Boredom and Flow: An Opportunity Cost Theory of Motivational Attention

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Abstract

The process of deciding where to direct attention itself consumes attention. Consequently, people must continually weigh the marginal value of devoting attention to their current focus against the marginal value of evaluating other attentional opportunities. We model this trade-off in a dynamic choice framework in which boredom and flow take the form of hedonic signals that influence behavior, including choices about the focus of attention. The model explains a range of empirical regularities documented in research on attention, generates novel economic predictions that cannot be captured by existing theories such as rational inattention, and has significant implications for welfare analysis. We illustrate the economic effects of boredom and flow with three applications to attentional addiction, workplace design, and industrial organization.

Keywords: Attention, Motivation, Dual-Self, Affect

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I Introduction

> *"A wealth of information creates a poverty of attention and the need to allocate that attention efficiently..."*
>
> —Herbert Simon, 1971

Herbert Simon was among the first to recognize attention as a scarce resource that constrains the behavior of both individuals (Simon, 1978) and organizations (Simon, 1971, 1973). Since he wrote the words above, the quantity of information available to the average household, business, or government has grown dramatically and, consequently, so has the role of limited attention in shaping economic affairs. Yet, while many authors have recently taken up the idea that attention is a scarce and valuable resource (e.g. Bordalo et al., 2013; Caplin, 2016; Gabaix and Laibson, 2006; Shapiro and Varian, 1998; Banerjee and Mullainathan, 2008; Heidhues et al., 2016, among many others), especially one that can be allocated "rationally," few have pursued the idea that hedonic motivational states, such as curiosity, mental effort, and—the focus of this paper—boredom and flow, also exert a strong influence on how people direct their attention.

We present a formal model in which boredom and flow influence behavior (including, most directly, the focus of attention) by altering the experienced utility of maintaining focus. In the model, boredom acts as an attentional self-control cost and arises when the decision maker *implicitly* expects—from past cue-based associative learning—that the opportunity cost of maintaining their focus is high; conversely, flow acts as an attentional self-control benefit that arises when the decision maker implicitly expects that the opportunity cost of focus is low.

We refer to the expectations that give rise to boredom and flow as "implicit" to distinguish them from the more familiar explicit expectations typically studied in economic decision making. This conceptual distinction can be illustrated by analogy to another drive state, hunger, which is automatically triggered by the presence of smells and other sensory cues that have been learned to predict the potential presence of food. In this way, cue-driven hunger can be said to reflect an implicit expectation that food is available. Notably, such states arise automatically on the basis of past associative learning, even when a decision maker knows, intellectually, that they are misleading—*e.g.*, that an appetizing smell is left over from food that others have already consumed.

The core argument of our paper is that boredom and flow similarly encode implicit expectations about attentional opportunity costs. Our model describes the process by which these expectations form, generate motivational states, and influence behavior. Although we conceive of implicit expectations in an as-if way, the expositional value of ascribing them to a secondary agent motivates our choice to model them using a dual-self framework (as in the self-control model of Fudenberg and Levine, 2006).

Boredom and flow explain a variety of phenomena that cannot be accounted for by existing economic frameworks for studying attention allocation based on "rational" (*i.e.*, explicit) expectations alone, such as why prolonged deprivation from stimulation increases risk-taking and generates self-control problems. The model also draws a link between boredom and flow, on the one hand, and a wide range of other motivational feeling states, such as hunger and drug craving, on the other. Similar to these other motivational states, boredom and flow give rise to cue-dependent shifts in preferences and produce powerful intertemporal complementarities in consumption that can lead to habit formation and—in extreme cases—addiction. Our model therefore sheds light on the mechanism underlying "attentional addiction" and provides concrete recommendations for policies to counteract it.

The fact that boredom and flow influence decision-making through a hedonic channel means that the decision maker can readily trade them off against other goals and motivational hedonic states. It also means that these states directly impact people's overall well-being and hence have significant welfare implications, even—and, indeed, especially—in instances where they do not change observed behavior. At the same time, boredom and flow depart from previously studied affective influences on behavior in that that they primarily bear on agent's attentional and informational choices.

Boredom and flow impact the economy in diverse and significant ways that are only becoming more apparent as society progresses further into the "Information Age." In post-industrial economies, a growing proportion of labor—especially in fields such as computer programming, accounting, or design—is mental rather than physical, making workplace boredom a more significant cost than physical exhaustion for many forms of modern production. Boredom and flow also play a key role in education, given that a student's immediate hedonic experience drives their level of motivation, engagement, and learning. Indeed, with much of the world's knowledge now available for free or at a low cost through the internet, boredom remains one of the last barriers to the widespread acquisition of diverse forms of human capital. Recent technological innovations have also led to the rapid growth of industries centered on generating flow, such as social media and gaming, often with the aim of redirecting consumer attention to embedded information and advertisements. Our model sheds light on some of the concerning trends that have accompanied these developments, including the paradox that intensive use of such products leaves people feeling worse despite their widespread and growing popularity (see, *e.g.*, Allcott et al., 2020).

The desire to avoid boredom has also have been associated with a variety of high-risk behaviors, such as gambling, physical thrill-seeking, substance abuse, and unsafe sex (Smith and Preston, 1984; Blaszczynski et al., 1990; Bonnaire et al., 2004; Mercer and Eastwood, 2010; Turner et al., 2006; Iso-Ahola and Crowley, 1991; Caldwell and Smith, 1995; Kılıç et al., 2020). Bouts of acute boredom can drive individuals—especially adolescents—to experiment with activities they might otherwise eschew. Insights into the relationship between boredom, flow, and risk-taking are therefore critical for public health initiatives aimed at minimizing the harms that can result from such behaviors. At a more pedestrian level, boredom and flow are central to sports, live performance, tourism, and other areas of the leisure economy, suggesting that a deeper understanding of motivational attention can provide insights into the structure of these markets (see Section III.C).

Our formal model starts with an insight of Simon (1967) who, in a different line of work from that quoted above, conjectured that emotions overcome a fundamentally attentional friction—namely, the quandary that deliberating about *what one might do* competes for the same scarce mental resources, such as working memory and cognitive control, that are required to productively engage in *what one is already doing.* Consequently, becoming deeply engrossed in a task can blind one to the potential availability of favorable alternatives. Simon argued that emotional "shocks" help to resolve this dilemma by interrupting a decision-maker focused on narrow goals when more promising opportunities or urgent needs arise. While we depart from Simon's claim that this is the general purpose of *all* emotions, we adopt this perspective for one specific emotion of concern in this paper: boredom. Conversely, if a decision maker tries to resolve all uncertainty about the utility consequences of engaging in various activities, they will be left with little attention to productively engage in any of them. In our model, flow overcomes this difficulty by focusing a decision maker on their current activity when few promising alternatives are likely to be available.

We explicitly model this tension between productive and deliberative attention in a dynamic attentional choice framework. As in other dual-self models (*e.g.* Thaler and Shefrin, 1981; Bernheim and Rangel, 2004; Fudenberg and Levine, 2006), we describe a decision maker's behavior as resulting from the interaction of two agents that we call the *executive* and the *advisor*. In each period, the executive decides both (i) which activity to focus on and (ii) how to split their attention between exploiting the current focus and thinking about the potential value of alternative activities. The advisor does not directly participate in these decisions, but can indirectly influence the executive by imposing hedonic self-control costs (boredom) and benefits (flow) that incentivizes the executive to maintain or change its attentional focus.

In our model, the advisor and executive share the same underlying utility function (as in the theory of teams; Marschak and Radner, 1972); however, the advisor alone remembers how fruitful deliberation concerning other possible actions or activities was in similar sensory environments and therefore has an advantage over the executive when it comes to predicting the opportunity cost of focus. When, on the basis of this cue-based associative learning,[1] past experience suggests that the return to deliberation will be relatively high, the advisor makes the prospect of investing attention in the current focus less appealing for the executive by inducing boredom; conversely, when the advisor predicts that the return to deliberation will be relatively low, they make the executive's present focus more appealing by inducing flow (Theorem 1). An employee experiencing boredom during a meeting, for example, will disengage their attention to look out of the window, daydream, or actually leave the meeting in search

[1]Or, more broadly, any form of learning that can be accessed without consuming attentional resources. In particular, the advisor does not engage in effortful deliberation.

of something else to do. As this example suggests, we use the term "attentional foci" in a broad sense that would encompass, for example, simply changing the direction of one's gaze, physically moving to a new location, or engaging in a new activity.

A key feature of our model is that it separates total utility into two distinct, additively-separable components: *material utility* and *stimulation*. Both of these components enter into diverse decisions. For example, the desire to gamble depends on both consequentialist preferences over potential wealth levels and their associated probabilities (material utility) and excitement derived from the sense of possibility it creates (stimulation). Similarly, one might solve crossword puzzles despite the absence of financial rewards (material utility) because it satisfies a drive for sense-making (stimulation).

Recognizing that utility decomposes in this way is motivated by the stylized fact that boredom and flow are largely orthogonal to the "extrinsic" incentives that are traditionally the focus of economic analysis, such as money, social image concerns, and the instrumental value of information, and indeed are often traded off against these benefits: filing one's taxes or working a menial job brings material benefits, but at the expense of boredom. However, attention-directing motivation is clearly influenced by other properties of a task, such as how novel, interesting, or engaging it is. This division accords with theoretical and empirical evidence from psychology showing that the brain generates its own "endogenous" rewards to incentivize cognitive enrichment in ways that agents would undervalue if they were to rely on instrumental reasoning (and material utility) alone (see Wojtowicz et al., 2022; Wojtowicz and Loewenstein, 2020; Chater and Loewenstein, 2016; Gopnik, 1998; Kidd and Hayden, 2015, for extended discussions).

In the model, the executive allocates a constant budget of attention to the material consequences of changing attentional focus—*e.g.*, of not paying attention in the meeting. The advisor has special insight (based on prior learning) into the marginal benefit of reducing uncertainty about the stimulation component of utility. Hence, the advisor's imposition of a hedonic cost indicates that it believes pondering—and hence reducing the uncertainty associated with—the stimulation afforded by alternative activities is likely to have a high return, and deserves more attention. By making the current focus less appealing, boredom incentivizes the executive to dislodge attention from its current focus and redirect it to such contemplation.

Reducing uncertainty about the stimulation value afforded by various foci, in turn, leads the decision maker to place greater weight on that dimension of utility. Boredom therefore increases the marginal rate of substitution between stimulation and material utility (Proposition 2); a person who is already bored will require greater compensation to engage in a task that provides little stimulation, on average. By similar logic, flow causes the DM to become less sensitive to changes in stimulation and reduces the marginal rate of substitution between these two types of utility; an individual who is already in a state of flow already, will not be motivated to seek out further mental stimulation. Thus, the model provides a principled explanation that connects the hedonic experience of motivational attention to the DM's level of focus and subsequent taste for stimulation.

