c_k}{\partial c_0} < 0, \quad \text{for all } k \geq 1.$$

Since $\frac{\partial \tau(s_k, c_k)}{\partial c_0} = \sigma(\tau_s^* + \tilde{c}'(s^*)\tau_c^*)[(1-\sigma) + \sigma\tilde{c}'(s^*)]^{k-1}$ with $\tau_s^* + \tilde{c}'(s^*)\tau_c^* < \tau_s^* + \tau_c^* < 0$, we have

$$0 > \frac{\partial \tau(s_{k+1}, c_{k+1})}{\partial c_0} > \frac{\partial \tau(s_k, c_k)}{\partial c_0}, \quad \text{for all } k \geq 1.$$

One implication of this inequality is that $\frac{\partial t_k}{\partial c_0} < 0$ implies $\frac{\partial t_{k+1}}{\partial c_0} < 0$.

Lemma 2 *There is a $\bar{k} > 1$ such that $\frac{\partial t_{\bar{k}}}{\partial c_0} < 0$.*

A.7.1 *Proof of Lemma 2*

Suppose not. Then $\frac{\partial t_k}{\partial c_0} > 0$ for all $k > 1$. Since lifetime utility under ZP is $U = -\sum \delta^{t_i}$, $\frac{\partial U}{\partial c_0} = -\ln(\delta) \sum \frac{\partial t_i}{\partial c_0} \delta^{t_i} > 0$. Therefore, lifetime utility is increasing in c_0, which contradicts the optimality of the steady-state consumption. Therefore the lemma holds. ■

Now,

$$\frac{\partial [\ell C_1]}{\partial c_0} = \sum_{i=1}^{I} \frac{\partial c_i}{\partial c_0} + \frac{\ell - t_I}{\tau^2} \left(\tau \frac{\partial c_{I+1}}{\partial c_0} - c_{I+1} \frac{\partial \tau(s_I, c_I)}{\partial c_0} \right) - \frac{\partial t_I}{\partial c_0} \cdot \frac{c_{I+1}}{\tau}.$$

If $\frac{\partial t_I}{\partial c_0} < 0$, then every term is positive. Therefore, $-\frac{\partial [\ell C_1]}{\partial c_0} > 0$ for all $\ell > t_{\bar{k}}$ from Lemma 2, so that measured adjacent complementarity holds for sufficiently large ℓ. Now observe $-\frac{\partial^2 [\ell C_1]}{\partial \ell \partial c_0} = -\frac{1}{\tau^2} \left(\tau \frac{\partial c_{I+1}}{\partial c_0} - c_{I+1} \frac{\partial \tau(s_I, c_I)}{\partial c_0} \right)$, which is finite and strictly less than zero for $I > 0$. Hence, since $-\frac{\partial [\ell C_1]}{\partial c_0} > 0$ for small ℓ, and $-\frac{\partial [\ell C_1]}{\partial c_0} < 0$ for large ℓ, and $-\frac{\partial [\ell C_1]}{\partial c_0}$ is strictly decreasing in ℓ, there exists a ℓ^0 such that $-\frac{\partial [\ell C_1]}{\partial c_0} > 0$ for all $\ell < \ell^0$ and $-\frac{\partial [\ell C_1]}{\partial c_0} < 0$ for all $\ell > \ell^0$. The result extends to NP due to continuity of all terms in the small θ limit as $s_H^* \to s^*$. ■

A.8 *Proof of Proposition* 5

A.8.1 *Proof of Proposition* 5*, part (i-a)*

Since C_n maximizes $U(C_n|\hat{\delta}_n)$, $U(C_n|\hat{\delta}_n) \geq U(0|\hat{\delta}_n)$. By NP, $U(0|\delta) > U(C_n|\delta)$. Adding the inequalities, substituting $U(C) = U^+(C) + \delta U^-(C)$, and rearranging gives $(\delta - \hat{\delta}_n)(U^-(C_n) - U^-(0)) < 0$. Since U^- is decreasing, $\hat{\delta} < \delta$. ■

A.8.2 *Proof of Proposition* 5*, part (i-b)*

By the first-order condition that defines $\hat{\delta}_n$, concavity of U, and $U(C_n|\hat{\delta}_n) > U(C|\hat{\delta}_n)$ for all $C \neq C_n$, $U(C|\hat{\delta}_n)$ is strictly increasing on $[0, C_n]$. ■

