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Intertemporal Spillovers in Consumer Experiences: Empirical Evidence and Service Design Implications

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In consumer experiences, the consumption of activities may impact the evaluation of future ones, either positively (due to assimilation) or negatively (due to contrast). How salient are these intertemporal spillovers and what are their implications for service experience design? To answer these questions, we develop a model that encompasses both types of spillover, by separating, for each activity consumed by a particular individual, its inherent quality from the consumer's individual satisfaction. To disentangle the positive and negative intertemporal spillovers, we test our model with retrospective data in four experiential contexts, namely: watching movies, reading books, visiting tourist attractions, and eating out. We consistently find the presence of both positive and negative intertemporal spillovers, with higher salience when activities are more similar to each other and when they are experienced in closer time intervals. Our empirical results have several implications for the design of experiences to maximize a consumer's total discounted utility. First, it may be optimal to schedule the best activity in the middle of an experience, in contrast to the common peak-end rule. Second, under uncertainty, it may be valuable to save the best activity as a "wild card" in case bad outcomes happen, to recover from them. Our study not only documents the salience of both positive and negative spillovers across four experiential contexts using large-scale observational datasets, it also offers new prescriptions for service experience design.

Key words: Service experience design, Behavioral operations management, Prospect theory, Analysis of reviews, Reduced-form econometric analysis, Dynamic programming.

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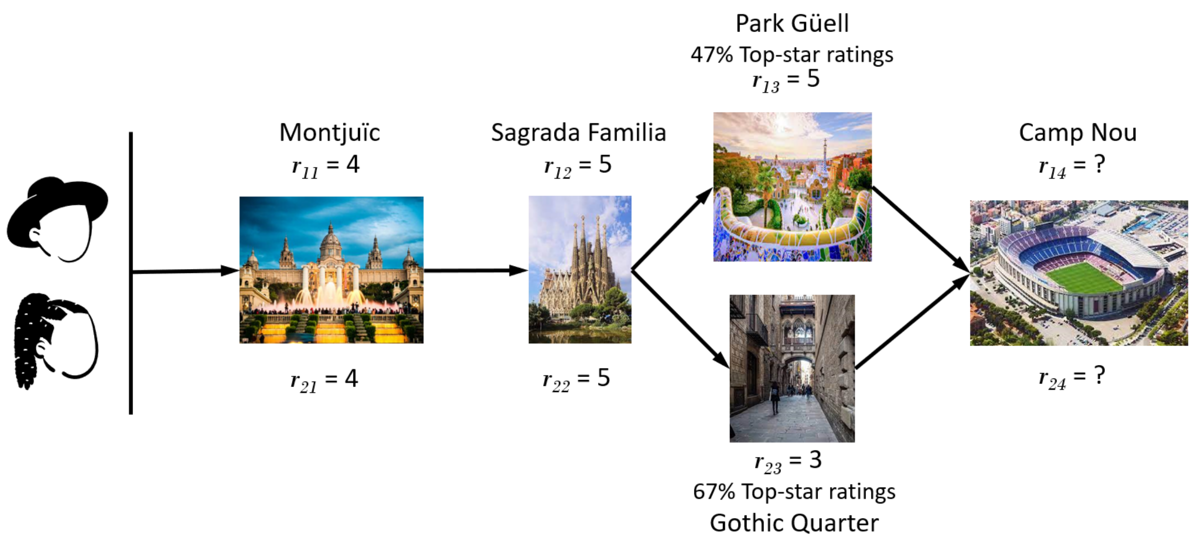
1. Introduction

When consuming and evaluating experiences, sequence matters (Dasu and Chase 2013). Numerous behavioral biases affect not only how we aggregate utilities in our retrospective evaluation of a multi-activity experience (Kahneman et al. 1997), e.g., due to memory decay, but also how much utility we derive from each activity, e.g., due to adaptation (Wathieu 1997), satiation (Baucells and Sarin 2007), or loss aversion (Tversky and Kahneman 1991). In particular, when evaluating our satisfaction from an activity, we are inherently affected by our past consumptions, attempting to either *contrast* or *assimilate* the focal activity to former activities (Herr et al. 1983, Bless and Schwarz 2010). That is, an activity consumption may have *negative* or *positive* spillovers onto the evaluation of future activities. While these phenomena have been well documented in lab experiments (Sinclair and Mark 1995, Miron-Shatz et al. 2009), what is the evidence from the field of such spillover effects? And what are their service design implications?

Figure 1 **An illustration of intertemporal spillovers in a touristic experience.**



Note. Here, r_{ij} denotes individual i's rating, out of a maximum of 5, of their j^{th} activity, $i \in \{1,2\}, j \in \{1,2,3,4\}$.