Our formal framework combines ideas from multiple existing theoretical literature and consequently reveals new connections among them. Firstly, our DM employs rational inattention to learn about and choose between multiple courses of action (Sims, 2003; Matějka and McKay, 2015; Steiner et al., 2017). However, unlike existing models, we fully endogenize the "cost" of both productive focus and rational inattention as the shadow price of an agent's finite attentional budget at each given point in time. This enables us to identify hedonic feeling states with dynamic fluctuations in the opportunity cost of attention, while at the same time establishing a principled framework for modeling why these costs respond to changes in context. It also clarifies why attentional costs sometimes appear to be "negative," *i.e.*, why focus can not only be pleasurable, but so much so that agents sometimes struggle to disengage from certain attentional foci, such as mindless video games, contrary to their better judgment.

In this way, our model also connects boredom and flow to the broader literature on temptation and self-control (Gul and Pesendorfer, 2001), particularly the dual-agent model of Fudenberg and Levine (2006). If, as our account holds, these states modify the price of maintaining focus, they are analogous to attentional self-control costs (in the case of boredom) and benefits (in the case of flow). However, unlike both the models of Gul (1991) and Fudenberg and Levine (2006), which portray self-control problems as arising from two sets of conflicting preferences, the agents in our model share identical underlying preferences but possess different *information*.

Furthermore, our model also differs from existing work in the more fundamental sense that it generates two distinct types of self-control problem—*distraction* and *captivation*—reflecting the fact that our model contains both self-control costs and benefits. In some situations, such as a dull meeting attended by one's boss, the executive must consciously choose to override the autonomous motivational signal by paying attention, even when it is aversive to do so (distraction). In other situations, such as when a person tries—successfully or not—to tear themselves away from their social media feed or a session of binge watching television, the executive may struggle to overcome the pleasure of maintaining flow (captivation). Our model captures both of these insights.

Finally, our model provides a novel account of how cue-based habit formation and addiction (Laibson, 2001; Bernheim and Rangel, 2004) extend to the domain of attentional choice. In recent years, the rapid proliferation of highly stimulating digital technologies has precipitated a concomitant rise in attentional disorders, with video games (Griffiths et al., 2012), smartphones (Kwon et al., 2013), and internet (Chou et al., 2005) addiction being the main causes of concern. In contrast to substance use disorders, however, which are driven by the direct action of chemical compounds on neural circuitry (Koob and Volkow, 2010), the mechanism by which attentional addiction occurs is less-well understood. In our model, the advisor draws upon their memory of past experiences to determine when to deliver boredom and flow. This opens up a channel for inter-temporal complementarities in consumption: high stimulation in the presence of a particular cue raises the advisor's belief that the cue signals a high return to deliberation, leading the advisor to transmit greater boredom in future instances where that cue is present. This in turn raises the DM's marginal sensitivity to stimulation in future periods which feature the same cue (Theorem 2). Hence, consumption of a highly stimulating good in one period raises the DM's sensitivity to stimulation in future periods featuring the same cue, the key criterion necessary for habit-formation and addiction.

Our model introduces an entirely new mechanism by which these positive intertemporal complementarities in consumption can arise, however. According to rational addiction accounts (*e.g.*, Becker and Murphy, 1988; Laibson, 2001), consumption of a habit-forming substance directly increases the marginal rate of substitution between it and alternatives in future periods. The usual interpretation of such models is that habituation makes consumption more *appealing* by making it more *satisfying*: addiction makes an individual more likely to take a drug because it magnifies the utility impact of consumption, even if only by making non-consumption more aversive. In our model, by contrast, boredom does not alter the underlying marginal utility of stimulation on an absolute or relative basis. Rather, boredom leads a decision maker to redirect attention to that dimension of utility, increasing the relative weight it exerts on decision making despite the fact that payoffs are fixed. As we show in our second application (Subsection III.B), this can lead to a vicious cycle of ever-increasing consumption of stimulating content (*e.g.*, social media) that nevertheless fails to elevate satisfaction or even diminish boredom.

This aspect of our model accords with existing evidence that learned associations between stimulation and sensory cues affect both the hedonic experience of focus and subsequent levels of attention. For example, Hebb (1958) showed that sensory deprivation increases willingness to listen to boring material, such as old stock reports. By contrast, elements of a workplace that increase the salience of counterfactual opportunities, such as overhearing the muffled conversations of co-workers (Fisher, 1993, 1987) or a television playing at low volume (Damrad-Frye and Laird, 1989), have been shown to increase boredom. Indeed, Ward et al. (2017) found that "the mere presence of one's own smartphone reduces available cognitive capacity." The prediction that opportunity cost expectations play an important role in motivational attention was recently verified in an experiment conducted by Perone et al. (2020), which showed that an under-stimulating task was perceived as more boring when it followed, rather than preceded, an optimally challenging one.

Finally, our modeling framework relates to the theory of search, including job search (McCall, 1970), particularly its emphasis on characterizing marginal decision to stay attached to a particular activity or expend effort on looking for a new one. We view human attentional choice as sharing features with this and other "exploration and exploitation" behaviors (March, 1991), and note that the effect of hedonics in our model is to modify the intensity of "search" behavior. Our work also provides a new perspective on disappointment models (Gul, 1991; Loomes and Sugden, 1986; Bell, 1985), which, like boredom and flow in our framework, involve a comparison of outcomes to expected values.

After introducing our model, we present three illustrative applications that explore its implications for economic theory. The first application show how workplace design impacts the hedonic experience of workers, and, consequently, the wages they demand. We use our model to show how the popular trend of introducing leisure activities such as pinball machines into office environments can backfire by triggering higher expectations for stimulation, increasing on-the-job boredom and thereby lowering welfare. The second application shows how boredom and flow can lead to habit-formation or even addiction to stimulation over time, and how these motivational states interact with risk preferences. Our model provides a new explanation for stylized features of casino design, game design, and gambling addiction, and for why these states are often associated with risky behaviors such as extreme sports, unsafe sex, and substance abuse. Finally, the third application provides an industrial-organization-level explanation for why boredom seem to be increasing despite the rapidly expanding availability of stimulating content online.

The rest of the paper proceeds as follows. In Section II, we introduce our formal model of boredom and flow. Subsection II.A introduces the decision maker's basic environment and attentional choice task. Subsection II.B fully characterizes the executive's behavior holding the advisor's behavior constant. Subsection II.C then describes how the advisor selects hedonic signals in response to the DM's changing circumstances. Finally, Subsection II.D examines how the advisor learns over time from experience and the dynamic behavioral implications that result. In Section III, we apply the model to workplace design, attentional addiction, and industrial organization. Section IV concludes.

II The Model

II.A General Setup

Time is discrete and unbounded $t \in T = \{1, 2, \dots\}$. Let $P = \{1, \dots, N\}$ for $N \geq 2$ be a set of potential attentional foci. A decision maker (DM) selects one focus from P each period. Let R denote the set of basis vectors for $\mathbb{R}^N$, *i.e.* vectors of length N

with one entry equal to 1 and the rest equal to 0, so that each element of R indexes a choice of focus from P. The DM is endowed with a focus $\rho_1 \in R$ in the first period and chooses a single focus $\rho_t \in R$ in each period $t > 1$ thereafter.

The marginal value of attending to each of the foci in P is determined by the sum of two random vectors, $u_t \in \mathbb{R}^N_{\geq 0}$ and $v_t \in \mathbb{R}^N_{\geq 0}$. We interpret u_t and v_t as two additively-separable dimensions of utility, which we refer to as *material utility* and *stimulation*, respectively. Stimulation utility, v_t, consists of how inherently interesting, engaging, or cognitively enriching an activity is; material utility u_t consists of all other factors—such as monetary incentives, social pressure, or the instrumental value of information—that might motivate one to undertake an activity. In the example of a boring work-meeting, material utility would capture the career implications of not paying attention, *e.g.* the wages one would lose by being fired for walking out of the meeting.

The DM[2] has priors over utility $u_t \overset{i.i.d.}{\sim} G_u$ and $v_t \overset{i.i.d.}{\sim} G_v$ for some fixed, known distributions $G_u, G_v \in \Delta(\mathbb{R}^N_{\geq 0})$. We make two assumptions about both distributions G_i for $i \in \{u, v\}$: first, that each focus yields different utility values with positive probabilities; and second, that the dimensions satisfy *a-priori homogeneity* in the sense of Matějka and McKay (2015), *i.e.* that the DM does not have an a-priori reason to believe one action will yield a different distribution of payoffs than another before receiving any information.[3]

As in other dual-self models, the DM is comprised of two agents, which we refer to as the *executive* and the *advisor*:

1. The executive decides what to focus on and how much attention to invest in the chosen focus each period.

2. The advisor influences the executive's decisions by modifying the appeal of investing productive attention.

As in the theory of teams, the executive and advisor's objectives align in that both care about maximizing the sum of material and stimulation utility. Their objectives

[2]Though the "decision maker" in our model encompasses both the executive and the advisor, because the executive makes ultimate decisions, it is natural to associate the term with the former.

[3]Formally, this requires that the various dimension of the prior are statistically exchangeable.

differ only in that the executive's utility additionally depends on a hedonic state $h_t \in \mathbb{R}$, which is determined by the advisor. The advisor, meanwhile, has access to private information that the executive does not. Hence, the advisor uses h_t to incorporate their private information into the executive's behavior. The executive treats the hedonic signal h_t as a completely exogenous, mean-zero random variable.

The executive is uncertain about the relative intrinsic payoffs associated with different possible future foci, v_t, but can learn about them by expending attention on deliberation. We model this using a multi-attribute extension of the standard framework of *rational inattention* (*e.g.*, that of Sims, 2003; Matějka and McKay, 2015; Steiner et al., 2017).

Each period takes place in one of two environments $\omega_t \in \Omega = \{H, L\}$ designated *high* and *low*, respectively, which influence the stimulation value, but not the material value, of different foci. We assume that the advisor has privileged insight into the likely environment, leading it to have different (and to some extent more refined) beliefs about the marginal return to deliberation. In the model, the advisor uses boredom/flow to get the executive to redirect the right amount of attention to deliberation, given this informational advantage.

Intuitively, the high environment is meant to capture situations in which there is a greater benefit to deliberation about the focus of attention. Such situations would include, most prominently, the existence of greater variability in the availability in opportunities for stimulation, such as at a social gathering full of strangers. It might also reflect the presence of one especially good option in cases where the payoff vector is sparse (*i.e.*, only a handful of foci yield stimulation and the rest yield no stimulation). The low environment, by contrast, is meant to capture situations in which there is little benefit to contemplating alternative focuses of attention—*e.g.,* when there is little unexpected variation in stimulation across actions, as might be the case in a doctor's waiting room.