A.8.3 *Proof of Proposition* 5*, part (ii-a)*

Solving for $\hat{\delta}_{n+1}$ after taking the first-order condition of the utility maximization problem for which it is defined gives

$$\hat{\delta}_{n+1} = -\frac{U^{(+)'}(C_{n+1})}{U^{(-)'}(C_{n+1})} = \frac{U^{(+)'}(C_{n+1})}{|U^{(-)'}(C_{n+1})|}. \tag{13}$$

Here, by concavity of both, $U^{(-)'} < 0$ implies $U^{(+)'} > 0$ (otherwise $C_{n+1} > 0$ would not satisfy measured optimality). Since u is strictly concave by NP, U is strictly concave, which means either U^+ or U^- is strictly concave (or both are). Therefore, $\hat{\delta}_{n+1}$ must fall with C_{n+1} since the magnitude of the numerator decreases and the magnitude of the denominator increases (and at most one of these magnitudes are weakly monotonic). Since the measured MRAS, $-\mathrm{E}\left[\frac{\partial C_{n+1}}{\partial C_n}\right]$, is positive for $\ell < \ell^0$ and negative for $\ell > \ell^0$ (proposition 4), increasing chosen consumption at $T(n)$ from the steady-state level decreases $\hat{\delta}_{n+1}$ if $\ell < \ell^0$ and increases $\hat{\delta}_{n+1}$ if $\ell > \ell^0$. ■

A.8.4 *Proof of Proposition* 5*, part (ii-a)*

Since $\frac{\partial[U'(C|\delta)]}{\partial\delta} = \frac{\partial[U^{(+)'}(C)+\delta U^{(-)'}(C)]}{\partial\delta} = U^{(-)'}(C) < 0$, $U'(C|\hat{\delta}_{n+1})$ moves in the opposite direction as $\hat{\delta}_{n+1}$. Hence, the desired result follows from (ii-a). ■

A.9 *Proof of Lemma* 1

Let τ^D denote any deterministic interval function. We first show there exists a τ^D such that the optimization problems with τ^D and with stochastic τ are equivalent in that optimal $\tilde{c}(s)$ is the same for all s. A crucial element of this existence is the fact that the stock transition equation, $s_{i+1} = (1-\sigma)s_i + \sigma c_i$, is retained in the stochastic cues model. Therefore, given s_i and c_i, the next-decision habit stock, s_{i+1}, is independent of whether the next decision is craving-induced at $\bar{\tau}$ or cue-induced prior to $\bar{\tau}$. Hence the optimization problem at t_{i+1} is also independent of whether the decision is craving- or cue-induced, since s_{i+1} is the only state variable at t_{i+1}.

Dynamic optimization with stochastic cues follows:

$$V(s) = -1 + \max_c \{u(c) + \mathrm{E}[\delta^{\tau(s,c)}]V((1-\sigma)s + \sigma c)\}.$$

The next-decision value function is factored out of the expectation because its value depends only on s and c. Comparing to the deterministic Bellman

$$V(s) = -1 + \max_c \{u(c) + \delta^{\tau^D(s,c)}V((1-\sigma)s + \sigma c)\},$$

we see the optimization problems are always equivalent if and only if $\delta^{\tau^D} = \mathrm{E}[\delta^\tau]$ for all s, c. Therefore, we need to show τ^0 satisfies $\delta^{\tau^0} = \mathrm{E}[\delta^\tau]$. With the known distribution of τ, the expectation of δ^τ is computed by decomposing it into its cue- and craving-components:

$$\mathrm{E}[\delta^\tau] = \underbrace{\left[\int_0^{\bar{\tau}} \delta^t \lambda e^{-\lambda t} dt\right]}_{\frac{-\lambda\delta^t e^{-\lambda t}}{\lambda - \ln(\delta)}\Big|_{t=0}^{\bar{\tau}}} + \underbrace{\Pr(\tau = \bar{\tau}) \cdot \delta^{\bar{\tau}}}_{e^{-\lambda\bar{\tau}} \cdot \delta^{\bar{\tau}}} = \frac{\lambda - e^{-\lambda\bar{\tau}} \ln(\delta)\delta^{\bar{\tau}}}{\lambda - \ln(\delta)}.$$

As desired, $\delta^{\tau^0} = \mathrm{E}[\delta^\tau]$, as seen by the definition $\tau^0 = \frac{\ln[(\lambda - e^{-\lambda\bar{\tau}} \ln(\delta)\delta^{\bar{\tau}})/(\lambda - \ln(\delta))]}{\ln(\delta)}$. ■

A.10 *Proof of Proposition* 6

Assimilating our steady-state notation with the notation of this section, we note $\bar{\tau}_L^* > \bar{\tau}_H^*$, which says the chipper's natural interval is greater than the addict's. Since an individual's steady-state consumption level (at each decision) is constant, the share of consumption that coincides with a stochastic cue is $1 - e^{-\lambda\bar{\tau}}$, which is the probability that a decision will be cue-induced. By inspection, we can verify the share is higher for $\bar{\tau} = \bar{\tau}_L^*$ than for $\bar{\tau} = \bar{\tau}_H^*$. Hence, (a) holds.