Motivating Example. To contextualize these questions, consider the following example, illustrated in Figure 1: Jack and Tina travel to Barcelona for a four-day vacation. They both visit Montjuïc and the Sagrada Familia on their first two days. They like these attractions equally, both rating the Montjuïc with 4/5 and the Sagrada Familia with 5/5. On the third day, they visit different attractions, namely, Park Güell and the Gothic Quarter, which historically received, respectively, 47% and 67% of top-star (i.e., 5/5) ratings. Jack visits Park Güell, which he enjoys a lot, giving it a rating of 5/5, while Tina visits the Gothic Quarter, which she finds not as exciting, resulting in a rating of 3/5. On their last day of vacation, they both visit Camp Nou. Given the difference in their experiences, how differently would they enjoy their Camp Nou visit?

Theories of Intertemporal Spillovers. To answer this question, we briefly review two potentially conflicting theories. On the one hand, *adaptation theory* (Helson 1948), wherein individuals adapt their references based on past consumption, would predict that, prior to visiting Camp Nou, Jack's reference point is lower than Tina's, since he visited a lower-quality activity (with only 47% top-star rating, compared to 67%). Accordingly, Jack would be more likely than Tina to enjoy his visit to Camp Nou.

On the other hand, their evaluations of Camp Nou may be affected by their affective state. Presumably, Jack's affective state at Camp Nou might be higher than Tina's given their difference in experiences on their third-day activities as reflected in their ratings. How their affect "infuses" their evaluation of Camp Nou can go either way according to *affect infusion theory* (Forgas 1989). It can be *congruent* if Jack's positive affect makes him see the bright side of Camp Nou, in contrast to Tina, who might instead find it less appealing; or *incongruent* in case Tina attempts to compensate her bad experience at Montjuïc by forcing herself to see the bright side of Camp Nou.

Preliminary Evidence. How prevalent are these intertemporal spillovers in practice? Upon an initial examination of individual Internet reviews of consumption streams within the contexts of watching movies (scraped from IMDb), reading books (scraped from GoodReads), visiting tourist attractions, and dining at restaurants (both scraped from TripAdvisor), we found evidence of both positive and negative spillovers.

Figure 2 reports some preliminary evidence across all four contexts. In the motivating example, Jack and Tina experience the same focal activity (Camp Nou), but if this were not true, we would need to control for the quality of their respective activities. (Throughout this discussion, we define quality of an activity as the fraction of the population who gave a top-star rating to it, i.e., its historical rating.) Accordingly, in Figure 2, we measure, in the ordinate, an individual's propensity to give a top-star rating to a particular activity, controlled for the quality of this activity.

The abscissa streams individuals according to the quality of the former activity they consumed. For instance, all individuals who experienced an activity quality of 47% (like Jack at Park Güell) will be lumped together. Within each sample, we further separate consumers into two classes, depending on whether they gave a top-star rating to their former activity (like Jack did) or not (like Tina did). In Figure 2, the former subsample is represented with a red solid curve, whereas the latter one is represented with a blue dashed curve. For instance, suppose that 100 individuals have a similar history to Jack's, namely visiting first a 47%-quality activity and giving a 5-star rating to it, and then visiting Camp Nou, which has a historical quality of 60%. If 70 of these 100 individuals give a top rating to Camp Nou, the reported ordinate of the red solid curve at the abscissa 47% is 70%-60%=10%. For another example, suppose that 100 individuals have a similar history to Tina's, namely visiting first a 67%-quality activity and not giving a 5-star rating to it, and then visiting Camp Nou. If 40 individuals give a top rating to Camp Nou, the reported ordinate of the blue dashed curve at the abscissa 67% is 40%-60%=-20%.

The four panels of Figure 2 show two consistent insights across the four application domains:

- First, irrespective of whether consumers gave a top-star rating to their former activity (blue or red curves), their (controlled) propensity of giving a top-star rating to the current activity is decreasing in the quality of the former activity they consumed. This suggests the presence of negative spillovers, i.e., *quality contrast*.

Figure 2 **Preliminary evidence of quality contrast and affect assimilation.**

Note. Fraction of individual consumers who gave a top rating to an activity (deviation against sample average for that activity), as a function of the quality of the former activity they consumed (measured as the fraction of the population who gave a top rating to it); we further separate consumers who gave a top rating to their former activity (red solid curve) from those who did not (blue dashed curve).

- Second, the (controlled) propensity of giving a top-star rating to the current activity is higher for consumers who gave a top-star to their former activity (red solid curve) than for those who did not (blue dashed curve). Hence, consumers' satisfaction with their former activity seems to carry over to their likelihood of being satisfied with the current one. This suggests the presence of positive spillovers, which we identify as *affect assimilation*.

Research Questions. Is this preliminary evidence of quality contrast and affect infusion still present once we formally control for both the consumer type and the activity quality? Is affect infusion always positive (congruent) or could it also be negative (incongruent)? Are these effects more salient when activities share more or fewer similar attributes and when they happen closer or further in time? What are the implications of the positive spillovers, in conjunction with the negative ones, on service experience design to maximize customer satisfaction—measured as their discounted sum of utilities? Understanding the valence of the spillovers should inform us about the optimal sequence of activities: Should the optimal sequence end with a highlight (consistent with the celebrated peak-end rule in Kahneman et al. 1993), be U-shaped (as would be the case with memory decay and adaptation in Das Gupta et al. 2015), or take another shape?