The DM's prior is that each environment is drawn *i.i.d.* from a non-degenerate Bernoulli distribution. In periods when the environment is high, the intrinsic utility payoff is multiplied by a factor of $\theta_H = 1 + \epsilon$ for some $\epsilon \in (0, 1)$. In periods when the environment is low, the intrinsic payoff is multiplied by a factor of $\theta_L = 1 - \epsilon$. Denote the realized multiplicative factor in period t as θ_t.

After selecting a focus ρ_t, the DM must also select *how much* attention to invest in the chosen focus $\alpha_t \in [0, 1]$. Attention not invested productively can be reserved to deliberate about the next focus $\delta_t \in [0, 1]$. Beyond this, however, attention is not storable between periods, *i.e.* we have $\alpha_t + \delta_t \leq 1$ for all $t \geq 1$. This sets up the key trade-off for the executive: how much to pay attention to the DM's current focus, and how much to, instead, contemplate alternative future focuses of attention.

Each period proceeds according to the following timeline:

1. Executive selects an informational strategy σ_t, which is constrained by the amount of attention reserved for deliberation in the prior period δ_{t-1}
2. Executive selects a productive focus ρ_t
3. Advisor observes the intrinsic value of the executive's current focus $\theta_t\, \rho_t \cdot v_t$ and receives a private signal s_t (to be defined below) that is informative about the coming environment
4. Advisor selects a hedonic signal h_t that changes the executive's marginal return to attention to $\rho_t \cdot (u_t + v_t) + h_t$
5. Executive decides how much attention α_t to invest in the current focus

For the sake of exposition, in the next subsection we first characterize the executive's problem for fixed hedonic signals. We then turn to a description of the advisor's problem. We then characterize how the two operate in tandem.

II.B The Executive's Problem

The key problems for the executive are: (1) what to focus on in the current period, and (2) *how much* attention to invest into the chosen focus. This latter decision, in turn, determines how much the executive will deliberate about what to focus on in the next period.

An executive strategy $\Gamma = (\sigma, A)$ is a pair consisting of:

1. A *focus strategy* σ consisting of a system of mappings $\sigma_t(u_t, v_t|\delta_{t-1}) : \mathbb{R}^N \times \mathbb{R}^N \times [0, 1] \to \Delta(R)$ that specify a probability distribution over ρ_t for each set of states u_t, v_t and level of deliberation δ_{t-1}.

2. An *attention strategy* A consisting of a system of mappings $A_t\left(\rho_t \cdot (u_t + v_t) + h_t\right) : \mathbb{R} \to [0,1]$ that maps marginal rates of productivity into productive attentional investments α_t. This implicitly determines the amounts of attention reserved for deliberation δ_t in each period.

As is standard in the rational inattention literature, we assume that the attentional cost of reducing uncertainty about each dimension of utility scales with the *mutual information* a focus strategy generates about the relevant state. To define this cost formally, first note that the *entropy*—or information-theoretic uncertainty—of a discrete[4] random variable X is defined as

$$\text{(1)} \qquad \mathrm{H}(X) = -\sum_{x \in \mathrm{supp}(X)} \mathbb{P}(X = x) \log \mathbb{P}(X = x)$$

For random variables X and Y, the mutual information is equal to

$$\text{(2)} \qquad \mathrm{I}(X;Y) = \mathbb{E}_Y\Big[\mathrm{H}(X) - \mathrm{H}(X|Y = y)\Big]$$

Mutual information measures the expected reduction in uncertainty about X one will experience upon observing Y. For example, flipping two unbiased coins generates two bits of entropy—the number of yes-no questions it would take to ascertain the coins' configuration from a truthful interlocutor. Learning the total number of heads would reduce this uncertainty from two bits to one half of a bit, on average, and therefore generate one and a half bits of mutual information.[5]

To simplify our analysis, we assume that the benefit of deliberating about potential foci accrues exclusively to stimulation utility.[6] In particular, we assume that the DM's

[4]The definition in the continuous case is similar, but replaces sums with integrals. See Cover and Thomas (2012) for a comprehensive treatment.

[5]If there are zero or two heads, one can immediately deduce that the flips must have been (T,T) or (H,H), respectively, and no uncertainty remains. If there is only one heads, then a single yes-no question can determine if it is in the first (H,T) or second (T,H) position. On average, therefore, only half a bit of uncertainty remains.

[6]A model in which the advisor is allowed to freely apply deliberative attention to reduce uncertainty about both dimensions of utility yields qualitatively similar results at the expense of significantly more formal complexity. In such a model, the advisor's belief in a high marginal return to deliberating about stimulation (large expected θ_t) leads it to apply relatively more attention to that dimension, which in turn increases the *relative* weight the DM places on it.

rational inattention budget for material utility is fixed at some level $0 < b < H(G_u)$. By contrast, the rational inattention budget for stimulation value is an increasing function of the amount of attention they reserved for deliberation in the prior period $g(\delta_{t-1})$. Here, $g : [0,1] \to \mathbb{R}$ is a production function that maps deliberative attention into units of uncertainty reduction.[7] We assume that g is differentiable and strictly convex and further that $g(0) = 0$, $g(1) \leq \mathrm{H}(G_v)$, and $\lim_{\delta \to 0^+} g'(\delta) = \infty$.

To capture the fact that our decision context features two categorically different types of utility (material and stimulation), we assume that the executive applies rational inattention to each separately when deciding which focus to adopt. Intuitively, this can be viewed as a stochastic choice analogue of the additive separability of the underlying utility dimensions and, indeed, generates additive separability in the resulting choice representation. Formally, let Σ denote the set of mappings $\sigma : \mathbb{R}^N \to \Delta(P)$. If $\sigma(u_t)$ and $\sigma(v_t|\delta_{t-1})$ solve the following two problems, respectively

$$\begin{aligned} &\max_{\sigma_t \in \Sigma} \quad \mathbb{E}\left[\sigma_t \cdot u_t \,|\, \sigma_t\right] \qquad\qquad &&\max_{\sigma_t \in \Sigma} \quad \mathbb{E}\left[\sigma_t \cdot v_t \,|\, \sigma_t\right] \\ &\quad \text{s.t.} \quad \mathrm{I}(\rho_t; u_t) \leq b &&\quad \text{s.t.} \quad \mathrm{I}(\rho_t; v_t) \leq g(\delta_{t-1}) \end{aligned} \tag{3}$$

then we require the executive's overall choice probabilities satisfy $\sigma_i(u_t, v_t|\delta_{t-1}) \propto \sigma_i(u_t)\sigma_i(v_t|\delta_{t-1})$ for all $i \in P$ where $\propto$ signifies proportionality.

Proposition 1. *For all $i \in P$, the DM's choice probabilities take the form of the multinomial logistic function*

$$\sigma_i(u_t, v_t|\delta_{t-1}) = \frac{\exp\left(\beta_t\, u_{t,i} + \gamma_t\, v_{t,i}\right)}{\sum_{j \in P} \exp\left(\beta_t\, u_{t,j} + \gamma_t\, v_{t,j}\right)} \tag{4}$$

for some $\beta_t, \gamma_t > 0$.

Proposition 1 tells us that the executive selects foci by applying a multinomial logistic stochastic choice rule to the values u_t and v_t, with coefficients that depend on the amount of decision attention they allocate to each dimension. The precision

[7] This would be "bits" if a logarithm of base 2 is used to calculate the entropy, although the choice of base simply re-scales the cost function by a constant factor. See Cover and Thomas (2012).

is governed by β_t and γ_t; as these parameters jointly grow, the executive more closely approximates the optimal choice rule of selecting the maximum value $\max_i u_{t,i} + v_{t,i}$. On the other hand, as β_t and γ_t becomes vanishingly small, the executive chooses more randomly. The following result characterizes the influence deliberation has on the precision parameters β_t and γ_t.

Lemma 1. $\gamma_t = \gamma(\delta_{t-1})$ *for some fixed function* $\gamma(\cdot)$ *which is a differentiable and satisfies*

1. $\gamma'(\delta_{t-1}) > 0$ *for all* $\delta_{t-1} \in (0, 1)$
2. $\gamma(0) = 0$
3. $\lim_{\delta_{t-1}\to\infty} \gamma(\delta_{t-1}) = \infty$

Moreover $\beta_t = \beta > 0$ *for all* t*.*

Lemma 1 follows from the fact that β_t and γ_t arise as the inverse Lagrange multipliers on the executive's rational inattention problems (3). It tells us that the DM's weight on stimulation value when deciding on a focus of attention is a function of how much attention they reserve for deliberation.[8] This, in turn, means that the weight they place on stimulation *relative* to material utility also increases with deliberation, as the following comparative statics make clear.

Definition 1. *The* ***marginal rate of substitution*** *(MRS) between* $v_{t,i}$ *and* $u_{t,i}$ *in determining the probability of focus* j *is*

$$\xi_t(i,j) = \frac{\partial \sigma_{t,j}}{\partial v_{t,i}} \Big/ \frac{\partial \sigma_{t,j}}{\partial u_{t,i}} \tag{5}$$

for $i, j \in P$*.*

[8] Given that we are interested in studying the way attention constrains choice, we have in mind cases in which the executive's fixed budget of uncertainty reduction b is small enough that it cannot fully pin down the relevant details of u_t and β is therefore comparable to the range of γ_t. Indeed, if one were to relax our simplifying assumption that deliberative attention flows exclusively to the stimulation dimension, the DM would try to equate the Lagrange multiplier on both dimensions' constraints, and hence β_t and γ_t. Hence, cases in which these variables are of similar magnitude are to be expected on normative grounds.

The MRS measures the marginal increase in material utility needed to keep the DM's stochastic tendency to choose a good constant in the face of a marginal decrease in stimulation utility. It is, in effect, the rate of exchange between these two dimensions of utility.

Proposition 2. *For $i, j \in P$, we have*

$$\begin{aligned} \frac{\partial}{\partial v_{t,i}} \sigma_j(u_t, v_t|b_t) &= \beta_t \, \sigma_i(u_t, v_t|b_t)\big(1_{i,j} - \sigma_j(u_t, v_t|b_t)\big) \\ \frac{\partial}{\partial u_{t,i}} \sigma_j(u_t, v_t|b_t) &= \gamma_t \, \sigma_i(u_t, v_t|b_t)\big(1_{i,j} - \sigma_j(u_t, v_t|b_t)\big) \end{aligned} \tag{6}$$

where $1_{i,j}$ represents a Kronecker delta that equals 1 if $i = j$ and 0 otherwise. Hence,

$$\xi_t(i, j) = \xi_t = \frac{\gamma_t}{\beta_t} \propto \gamma(\delta_{t-1}) \tag{7}$$

for all $i, j \in P$. We can therefore speak of "the" MRS, which is a strictly increasing function of δ_{t-1}.