To prove (b), decompose variance as $\mathrm{Var}[\tau] = \mathrm{E}[\tau^2] - \mathrm{E}[\tau]^2$ and compute:

$$\mathrm{E}[\tau] = \left[\int_0^{\bar{\tau}} t\lambda e^{-\lambda t} dt\right] + e^{-\lambda\bar{\tau}} \cdot \bar{\tau} = \tfrac{1-e^{-\lambda\bar{\tau}}}{\lambda}$$
$$\mathrm{E}[\tau^2] = \left[\int_0^{\bar{\tau}} t^2\lambda e^{-\lambda t} dt\right] + e^{-\lambda\bar{\tau}} \cdot \bar{\tau}^2 = \tfrac{2}{\lambda^2}\big(1 - e^{-\lambda\bar{\tau}}(1+\lambda\bar{\tau})\big)$$

Therefore $\mathrm{Var}[\tau] = \frac{1-e^{-2\lambda\bar{\tau}}-2\lambda\bar{\tau}e^{-\lambda\bar{\tau}}}{\lambda^2}$. Differentiating with respect to $\bar{\tau}$ gives

$$\frac{\partial \mathrm{Var}[\tau]}{\partial \bar{\tau}} = \frac{2e^{-2\lambda\bar{\tau}}}{\lambda}(e^{-\lambda\bar{\tau}} + \lambda\bar{\tau} - 1),$$

which is positive for all $\bar{\tau} > 0$. Hence variance is higher at $\bar{\tau}_L^*$ than at $\bar{\tau}_H^*$. ■

A.11 *Proof of Proposition 7*

Part (ii) is proven first because the result will be used in the proof of part (i).

A.11.1 *Proof of Proposition 7, part (ii)*

First note $\lim_{\theta\to 0^+} \frac{\partial\bar{\mu}^\theta(s)}{\partial\lambda} = \frac{\partial\bar{\mu}(s)}{\partial\lambda}$ since $\lim_{\theta\to 0^+} u'(c|\theta) = 0$. Now let $s \in (s_L^*, s_H^*)$ be either nonzero steady-state. Then

$$\frac{\partial\bar{\mu}(s)}{\partial\lambda} \propto \frac{\partial}{\partial\lambda}\left[\tau_c^0 + \delta^{\tau^0}(\sigma\tau_s^0 - (1-\sigma)\tau_c^0)\right],$$

where all functions are evaluated at s and $c = s$. Using $\tau^0 = \frac{\ln[(\lambda - e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}})/(\lambda-\ln(\delta))]}{\ln(\delta)}$, we get that, for $x \in \{s, c\}$, $\tau_x^0 = \frac{e^{-\lambda\bar{\tau}}\delta^{\bar{\tau}}\bar{\tau}_x(\lambda-\ln(\delta))^2}{\lambda - e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}}}$, which implies

$$\begin{aligned}\frac{\partial\bar{\mu}(s)}{\partial\lambda} \propto& \frac{\partial}{\partial\lambda}\left[\bar{\tau}_c(\lambda - \ln(\delta)) + (\lambda - e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}})(\sigma\bar{\tau}_s - (1-\sigma)\bar{\tau}_c)\right]\\ \propto&(\lambda - \ln(\delta))[\bar{\tau}_c + (1+\bar{\tau}e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}})(\sigma\bar{\tau}_s - (1-\sigma)\bar{\tau}_c)].\end{aligned}$$

Using the fact that $\lim_{\theta\to 0^+}\bar{\mu}^\theta(s) = 0$ at a steady-state, we get

$$\begin{aligned}\frac{\partial\bar{\mu}(s)}{\partial\lambda} \propto&(\sigma\bar{\tau}_s - (1-\sigma)\bar{\tau}_c)[-\ln(\delta) + e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}} + \bar{\tau}e^{-\lambda\bar{\tau}}\ln(\delta)\delta^{\bar{\tau}}(\lambda - \ln(\delta))]\\ \propto&(1+\bar{\tau}(\lambda-\ln(\delta)))e^{-\lambda\bar{\tau}}\delta^{\bar{\tau}} - 1.\end{aligned}$$