Proposition 2 follows from differentiating Proposition 1 and combining the result with Lemma 1. It shows that deliberation has the effect of increasing the MRS between stimulation and material utility—namely, that deliberation increases the DM's sensitivity to stimulation.

The result also shows that this sensitivity is an increasing function of deliberative attention. Note that here "sensitivity" refers to the weight this dimension receives in decisions about where to allocate attention relative to material utility. This does *not* mean that the decision maker will actually obtain greater utility from sensitivity—a point which plays an important role in the applications we discuss in Section III.

After choosing a focus, the executive updates their expectations about the marginal utility of productive attention to $\mathbb{E}[\rho_t \cdot (u_t + v_t) \,|\, \rho_t]$ (for details on belief updating in the rational framework, see Caplin and Dean, 2013). The executive then select how much productive attention α_t to invest. Define

$$c(\alpha_t) = \frac{1}{\gamma(g(1 - \alpha_t))} \tag{8}$$

which equals the executive's expected opportunity cost of productive attention, *i.e.* the Lagrange multiplier of deliberative attention from (3). Note that, by Lemma 1 and the properties of g, $c(\alpha)$, this will be strictly increasing and strictly concave with $\lim_{\alpha \to 0^+} c'(\alpha) = 0$ and $\lim_{\alpha \to 1^-} c'(\alpha) = \infty$.

Definition 2. *The* ***executive's attention problem*** *takes the form*

$$\max_{\alpha_t \in [0,1]} \quad \alpha_t \left(\mathbb{E}[\rho_t \cdot (u_t + v_t) \mid \rho_t] + h_t \right) - c(\alpha_t) \tag{9}$$

at each point in time t.

Lemma 2. *The executive's attention strategy takes the form $\alpha_t = A(\rho_t \cdot (u_t + v_t) + h_t)$ where $A(\cdot)$ is a twice-differentiable function such that*

1. *$A(0) = 0$ and $A'(x) > 0$, $A''(x) < 0$ for all $x > 0$*
2. *$\lim_{x \to \infty} A(x) = 1$*
3. *$\lim_{x \to \infty} A'(x) = 0$*

Therefore $\alpha_t \in (0, 1)$ and $\delta_t \in (0, 1)$ for all t.

Deliberative attention at time t reflects the share of attention not used by the executive, *i.e.* $\delta_t = 1 - \alpha_t$. In particular, it tells us that the executive always allocates *some* attention to both production and deliberation, with the former's share a convex function of the current focus's value.

Taken together, these results fully characterize the executive's behavior: First, the executive always divides attention between production and deliberation, with the share allocated to the former a strictly increasing, concave function of the marginal value of the current focus; second, the executive selects foci using a stochastic choice rule that becomes more precise—and, importantly, more sensitive to stimulation—with increased deliberation; third, increased deliberation raises the DM's expected marginal intrinsic utility in the next period.

II.C The Advisor's Problem

The advisor possesses privileged information about the potential for stimulation value in the next period based on relationships it learns, over time, between the presence of different environmental cues and the expected return from a change in focus of attention. The advisor cannot directly communicate this information to the executive, but can indirectly influence their behavior using a hedonic state—boredom or flow. The advisor's goal is to translate their private information into a signal of appropriate sign and magnitude that will induce the executive to act *as if* they shared this private information.

The advisor strategy consists of:

- A *hedonic strategy* h consisting of a system of mappings $h_t(\theta_t \, \rho_t \cdot v_t, \pi_t) : \mathbb{R} \times [0, 1] \rightarrow \mathbb{R}$ that map the marginal implicit utility and advisory belief states into hedonic states h_t.

At the start of each period, the advisor receives two pieces of private information. First, they observe the executive's current focus ρ_t and the stimulation it affords, inclusive of the environment's influence $\theta_t \, \rho_t \cdot v_t$. Note that the advisor does not directly observe the multiplier θ_t and therefore must rely on the realized stimulation value $\theta_t \, \rho_t \cdot v_t$ to infer the likely environment and, from it, the predictive content of each cue. As we will see, this has the important implication that a particularly stimulating activity can be misinterpreted as evidence for the high environment and influence the future trajectory of boredom and flow.

Second, they observe a private sensory cue $s_t \in S = \{b, y\}$ ("blue" and "yellow") that is informative about the coming environment ω_{t+1}. The cue correctly predicts the coming environment with probability $\zeta \in (\frac{1}{2}, 1]$ and incorrectly predicts it with probability $1 - \zeta$. However, at the start of time, the advisor does not know which signal is associated with which environment. Denote the advisor's beliefs that the next state will be high after seeing the cue as $\pi_t = p(\omega_{t+1} = H | s_t)$. We will also allow the possibility that the advisor does not observe a cue in some periods, in which case we will write $s_t = \varnothing$ and note that $\pi_t = \frac{1}{2}$ in such cases.

Given this private information, the advisor has different (and, on average, more accurate) beliefs than the executive about the return to deliberative attention along each utility dimension in the upcoming period. The advisor can modify the marginal value of investing productive attention using a hedonic signal $h_t \in \mathbb{R}$ to induce the executive to behave as if they also knew this private information.

Let $U_t(h_t)$ denote the expected value the executive attains by solving (9) conditional on hedonic strategy h_t. We can state the advisor's objective as follows.

Definition 3. *The **advisor's hedonic problem** is*

$$\max_{h_t} U_t(h_t) \tag{10}$$

Definition 4. *We say the DM experiences **boredom** when $h_t < 0$ and **flow** when $h_t > 0$.*

The advisor cannot communicate their information directly to the executive. Rather, they influence the executive indirectly by engendering boredom and flow. These states have a variety of effects, which follow from the comparative statics derived in the prior section.

Remark 1. *An increase in the hedonic state induces the following changes:*

$$\frac{\partial \alpha_t}{\partial h_t} > 0 \qquad \frac{\partial \delta_t}{\partial h_t} < 0 \qquad \frac{\partial \xi_{t+1}}{\partial h_t} < 0 \tag{11}$$

Therefore, an decrease in boredom (or an increase in flow) leads to:

1. *Increased productive focus*
2. *Decreased deliberation*
3. *Decreased sensitivity to stimulation when choosing the next focus*

A decrease in flow (or an increase in boredom) leads to the opposite of all these effects.

The advisor's private information only directly bears on the optimal division of attention between production and deliberation. In order to select the optimal hedonic signal, the advisor must therefore re-solve the executive's attention-division problem conditional on its updated beliefs. The advisor can then invert the the executive's attentional policy A at this optimal level to deduce which marginal value would bring the executive's choice into line with its recommendation. The advisor then uses h_t to close the gap between the executive's current margin $\rho_t \cdot (u_t + v_t)$ and this target value.

Theorem 1. *The unique solution to the advisor's problem generates a hedonic signal which takes the form*

$$h_t = m\big(\mathbb{E}[\rho_t \cdot u_t|\rho_t] + \theta_t\, \rho_t \cdot v_t \,\big|\, \pi_t\big) - \mathbb{E}[\rho_t \cdot (u_t + v_t) \,|\, \rho_t] \tag{12}$$

where m parameterizes a family of strictly increasing function with $m(x|\pi) < m(x|\pi')$ whenever $\pi > \pi'$ and $m(x|\frac{1}{2}) = x$.

This explicit form of the advisor's solution has a variety of noteworthy features. First, the hedonic signal is a strictly decreasing function of the advisor's conviction that the coming environment is rich in attentional opportunities π_t; in such cases, the advisor makes the current focus *worse* to shift the executive's the advisor's strong conviction that the decision maker is in a stimulation-plentiful environment will lead it to generate boredom, whereas the opposite conviction, that the environment is impoverished stimulation-wise will lead it to generate a flow state. Whereas most existing accounts of boredom (*e.g.*, Berlyne, 1960; Westgate and Wilson, 2018) assume that boredom depends solely on the stimulation provided by the advisor's current focus, in the current model, boredom is a function of *both* the stimulation afforded by the decision maker's current focus *and* the opportunity cost of that focus—the advisor's appraisal of the stimulation provided by alternative focuses.

Corollary 1. *For all t, we have*

$$\frac{\partial h_t}{\partial \pi_t} < 0 \tag{13}$$

An increase in the advisor's beliefs π_t therefore lead to the effects listed in Remark 1.

Theorem 1 also verifies the intuition that attention-directing motivational states are highly sensitive to changes in stimulation but not sensitive to material incentives—*e.g.*, allowing someone to listen to an audiobook while performing a rote motor task will substantially reduce their boredom, but simply paying them more will not.

Corollary 2. *The hedonic influence of a change in intrinsic value is greater than that of a change in extrinsic value. Formally,*

$$\frac{\partial h_t}{\partial(\rho_t \cdot v_t)} > 0 \qquad\qquad \frac{\partial h_t}{\partial(\rho_t \cdot u_t)} = 0 \tag{14}$$

Theorem 1 also explains one reason why boredom tends to worsen over time when one is stuck in an under-stimulating situation. By design, boredom in one period spurs the executive to invest more attention in deliberation. On average, this increases the executive's implicit expectation about how much intrinsic utility it should get. If the activity's actual payoff does not increase, because the decision maker maintains their current focus, however, the advisor will attempt to correct these rising implicit expectations even more aggressively in the subsequent round.

Corollary 3. *Increasing the hedonic state h_t in one period raises the DM's average implicit expectation for stimulation value $\mathbb{E}[\rho_{t+1} \cdot v_{t+1}]$ in the next, meaning that the same marginal payoff and advisory belief state will generate more boredom or less flow in $t + 1$, all else being equal.*

The model also generates two types of self-control problems, which we refer to as *distraction* and *captivation*. The first—distraction—occurs when the DM judges an activity to be materially important, but is tempted to abandon it due to boredom. This occurs because boredom both directly incentivizes the DM to disengage productive attention— *e.g.*, by gazing out the window during a tedious meeting—and sensitizes them to stimulation, making them more likely to switch to something less important but more fun. Self-control itself would then refer to instances in which the DM feels boredom but does not act to mitigate it, such as when one resists the temptation to check one's phone, despite a waning dinner conversation, because one does not wish to be rude.

The second self-control problem—captivation—occurs when the DM judges the current activity to be of low importance, but experiences a state of flow, making it difficult for them to tear themselves away. This occurs both because flow directly incentivizes greater focus—for example, becoming engrossed in a mindless video game on one's phone. Self-control itself would occur in instances where the DM feels flow but acts to overcome it, such as when one resists binge watching another television episode to attend to other more important, but less entertaining, matters.

II.D Advisor Dynamic Learning

The advisor learns the present focus ρ_t and the stimulation value it provides $\theta_t\, \rho_t \cdot v_t$ in each period. We assume that the advisor jointly uses these two pieces of information to infer whether the environment was likely high or low by examining the liklihood ratio

$$\frac{p(\theta_t \rho_t \cdot v_t = x | \rho_t, \theta_t = \theta_H)}{p(\theta_t \rho_t \cdot v_t = x | \rho_t, \theta_t = \theta_L)} \tag{15}$$

The advisor uses this inference to update its beliefs about which sensory cues ("blue" and "yellow") is associated with which environment ("High" and "Low").

Definition 5. *We say a prior G_v is **simple** if it has full support on $\mathbb{R}^N_{\geq 0}$ and each of its marginal distributions are unimodal.*

Definition 6. *We say a prior G_v is **decreasing** if it has full support on $\mathbb{R}^N_{\geq 0}$ and each of its marginal distributions are strictly decreasing.*

Note that all decreasing priors must also be simple. In this section, we restrict our attention to simple G_v, which rules out pathological situations in which relatively large observed values of stimulation are counted as evidence for the low environment due to wiggliness in the liklihood function. We provide a few constructive examples of simple priors in the applications, below. Consider the following comparative static on the realized intrinsic marginal utility.

Theorem 2. *There exists a cutoff value for each focus $k(\rho_t) > 0$ such that if, in period t, the DM experiences a high intrinsic payoff $(\theta_t\, \rho_t \cdot v_t)' > k(\rho_t)$ associated with a particular sensory cue $s_t \neq \varnothing$, then in all subsequent periods $\tau > t$ with the same signal $s_\tau = s_t$ they will experience strictly:*

1. *Higher boredom/lower flow: $h'_\tau < h_\tau$*
2. *Lower attentional investment: $\alpha'_\tau < \alpha_\tau$*

3. Higher deliberation: $\delta'_\tau > \delta_\tau$

4. Higher subsequent intrinsic sensitivity: $\xi'_{\tau+1} > \xi_{\tau+1}$

relative to the case where $\theta_t \rho_t \cdot v_t = k(\rho_t)$*. Observing a low intrinsic payoff* $(\theta_t\, \rho_t \cdot v_t)' < k(\rho_t)$ *leads to the opposite of all these effects. If, in addition, the DM's prior* G_v *is decreasing, then* h'_τ*,* α'_t*,* δ'_τ*, and* $\xi'_{\tau+1}$ *are all strictly monotonic functions of* $(\theta_t\, \rho_t \cdot v_t)'$ *in the directions indicated.*

The intuition behind this result is that, conditional on a given focus, the distributions of stimulation across environments satisfy a single-crossing condition. For values above the cutoff, the advisor infers that the environment was more likely to be high and therefore revises future expectations upwards when presented with the same cue; for values below the cutoff, the advisor does the reverse. This mechanism has the following effect on consumption.

Corollary 4. *The DM's preferences exhibit positive intertemporal complementary for intrinsic consumption.*

As identified by Becker and Murphy (1988) in their theory of "rational addiction," positive intertemporal complementary in consumption of a particular good (or good attribute) is the critical driver of habit formation. In our model, high consumption of intrinsic utility in the presence of a particular cue s increases marginal sensitivity to intrinsic utility in future periods featuring that same cue. This parallels the model of Laibson (2001), which generates cue-dependent complementarities in reduced form using "compensatory processes." Theorem 2 provides a cognitive micro-foundation for how cue-based associations form in the context of "mental" consumption. Moreover, it shows that the hedonic states of boredom and flow mediate, by their very design, this process of sensitization.

II.E Summary

Because they have been discussed in stages as the model was laid out, here we provide a compact review of the model's diverse insights and predictions.

Insights:

1. Boredom and flow are hedonic feeling states that improve the allocation of attention without drawing on attention.

2. The fact that boredom and flow are hedonic states means that the decision maker can—and in fact will—trade off boredom against other utility flows, including extrinsic economic incentives and other hedonic motivators such as hunger, thirst, and pain.

3. The advisor (which is responsible for delivering boredom or flow) learns, over time, which cues signal an environment with stimulation payoffs of greater magnitude. The advisor delivers boredom when payoff magnitudes are expected to be relatively high and flow when they are expected to be relatively low.

4. Boredom and flow therefore reflect *implicit expectations* about opportunity costs formed on the basis of cue-based associative learning.

5. Contrary to "optimal arousal" accounts (*e.g.*, Berlyne, 1960), boredom can sometimes occur in moderately or even highly stimulating environments—*e.g.*, in a disappointing but objectively stimulating work meeting.

Predictions:

1. Boredom increases the marginal rate of substitution between stimulation and material utility. Flow, on the other hand, reduces it.

2. Experiencing a high degree of stimulation in the presence of a particular sensory cue on one occasion increases boredom (or reduces flow) in the presence of that same cue on future occasions.

3. Taken together, the previous two points imply that boredom and flow generate positive intertemporal complementarities in consumption that can lead to habit formation and, in extreme cases, "attentional addiction."

4. Boredom and flow are the positive and negative parts of a single underlying motivational signal and therefore cannot be experienced simultaneously.

III Applications

In this section, we demonstrate the model's economic implications in three illustrative applications, workplace design, gambling, and digital platform competition. In the first application, we discuss the model's implications for workplace effort, productivity, and wage demand, on the one hand, and leisure consumption experience, on the other. In particular, we show how workplace design that conflates the distinction between work and leisure can introduce internalities due to the cue-based nature of boredom and flow.

In the second application, we discuss how attention-directing motivational states interact with risk preferences. Our model provides a new explanation for stylized features of casino design, game design, and gambling addiction. We also use this analysis as a launching point to discuss how boredom and flow relate to non-financial risky behaviors such as extreme sports, unsafe sex, substance abuse, *etc.*

In the third and final application, we highlight a perverse feature of what is sometimes called the "Information Age": the irony that levels of boredom seem to be increasing in a era characterized by quantum-improvements in the quantity and quality of available informational content. In this application, we embed our model of boredom and flow in a stylized industrial organization setup, and also show that attention-directing motivational states can strengthen competition.

III.A Workplace Design

We first apply our model to workplace design. In this application, we show that increasing the value of leisure outside the workplace can create a hedonic internality while on the job. This internality is worsened by policies that further conflate the two environments, such as when companies introduce leisure activities into the workplace with the intention of improving employee welfare during breaks. In essence, work seems more boring when the DM gets "mixed signals" about the presence of highly stimulating leisure opportunities in the office. Thus, our analysis highlights the role of counterfactual expectations generally, and for workplace boredom, specifically. The model also provides a novel perspective on empirical studies of workplace design—*e.g.* the finding of Dabbish et al. (2011) that open offices hurt worker productivity in part because they engender higher "self-interruption" (endogenous task switching) and fragmented work patterns.

Consider a DM who can engage in either work w or leisure l each period. Work generates a fixed material utility $u_w > 0$ and no stimulation, $v_w = 0$, whereas leisure generates less material utility $u_l < u_w$ and a positive random amount of stimulation v_l. We assume that the distribution of v_l can be represented by a strictly decreasing probability distribution function and that the DM has accurate priors over v. In the context of this problem, we reinterpret the high and low environments as the office and the home, respectively. The fact that $\theta_H > \theta_L$ reflects the fact that engaging in *bona fide* leisure at home is more enjoyable than "slacking off" at work. We will call whichever sensory cue $s \in S$ is more strongly associated with the office the "office cue." Likewise, we will call the cue more strongly associated with the home the "home cue."

We first note in passing that a corollary of Theorem 2 implies the existence of hedonic internalities from leisure stimulation when the DM is learning the cue associations. In particular, there exists a $\bar{v}$ such that, if the DM experiences a high intrinsic payoff $v_q > \bar{v}$ from leisure after observing the home cue, then they will experience strictly higher boredom/lower flow in subsequent periods where they observe it again. This makes it less pleasurable for the DM to work in the presence of the home cue, even when they are, in fact, at the office.

In what follows, we assume that the DM has already ascertained the correct association between signals and states, *i.e.* knows which cues are *more likely* to signal which environment, even if they do not do so perfectly. First, we note a second sense in which making leisure at home better can impact the hedonic experience of work. Recall that ϵ parameterizes the difference between θ_H and θ_L.

Proposition 3. *At any given point in time t, increasing ϵ strictly increases the magnitude of h_t. That is, the greater is the difference in stimulation between the home and work environments, the stronger will be the boredom signal, holding all else equal.*

We next turn our attention to the hedonic consequences of changes to the cue precision parameter $\zeta \in (\frac{1}{2}, 1)$ which, as described in Subsection II.C, defines the accuracy with which the different environments emit their associated cue. One effect of reducing cue precision is to dampen the magnitude of hedonic states. In particular, if the DM receives the office-related signal while working, the hedonic signal is (by Theorem 1)

$$m(u_w|\zeta) - u_w \tag{16}$$

This is always positive (*i.e.*, engenders a flow state), but weakens as ζ is decreased (because m is strictly decreasing in its second argument). By the same token, receiving the leisure-related cue will always engender boredom while working $m(u_w|1-\zeta)-u_w$, albeit to a lesser degree when cue precision is decreased. But changing the cue precision ζ also changes the *proportion* of each cue the working DM will receive.

Remark 2. *A decrease in signal accuracy ζ leads to more frequent workplace boredom (h_t). Moreover, starting from $\zeta = 1$, introducing a small amount of conflation unambiguously decreases the marginal utility of work:*

$$\frac{\partial}{\partial(-\zeta)}\mathbb{E}[u_w + h_t|\omega_t = \mathit{office}] < 0 \tag{17}$$

In sum, the model predicts that workplace boredom will be increased by the presence of cues associated with the home environment, and that such boredom will be increased, the greater the difference in stimulation between the two environments, and the stronger the signal-value of the cues. More generally, environmental cues that are associated with high stimulation—*e.g.*, the presence of co-workers in the immediate environment, as in Dabbish et al. (2011)—will increase workplace boredom and lead to greater attention-refocusing, as Dabbish et al. finds.[9]

[9] A trivial simplification of this two-environment model would involve only a single environment—*e.g.*, "life"—with no cues. Suppose, in this environment, that there are two types of activities—'old" activities such as cooking and childcare, and 'new' activities, such as tweeting, watching TV series, and internet dating. As the new types of activities become more plentiful and/or stimulating, the advisor will come to expect, on average, a higher level of stimulation which will lead the old activities to become more boring. This could result in the decision maker either spending less time on these activities or in multi-tasking (*e.g.*, listening to a podcast while cooking).

III.B Attentional Addiction

In this section, we study the potential for boredom and flow to reinforce behavioral patterns over time, leading to habit formation or, in extreme cases, "attentional addiction." This aspect of the model aligns with the longstanding observation that the desire to alleviate boredom and sustain flow can lead people to experiment with and sustain a variety of activities with high potential costs.