Define $Z(\delta) = (1-\bar{\tau}\ln(\delta))\delta^{\bar{\tau}}$. Therefore at $\lambda = 0$ and given s is a steady-state, $\frac{\partial\bar{\mu}(s)}{\partial\lambda} < 0$ if and only if $Z(\delta) < 1$. Note that $Z(1) = 1$. Since $\delta \in (0,1)$, we have $\frac{dZ(\delta)}{d\delta} = -\bar{\tau}^2 \ln(\delta)\delta^{\bar{\tau}-1} > 0$. Therefore $Z(\delta) < 1$ for $\delta \in (0,1)$. Thus, $\frac{\partial \bar{\mu}(s)}{\partial \lambda} < 0$, which in turn implies $0 < \tilde{c}(s) < s$ as λ increases from $\lambda = 0$, as desired. ■

A.11.2 *Proof of Proposition 7, part (i)*

For part (ii), note $\mathrm{E}[\tau]$ is decreasing in λ (so that the contemporaneous expected frequency is increasing in λ) holding $\bar{\tau}$ fixed. Also, $\mathrm{E}[\tau]$ is increasing in $\bar{\tau}$ holding λ fixed, where $\bar{\tau}$ is decreasing in λ because $\bar{\tau}_c > 0$ and $\tilde{c}(s)$ is decreasing in λ from part (i). Therefore, $\frac{d\mathrm{E}[\tau]}{d\lambda} < 0$, implying that the expected frequency is increasing in λ, as desired. ■

A.12 *Proof of Corollary 3*

Without loss of generality, let s_0 denote the initial steady-state. Recall $\tilde{c}(s)$ is increasing near $s = s_0$ from Corollary 1. Raising the cue-arrival rate from $\lambda = 0$ decreases the per-decision consumption level so that $c_0 = \tilde{c}(s) < s$ from part (ii) of Proposition 7. Given that the new $\lambda > 0$ is arbitrarily small, the new steady-state is arbitrarily close to (but smaller than) s_0, which follows from the definition of τ^0 and the steady-state condition $\bar{\mu}(s) = 0$. Therefore $s_1 = (1-\sigma)s_0 + \sigma c_0 < s_0$, which implies $c_1 = \tilde{c}(s_1) < \tilde{c}(s_0) = c_0$. If s denotes the new steady-state, it follows that $s_i > s$ implies $\tilde{c}(s_i) \in (s, s_i)$, so that $s_{i+1} = (1-\sigma)s_i + \sigma\tilde{c}(s_i) \in (s, s_i)$. Thus $c_{i+1} = \tilde{c}(s_{i+1}) < \tilde{c}(s_i) = c_i$ for all i. ■

A.13 *Proof of Proposition 8*

$$\begin{aligned}
\mathrm{E}[\delta^{\tau(s,c)}] =& \Pr(\tau(s,c) < \bar{\tau}(s,0))\mathrm{E}[\delta^{\tau(s,c)}|\tau(s,c) < \bar{\tau}(s,0)] \\
&+ (1 - \Pr(\tau(s,c) < \bar{\tau}(s,0)))\mathrm{E}[\delta^{\tau(s,c)}|\tau(s,c) \geq \bar{\tau}(s,0)]
\end{aligned}$$

As $\lambda \to \infty$, $\Pr(\tau(s,c) < \bar{\tau}(s,0)) \to 1$, which implies $\mathrm{E}[\delta^{\tau(s,c)}] \to \mathrm{E}[\delta^{\tau(s,c)}|\tau(s,c) < \bar{\tau}(s,0)]$. This expectation is independent of c since its associated probability distribution is the right-truncated exponential distribution on $(0, \bar{\tau}(s,0))$ for all c. Note since $c = 0$ minimizes $\bar{\tau}(s,c)$, this means the probability of a craving-induced decision converges to zero regardless of chosen consumption.

Now inspect the optimization problem given by the Bellman:

$$V(s) = -1 + \max_{c} \{u(c) + \mathrm{E}[\delta^{\tau(s,c)}]V((1-\sigma)s + \sigma c)\}.$$

As $\lambda \to \infty$, $\mathrm{E}[\delta^{\tau(s,c)}] > 0$ converges to a constant and $V((1-\sigma)s + \sigma c)$ falls with c. Since $u(c)$ is strictly decreasing for fixed $\theta > 0$, it follows that

$$0 = \lim_{\lambda \to \infty} \big\{\arg\max_{c} \{u(c) + \mathrm{E}[\delta^{\tau(s,c)}]V((1-\sigma)s + \sigma c)\}\big\},$$

which implies $\lim\limits_{\lambda \to \infty} \tilde{c}(s) = 0$ for all s, as desired. ■

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