Some such activities—especially pathological smartphone, internet, or video game use (Kwon et al., 2013; Chou et al., 2005; Griffiths et al., 2012)—are obviously attentional in nature, but boredom and flow may also play a role in other compulsive activities, such as gambling and substance use. For example, one study conducted in Las Vegas found that 45% of casino patrons interviewed reported engaging in gambling activities as a means of relieving boredom and generating excitement, a percentage notably higher than those who reported gambling for monetary gain (39%) (Smith and Preston, 1984).[10] Boredom is also a frequent correlate of risky behavior such as substance abuse, heavy alcohol consumption, and smoking (Blaszczynski et al., 1990; Bonnaire et al., 2004; Mercer and Eastwood, 2010; Turner et al., 2006), especially in adolescents (Iso-Ahola and Crowley, 1991; Caldwell and Smith, 1995), and has been shown to increase financial risk-taking experimentally (Kılıç et al., 2020). To the degree that these activities are highly stimulating (in the cognitive sense under study in this paper), they may engender attentional addiction, regardless of what other habit-forming channels they may operate on (*e.g.*, opoids directly influencing dopamine regulation in the brain; Koob and Volkow, 2010). It also helps to explain the appeal of mind-altering drugs, such as those that induce hallucinations, which don't have obvious effects *other than* the mental stimulation they provide (*c.f.*, Goldstein, 2001)

Consider a DM who normally pursues a safe default activity d, but is sometimes confronted with the option to engage in a "thrilling" high-stimulation activity q. For example, the DM sometimes stops at gas stations that have video slot machines, spends time with friends who take drugs, or encounters a jump on the ski course. To streamline the analysis, we assume that the default activity generates no stimulation $v_d = 0$ and consider the DM's behavior in response to changes in the thrilling activity's

[10] Other attentional phenomena also play a role in gambling, as we discuss in a recent paper on the economics of attention (Loewenstein and Wojtowicz, 2023), Section 5.2.

stimulation level v_q. The material utility afforded by both options can take any values, but we have in mind cases where the thrill is harmful, *i.e.* $u_q \ll u_q$.

Let $T_r \subset T$ contain a subsequence of non-consecutive periods wherein the thrill is available, $T_d = T \backslash T_r$ denote the remaining safe periods, and $T_q^{-1} = \{t \in T \mid t{+}1 \in T_q\}$ denote the set of periods just before the thrill is available. We have $P_t = \{r, d\}$ for $t \in T_q$ and $P_t = \{d\}$ otherwise. Further, in periods just preceding those wherein the thrill is available, the DM always sees the blue signal, but doesn't see a signal otherwise, *i.e.* $s_t = b$ if $t \in T_q^{-1}$ and $s_t = \varnothing$ for all other t. The signal is not perfectly informative, *i.e.* $\xi < 1$. We assume that the prior G_v can be represented by a probability density function that is strictly decreasing in v_q, has $\mathbb{E}[v_q] > u_d - u_q$, and correctly assigns unit mass to $v_d = 0$.

Denote the DM's probability of choosing the thrilling option in period t as σ_t^q, and let $\mathbb{E}_0[\cdot]$ denote the *a-priori* expected value of a random variable at the start of time.

Proposition 4. *There exists a threshold level of stimulation $\bar{v} \in \mathbb{R}$ such that if $v_q > \bar{v}$, then:*

1. *Choosing the thrilling option at one point in time increases the probability of choosing it again the next time it is available.*

2. *The DM becomes increasingly more bored in the presence of the thrill and more likely to choose it over time in expectation,* i.e., *the series $\{\mathbb{E}_0[h_\tau]\}_{\tau \in T_q^{-1}}$ is strictly decreasing and $\{\mathbb{E}_0[\sigma_\tau^r]\}_{\tau \in T_r}$ is strictly increasing.*

The model also identifies possible approaches to combating attentional addiction. First, keeping a decision-maker engaged in the period wherein the thrill-related cue appears will reduce the amount of attention the DM diverts to deliberation and their subsequent sensitivity to stimulation; for example, paying a teenager to do chores over the weekend not only occupies their time in a direct way, but also crowds out mind wandering and the "fear of missing out" on exciting, but potentially deleterious, social activities. Second, the complement to Proposition 4 is that there is a cutoff value for stimulation below which the DM becomes *less* bored in the presence of the cue. This suggests that the same types of cue desensitization techniques that work for drug-based addiction and other compulsive habits should translate to domains such as compulsive gambling and thrill-seeking. In the case of attentional addiction, this would predict that exercising restraint in the presence of one's phone (*e.g.*, placing it face-down on a table and not checking it while socializing with friends) becomes easier over time.

III.C Technology Development

The final application of the model is to a problem in behavioral industrial organization in which a series of firms—for example technology companies that develop apps—attempt to capture the attention of consumers. This applications demonstrate how hedonic effects can link markets and create strategic complementarities, even when firms do not directly compete for user attention.

Our setup builds upon the setup of the previous example. Now, however, the high-stimulation activity is interpreted as a sequence of technology products that are produced by different firms that differ in stimulation value. At each point in time $t \in T_q$, a new technology company starts up, offers its product to the consumer, then closes. As before, the DM chooses between a default option d and the new product q. Firms generate revenue by selling the DM's attention to advertisers on a secondary market at the fixed price that we normalize, without loss, to 1. Firms attract DMs' attention by making investments in the quality of their platform, which increases the liklihood that it produces a hit of stimulation. By Proposition 4, there exists a $\bar{v}$ such that $\rho_t \cdot v_t > \bar{v}$ reinforces boredom.

Each firm t can select the probability $\zeta_t \in [0, 1]$ with which their product generates a hit of stimulation $v_H > \bar{v}$. However, they pay a cost $c(\zeta_t)$ for doing so that is increasing, differentiable, and strictly convex with $c'(0) = 0$ and $\lim_{\zeta_t \to 1^-} c'(\zeta_t) = \infty$. Firm t chooses a level of investment ζ_t that maximizes profit

$$\Pi_t = \mathbb{E}\big[\sigma_q(u_d, v(\zeta_t)|\delta_{t-1})\big] - c(\zeta_t) \tag{18}$$

by solving the first-order condition

$$\frac{\partial}{\partial \zeta_t}\mathbb{E}\big[\sigma_i(u_d, v(\zeta_t)|\delta_{t-1})\big] = c'(\zeta_t) \tag{19}$$

Proposition 5. *Investment is an increasing function of deliberation,* i.e. *there exists an increasing function $\zeta(\cdot)$ such that $\zeta_t = \zeta(\delta_{t-1})$. Thus, the expected level of investment $\{\mathbb{E}_0[\zeta_\tau]\}_{\tau \in T_q}$ is strictly increasing over time. As in Proposition 4, the DM becomes more bored in the presence of the product but increasingly likely to choose it over time.*

Each firm makes investment decisions on their own. However, investment by one firm generates a positive externality on all that follow: by increasing the chance that their product will deliver a "hit" of stimulation, they increase the chance that the DM will reinforce their implicit association between stimulation and the common cue that signals the presence of technology. Paradoxically, societal boredom increases as the environment becomes ever more stimulating.

IV Conclusion

This paper develops a theory of two important attention-directing motivation states: boredom and flow. The theory draws on two key insights: (1) that attention is an important scarce resource, and (2) that attention-directing motivational states guide the efficient use of this resource. In Section II, we showed how a utility representation of these hedonic inducements can be derived using standard economic arguments. Our model provides new explanations for a number of empirical findings regarding boredom and flow that have mainly been reported in the psychology literature. The model also helps to explain salient properties of these motivational feeling states that have gone largely unobserved, such as why boredom often occurs in surprisingly stimulating environments, such as work meetings, but does not occur in relatively unstimulating environments such as when lying in bed awaiting sleep.

Another contribution of the paper is to help make sense of why boredom and flow commonly create self-control problems, such as when it would be beneficial to pay attention to a seminar or conversation, but one finds it difficult to do so, or when one realizes that watching a movie or playing an electronic game are not good uses of one's time, but one finds it difficult to tear oneself away from them. We argue that conflict between executive intentions and hedonic inducements is not only natural, but essential; according to our account, if boredom and flow never conflicted with executive judgment, they would have no reason to exist.

In our framework, boredom and flow encode implicit expectations about the magnitude of stimulation rewards available in the DM's environment. This reflects the fact that, in rational inattention models, the marginal benefit of deliberation is sensitive to the variance, but not the mean level of rewards; if rewards barely differ across options, then one can get away with giving little thought to choice. While we focus on the marginal opportunity cost of rational-inattention style deliberation, one might also consider what would happen if boredom instead encoded average expectations about the mean level of rewards in an environment. In such a model, an optimal boredom signal would incentivize the decision maker to simply try anything other than what they are doing, engendering a form of restlessness. Closer inspection of attention-directing motivational states suggests they potentially do contain multiple forms of implicit expectations, each of which is responsible for slightly different aspects. Berlyne (1960), for example, proposed a distinction between "specific" curiosity targeted at a particular focus—*e.g.*, opening a present—and "diversive" curiosity that simply motivates pure exploration—*e.g.*, the desire to wander around a foreign city while on vacation. Boredom may likewise contain two sub-states: the "specific" boredom we study here that signifies high variability in—and sensitizes a decision maker to—stimulation value; and a "diversive" boredom, whose study we leave to future work, that signifies high average stimulation and motivates pure restlessness.

Increasingly, in the internet age, both work and leisure are associated with mental tasks, such as programming, web-surfing, and playing electronic games rather than physical activities. It has, therefore, never been more important to understand the costs and benefits associated with these activities. Boredom and flow are clearly prominent among the motivations driving mental activity, as well as among their hedonic consequences, and so are worthy of study in their own right, but boredom and flow are also important as examples of the larger set of motivational feeling states, such as curiosity and mental effort, that regulate mental activity. Our hope is, therefore, that the analyses presented in this paper pave the way for analogous treatments of a broader range of motivational influences on behavior. At the same time, the present theory is a new addition to a still relatively small collection of papers that use concepts from economics to model psychological phenomena, such as reference-dependence (Rayo and Becker, 2007), that are of special interest to economists.

V Appendix

Proof of Proposition 1. The solutions for both problems follow directly from Proposition 1 of Matějka and McKay (2015):

$$\sigma_{t,i}(u_t) = \frac{\exp\left(\beta_t \, u_{t,i}\right)}{\sum_j \exp(\beta_t \, u_{t,j})} \qquad \sigma_{t,i}(v_t|\delta_{t-1}) = \frac{\exp\left(\gamma_t \, v_{t,i}\right)}{\sum_k \exp\left(\gamma_t \, v_{t,k}\right)} \tag{20}$$

where $\beta_t > 0$ and $\gamma_t > 0$ are the inverse Lagrange multipliers on the respective budget constraints. Therefore

$$\sigma_{t,i}(u_t, v_t|\delta_{t-1}) \propto \sigma_{t,i}(u_t)\sigma_{t,i}(v_t|\delta_{t-1}) = \frac{\exp\left(\beta_t \, u_{t,i} + \gamma_t \, v_{t,i}\right)}{\sum_j \sum_k \exp(\beta_t \, u_{t,j} + \gamma_t \, v_{t,k})} \tag{21}$$

Renormalization yields the result. ■

Proof of Lemma 1. Let

$$\mu_v(\delta_{t-1}) = \mathbb{E}[\sigma_t(v_t|\delta_{t-1}) \cdot v_t] \tag{22}$$

Therefore $\mu_v(\delta_{t-1})$ is the objective value attained by solving maximization over $\sigma_t(v_t|\delta_{t-1})$ when the mutual information constraint is at level δ_{t-1}. Note that this definition immediately implies $\mu_v(\delta_{t-1})$ is a non-decreasing function.

We first show that the subgraph of $\mu_v(\delta_{t-1})$ is convex. Let $\hat{\sigma}$ and $\tilde{\sigma}$ be any two pairs of single-period focus rules that generate $\hat{\mu} = \mathbb{E}[\hat{\sigma} \cdot v_t)]$ and $\tilde{\mu} = \mathbb{E}[\tilde{\sigma} \cdot v_t]$ expected utility and cost $\hat{c}$ and $\tilde{c}$ units of mutual information, respectively. Let $q \in (0, 1)$ be given, and consider a new information and focus rule where the DM uses $\hat{\sigma}$ with probability q and $\tilde{\sigma}$ with probability $1 - q$. The new rule generates expected utility $q\,\hat{u} + (1 - q)\,\tilde{u}$ and costs $q\,\hat{c} + (1 - q)\,\tilde{c}$. By definition of $\mu_v(\delta_{t-1})$, we must have that $\hat{\mu} \leq \mu_v(\hat{c})$, $\tilde{\mu} \leq \mu_v(\tilde{c})$, and $q\hat{\mu} + (1 - q)\tilde{\mu} \leq \mu_v(q\,\hat{c} + (1 - q)\,\tilde{c})$, so the subgraph of $\mu_v(\delta_{t-1})$ is convex. This implies that $\mu''_u(\delta_{t-1}) \leq 0$ for all δ_{t-1}. Finally, note that, because we have assumed G_v takes different relative values with positive probability, we have $\mu_u(0) < \mu_v(\infty)$. Taken together, these facts imply that $\mu'_v(\delta_{t-1}) > 0$ on some interval $\delta_{t-1} \in [0, \bar{\delta}]$.

As can be shown from the Lagrangian formulation of the sub-problem for $\sigma_t(v_t|\delta_{t-1})$

(see, *e.g.*, Matějka and McKay, 2015), the marginal value of information at an optimum is equal to the inverse of γ:

$$\mu_v'(\delta_{t-1}) = \frac{1}{\gamma(\delta_{t-1})} \tag{23}$$

The fact that μ is a strictly concave and strictly increasing function implies that γ is a strictly increasing function of δ_{t-1}. This, combined with the fact that $\lim_{\delta_{t-1}\to\infty} \mu'(\delta_{t-1}) = 0$ implies that $\lim_{\delta_{t-1}\to\infty} \gamma(\delta_{t-1}) = \infty$. Finally, it is clearly the case that the only optimal strategy which generates zero mutual information occurs when $\gamma = 0$, so we have $\gamma(0) = 0$. ■

Proof of Lemma 2. The executive's attention problem takes the form

$$\max_{\alpha} \alpha\, x - c(\alpha) \tag{24}$$

Let $A(x)$ denote the optimal solution of (24) for a given x. The first-order condition is

$$x = c'(A(x)) \tag{25}$$

From the properties of the cost function $c(\cdot)$, we have that A is a strictly increasing, concave, and differentiable function with $A(0) = 0$, $\lim_{x\to\infty} A(x) = 1$. ■

Proof of Proposition 2. For any vector $x \in \mathbb{R}^N$, define the softmax function $r_i(x) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$. Differentiation yields $\frac{\partial}{\partial x_i} r_j(x) = r_i(x)(1_{i,j} - r_j(x))$. Both results follow directly from the chain rule. ■

Proof of Theorem 1. Denote the advisor's time-t expectations of next period's multiplier $\theta(\pi_t) = \mathbb{E}[\theta_{t+1}|\pi_t]$. Dropping time subscripts for compactness, define

$$\mu(\delta \,|\, \pi) = \mathbb{E}\Big[\sigma(u, v \,|\, \delta) \cdot (u + \theta(\pi)\, v)\Big] \tag{26}$$

First, note that

$$(27)\quad \frac{\partial}{\partial\gamma}\sum_i \sigma_i(u,v)\,v_i = \frac{\sum_i \exp(\beta\,u_i+\gamma\,v_i)\,v_i^2}{\sum_j \exp(\beta\,u_j+\gamma\,v_j)} - \left(\frac{\sum_i \exp(\beta\,u_i+\gamma\,v_i)\,v_i}{\sum_j \exp(\beta\,u_j+\gamma\,v_j)}\right)^2$$

$$= \sum_i \sigma_i(u,v)\,v_i^2 - \left(\sum_j \sigma_j(u,v)\,v_j\right)^2 = \sum_i \sigma_i(u,v)\left(v_i - \sum_j \sigma_i(u,v)\,v_j\right)^2 = \mathrm{Var}_v(u,v)$$

A similar derivation shows that

(28)

$$\frac{\partial}{\partial\gamma}\sum_i \sigma_i(u,v)\,u_i = \sum_i \sigma_i(u,v)\left(u_i - \sum_j \sigma_i(u,v)\,u_j\right)\left(v_i - \sum_j \sigma_i(u,v)\,v_j\right) = \mathrm{Cov}(u,v)$$

Putting these together, we have

$$(29)\qquad \frac{\partial}{\partial\gamma}\sigma(u,v)\cdot(u+\theta\,v) = \mathrm{Cov}(u,v) + \theta(\pi)\,\mathrm{Var}_v(u,v)$$

Which in turn implies

$$(30)\qquad \mu'(\delta|\pi) = \gamma'(\delta)\,\mathbb{E}\big[\mathrm{Cov}(u,v) + \theta(\pi)\,\mathrm{Var}_v(u,v)\big]$$

This expression is clearly positive. Moreover, increasing $\theta(\pi)$ raises the marginal value of δ_{t-1}. Consider the shadow price of deliberative attention as a function of the advisor's beliefs $\lambda(\delta_{t-1}|\pi_t) = \mu'(\delta_{t-1}\,|\,\pi_t)$. Equation 30 implies that $\lambda(\delta_{t-1}|\pi_t)$ parameterizes a family of functions which are strictly decreasing in δ_{t-1} and satisfy $\lambda(\delta_{t-1}|\pi_1) > \lambda(\delta_{t-1}|\pi_0)$ whenever $\pi_1 > \pi_0$.

The advisor therefore has a refined belief about the shadow cost of deliberative attention, and so wishes for the executive to solve

$$(31)\qquad \max_{\alpha_t}\ \alpha_t\big(\mathbb{E}[\rho_t\cdot u_t|\rho_t] + \theta_t\,\rho_t\cdot v_t)\big) - \lambda(1-\alpha_t|\pi_t)$$

Denote the solution to the advisor's refined problem as a function of the marginal value as $B(\mathbb{E}[\rho_t\cdot u_t|\rho_t] + \theta_t\,\rho_t\cdot v_t|\pi_t)$. Given the properties of $\lambda(\delta_t|\pi_t)$, $B(x|\cdot)$ is an increasing function for every fixed x. Moreover, when $\pi_t = \frac{1}{2}$, $\theta_t(\pi_t) = 0$ so that the advisor's refined first-order condition collapses back to the executive's original first-order condition, hence $B\big(x \,\big|\, \frac{1}{2}\big) = A(x)$. Therefore, $B(\cdot|\pi_t)$ parameterizes a family of functions that lie above $A(\cdot)$ when $\pi_t > \frac{1}{2}$ and below when $\pi_t < \frac{1}{2}$.

The advisor uses h_t to induce the executive to invest the amount of decision attention they think is appropriate. This amounts to solving

$$A\big(\mathbb{E}[\rho_t \cdot (u_t + v_t) \,|\, \rho_t] + h_t\big) = B\big(\mathbb{E}[\rho_t \cdot u_t|\rho_t] + \theta_t\, \rho_t \cdot v_t \,\big|\, \pi_t\big) \tag{32}$$

Define $m(\,\cdot\,) = A^{-1}\big(B(\cdot)\big)$. With h_t as defined in the Theorem, we have

$$\begin{aligned}(33)\quad & A\big(\mathbb{E}[\rho_t \cdot (u_t + v_t|\rho_t]) + h_t\big) \\ &= A\Big(\mathbb{E}[\rho_t \cdot (u_t + v_t) \,|\, \rho_t] + m\big(\mathbb{E}[\rho_t \cdot u_t|\rho_t] + \theta_t\, \rho_t \cdot v_t) \,\big|\, \pi_t\big) - \mathbb{E}[\rho_t \cdot (u_t + v_t|\rho_t])\Big) \\ &= A\Big(m\big(\mathbb{E}[\rho_t \cdot u_t|\rho_t] + \theta_t\, \rho_t \cdot v_t \,\big|\, \pi_t\big)\Big) = B\big(\mathbb{E}[\rho_t \cdot u_t|\rho_t] + \theta_t\, \rho_t \cdot v_t \,\big|\, \pi_t\big)\end{aligned}$$

as intended.

■

Lemma 3. *For each value of ρ_t, there exists a cutoff point $k(\rho_t)$ such that the log-liklihood ratio*

$$\ell(x|\rho_t) = \log\left(\frac{p(\omega_t = H \mid \theta_t\, \rho_t \cdot v_t = x, \rho_t)}{p(\omega_t = L \mid \theta_t\, \rho_t \cdot v_t = x, \rho_t)}\right) \tag{34}$$

is positive for all $x > k(\rho_t)$ and negative for all $x < k(\rho_t)$.

Proof of Lemma 3. Denote the advisor's revised belief that the environment was H in period t after seeing the realized implicit utility as $\pi^t = p(\omega_t = H|s_{t-1}, \theta_t\, \rho_t \cdot v_t, \rho_t)$. Define the random variables $X = \rho_t \cdot v_t$. By the assumption that G_v is simple, X is unimodal. Let x_0 denote the location of this mode and $F(x)$ denote the cumulative density function of X. An implication of unimodality is that F is convex to the left of x_0 and convex to the right. The *c.d.f.* of θX is $F_\theta(x) = F(\frac{x}{\theta})$ and its mode is θx_0, implying that its *p.d.f.* $f_\theta(x) = \frac{1}{\theta} f(\frac{x}{\theta})$ where f is density of F. In the region $x \le \theta_L x_0$ we therefore have that $f_{\theta_H} x \ge f_{\theta_L}(x)$; in the region where $x \ge \theta_H x_0$, we have that $f_{\theta_L}(x) > f_{\theta_H}(x)$; and in the region $x \in (\theta_L x_0, \theta_H x_0)$, we have $f_{\theta_H}(x)$ weakly decreasing and $f_{\theta_L}(x)$ weakly decreasing. It must therefore be that $\ell(x|\rho_t)$ is negative for $x < \theta_L x_0$, positive for $x > \theta_H x_0$, and only switches sign one time in the interval $x \in (\theta_L x_0, \theta_H x_0)$. Denote this point as $k(\rho_t)$. ■

Proof of Theorem 2. Let $d_t = (s_t, \theta_t\, \rho_t \cdot v_t, \rho_t)$ and denote the history of data the advisor has seen up through time t as $d^t = \{d_\tau\}_{\tau=1}^t$. Further, let $\kappa(s)$ denote the event that the cue $s \in S$ is in fact associated with the high environment H and $\eta_t(s)$ denote the agent's log-odds belief in $\kappa(s)$ at time t. We have

(35)
$$\eta_t(s_t) = \log\left(\frac{p(\kappa(s_t)|d^t)}{p(\neg\kappa(s_t)|d^t)}\right) = \log\left(\frac{p(d^t|\kappa(s_t))}{p(d^t|\neg\kappa(s_t))}\frac{p(\kappa(s_t))}{p(\neg\kappa(s_t))}\right) = \log\left(\frac{p(d_t|\kappa(s_t))}{p(d_t|\neg\kappa(s_t))}\right) + \eta_{t-1}(s_t)$$

given the d_t are independent given $\kappa(s_t)$ and $p(\kappa(s_t)) = p(\neg\kappa(s_t))$. Now,

(36)
$$\begin{aligned} p(d_t|\kappa(s_t)) &= p(d_t|\omega_t = H, \kappa(s_t))p(\omega_t = H|\kappa(s_t)) + p(d_t|\omega_t = L, \kappa(s_t))p(\omega_t = L|\kappa(s_t)) \\ &= \frac{1}{2}\,\zeta\, p(\theta_t\,\rho_t \cdot v_t|\omega_t = H) + \frac{1}{2}\,(1-\zeta)\, p(\theta_t\,\rho_t \cdot v_t|\omega_t = L) \end{aligned}$$

and likewise for $p(d_t|\neg\kappa(s_t))$, which implies that

$$\log\left(\frac{p(d_t|\kappa(s_t))}{p(d_t|\neg\kappa(s_t))}\right) \tag{37}$$

is positive if $\theta_t\,\rho_t \cdot v_t > k(\rho_t)$ and negative if $\theta_t\,\rho_t \cdot v_t < k(\rho_t)$. If we let $r(x) = \frac{\exp(x)}{1+\exp(x)}$ denote the (strictly increasing) sigmoid function, then the advisor's posterior $p(\kappa|d^t) = r(\eta_t)$ is a martingale. Hence, for all $\tau \geq t$ such that $s_\tau = s_t$, we have

(38)
$$\begin{aligned} \mathbb{E}[\pi_\tau|s_\tau, d^t] &= \mathbb{E}\Big[p(\omega_\tau = H|\kappa, s_\tau)p(\kappa|d^t) + p(\omega_\tau = H|\neg\kappa, s_\tau)p(\neg\kappa|d^t)\Big|d^\tau\Big] \\ &= \zeta\, r(\eta_t) + (1-\zeta)\,(1 - r(\eta_t)) \end{aligned}$$

An observation $\theta_t\,\rho_t \cdot v_t > c(\rho_t)$ therefore raises $\mathbb{E}[\pi_\tau|s_\tau, d^t]$ for all $\tau \geq t$ such that $s_\tau = s_t$. The comparative statics then follow directly from Corollary 1 and Remark 1. If in addition the prior G_v decreasing, then the log-liklihood ratio $\ell(x|\rho_t)$ defined in (34) is strictly increasing, and its impact on $\eta_t(s_t)$ and subsequent expectations

$\mathbb{E}[\pi_\tau | s_\tau, d^t]$ therefore become strictly monotonic. ■

Proof of Proposition 3. Recall from the Proof of Theorem 1 that the advisor's refined belief about the shadow cost of attention is

$$\lambda(\delta_t|\pi_t) = \mu'(\delta_t|\pi_t) = \gamma'(\delta_t)\,\mathbb{E}[\mathrm{Cov}(u,v) + \theta(\pi_t)\,\mathrm{Var}_v(u,v)] \tag{39}$$

Moreover, note that $c(1-\delta_t) = \lambda(\delta_t|\frac{1}{2})$ by construction. The difference between the executive's static shadow cost and the advisor's revised one is

$$\lambda(\delta_t|\pi_t) - \lambda(\delta_t|.5) = \gamma'(\delta_t)\,\mathbb{E}[\mathrm{Var}_v(u,v)](2\pi - 1)\epsilon \tag{40}$$

The hedonic signal is a strictly decreasing function of this difference, so h_t is a strictly decreasing function of ϵ holding the other variables constant. ■

Proof of Remark 2. The DM experiences workplace boredom whenever they receive an incongruent cue, which is directly parameterized by ζ. In expectation, their experience of working in the office is

$$\zeta(m(u_w|\zeta) - u_w) + (1-\zeta)(m(u_w|1-\zeta) - u_w) \tag{41}$$

Evaluated at $\zeta = 1$, the derivative $\frac{\partial}{\partial\zeta}$ is

$$m(u_w|1) - m(u_w|0) + \frac{\partial}{\partial\zeta} m(u_w|\zeta) \tag{42}$$

which is positive, meaning the derivative $\frac{\partial}{\partial(-\zeta)}$ is negative. ■

Proof of Proposition 4. First, note that whenever $\rho_t = q$, the liklihood ratio

$$\ell(x|q) = \log\left(\frac{p(\theta_H\,\rho_t \cdot v_t = x|\rho_t = q)}{p(\theta_L\,\rho_t \cdot v_t = x|\rho_t = q)}\right) = \log\left(\frac{p(\theta_H\, v_q = x)}{p(\theta_L\, v_q = x)}\right) \tag{43}$$

is strictly increasing in x, which means that it equals zero at a single point. Call this $\bar{v}$. Note that when $v_q > \bar{v}$, the liklihood ratio above is a strictly positive constant c. On the other hand, when $\rho_t = d$, $p(\theta_H v_d = x) = p(\theta_L v_d = x)$ and the log-liklihood is equal to 0.

Let κ denote the event that the observed "blue" signal in fact is associated with the high state, d^t denote the advisor's entire history of observed data up until time t, and $\eta_t = \log\left(\frac{p(\kappa|d^t)}{p(\neg\kappa|d^t)}\right)$ denote the log-liklihood of κ (similar to the proof of Theorem 2). For any $t \in T_q$, we have

$$\eta_t = \begin{cases} c + \eta_{t-1} & \rho_t = q \\ \eta_{t-1} & \rho_t = d \end{cases} \tag{44}$$

which shows that the advisor's posterior belief $p(k|d^t) = r(\eta_t)$ increases each time they choose the thrilling option and stays the same otherwise (where $r(x) = \frac{\exp(x)}{1+\exp(x)}$ denotes the sigmoid function). Fix t and let τ denote the smallest value in T_q^{-1} such that $\tau > t$. By Corollary 1 and Remark 1, h_τ will be smaller, δ_τ will be larger, $\beta_{\tau+1}$ will be larger, and $\sigma^q_{\tau+1}$ will be larger if $\rho_t = q$. On the other hand, $\sigma^q_{\tau+1}$ will stay the same if $\rho_t = d$.

Denote the value of $\sigma^q_{\tau+1}$ if $\rho_t = q$ as σ^+. We therefore have that $\mathbb{E}_t[\sigma^q_{\tau+1}] = \sigma^q_t\sigma^+ + (1-\sigma^q_t)\sigma^q_t > \sigma^q_t$, which shows that $\sigma^q_{\tau+1}$ is strictly increasing in expectation over T_q. Moreover, by (44), we have that each distributions of $\{\eta_t\}_{t\in T_q}$ in the sequence first-order stochastically dominates the last. But h_t is a strictly decreasing function of η_t on T_q^{-1}, so it must therefore be strictly decreasing in expectation. ■

Proof of Proposition 5. Define a random vector $v(\zeta_t)$ that takes the value $v_H = (0, v_q)$ with probability ζ_t and $v_L = (0,0)$ with probability $1-\zeta_t$. First, note that

$$\mathbb{E}\big[\sigma_q(u_t, v(\zeta_t)|\delta_{t-1})\big] = \zeta_t\,\sigma_q(u_t, v_H|\delta_{t-1}) + (1-\zeta_t)\,\sigma_q(u_t, v_L|\delta_{t-1}) \tag{45}$$

so the first order condition becomes

$$\sigma_q(u_t, v_H|\delta_{t-1}) - \sigma_q(u_t, v_L|\delta_{t-1}) = c'(\zeta_t) \tag{46}$$

Next, note that

$$
\begin{aligned}
(47) \quad \frac{\partial}{\partial \delta_{t-1}} \Big[\sigma_q(u_t, v_H | \delta_{t-1}) - \sigma_q(u_t, v_L | \delta_{t-1}) \Big] &= \frac{\partial}{\partial \delta_{t-1}} \int_{v_L}^{v_H} \frac{\partial}{\partial v_q} \sigma_q(u_t, v_q | \delta_{t-1}) d_{v_q} \\
&= \frac{\partial}{\partial \delta_{t-1}} \int_{v_L}^{v_H} \gamma_t \sigma_q(u_v, v_q | \delta_{t-1})(1 - \sigma_q(u_v, v_q | \delta_{t-1})) d_{v_q} \\
&= \gamma'(\delta_{t-1}) \int_{v_L}^{v_H} \gamma_t \sigma_q(u_v, v_q | \delta_{t-1})(1 - \sigma_q(u_v, v_q | \delta_{t-1})) d_{v_q} > 0
\end{aligned}
$$

This shows that ζ_t is an increasing function of δ_{t-1}. The proof of Proposition 4 showed that the distribution of η_τ stochastically dominates η_t for $t, \tau \in T_q^{-1}$ such that $\tau > t$. But δ_t is a strictly decreasing function of η_t, so $\{\mathbb{E}_0[\zeta_\tau]\}_{\tau \in T_q}$ is strictly increasing over time. ■

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