Contributions. We answer these questions, adopting first a deductive and then a prescriptive approach, and make the following three contributions. First, we formulate in §3 a utility model disentangling the intertemporal spillovers across activities after controlling for the focal individual's agreeableness and the focal activity's quality. Specifically, we distinguish the following effects:

- Quality contrast, which measures how much the inherent quality of the activities previously consumed influences the utility from the focal activity. This effect is objective, deterministic, and cognitive. In line with adaptation theory, we expect satisfaction from the focal activity to be decreasing in the quality of past activities.

- Affect infusion, which measures the "clouding" of individual judgments while assessing an activity by their current affective state. This effect is subjective, stochastic, and affective. Depending on whether the evaluation is affect-congruent or incongruent, this effect could be positive or negative.

Second, we empirically test the salience of these effects across the four aforementioned experiential contexts (watching movies, reading books, visiting tourist attractions, and eating out) for external validity. Using a reduced-form expression of our utility model, proposed in §4, we predict the likelihood of an individual to give a top rating for the focal activity in §5. One of the major challenges of our inferences is the self-selection bias associated with choosing to consume a particular activity. To tackle this issue, we use Heckman's selection model with an exclusion restriction that accounts for market thickness at the time of decision-making. Across all contexts, we consistently find evidence for the presence of quality contrast and affect infusion. However, the valence of affect infusion is context-specific: While we observe positive spillovers (affect-congruent assessments) in the contexts of watching movies, reading books, and visiting tourist attractions, we find negative spillovers (affect-incongruent assessments) in the context of eating out. In addition, we show that both quality contrast and affect infusion become less salient as the difference in content and time lapse between the focal and penultimate activities increases.

Third, we characterize the service design implications of such positive and negative spillovers by formulating and solving a problem of sequencing activities in an experience in §6, taking the perspective of an "experience curator" who seeks to schedule a set of activities to maximize a consumer's total discounted utility. This dynamic optimization problem is solvable both in closed- and open-loop. For a special case of linear affect transition probabilities, we show that the optimal closed-loop policy is identical to the open-loop policy; that is, the optimal sequence can be determined *ex-ante* and applies to all consumers, irrespective of their initial affect levels or reference points. The optimal sequence consists in general of a U-shape followed by an inverted U-shape, or *vice versa*, and resolves the following trade-off: experiencing a high-quality activity has a higher likelihood to boost affect, which increases future utility, but it also raises the quality baseline, which has a negative effect on future utility. As a result, it may be optimal to schedule the best activity in the middle of an experience, contrary to the established peak-end rule (Kahneman et al. 1993) or U-shaped designs (Das Gupta et al. 2015). Outside this special case of linear affect transition probabilities, the closed-loop policy may differ from the open-loop one, and it may be valuable to save the best activity as a "wild card" in case of bad outcomes, to recover from them. We apply these insights to a counterfactual study calibrated on our experimental study of tourist attraction visits to optimize the design of a tourist trip. Other potential applications using our collected data could be the design of a movie festival or a book reading club's schedule.

In sum, we document the salience of both positive and negative intertemporal spillovers across four experiential contexts using large-scale observational datasets and discuss their implications for service experience design, demonstrating the optimality of interior peaks and keeping high-quality activities as "wild cards" to be played to recover from bad outcomes.

2. Contribution to the Literature

Our work contributes to the fields of behavioral operations and service experience design.

Behavioral Operations. A large body of research on behavioral operations relies on the construct of reference point (Tversky and Kahneman 1991) and, in a dynamic setting, its adaptation, building on the works by Helson (1948) and Wathieu (1997) among others. See Baucells and Sarin (2012) for a general treatment on engineering happiness. Applications of reference dependence to operations management problems include pricing (Popescu and Wu 2007, Tereyağoğlu et al. 2018), assortment optimization (Caro and Martínez-de Albéniz 2012), and product design strategies (Chan et al. 2021). Here, we focus on the design of service experiences, which we review in detail below.

We contribute to this literature by modeling the concept of affect infusion. Affect infusion and, more broadly, mood- and emotion-driven judgment processes of individuals have been theorized upon and studied in psychology; see Schwarz and Clore (2003) for a succinct review. Forgas (1995) describes four different judgment strategies, how the mechanism of affect infusion functions in each of the cases, and their boundary conditions. Experimental studies such as Schwarz and Clore (1983), Sinclair and Mark (1995), and Reber et al. (1998) have been instrumental in providing empirical evidence of this phenomenon in a lab-controlled environment using normalized mood scales (Watson et al. 1988). In contrast with this literature, we use retrospective data. To our knowledge, this work is the first to document from practice the existence of affective judgments for thousands of individuals. For external validity, we consider four different experiential contexts, which are economically and culturally relevant.

Service Experience Design. Following the modeling by Karmarkar and Pitbladdo (1995) of a service as a multi-stage process, various authors have investigated how to engineer experiences to maximize customer satisfaction, considering decisions such as activity sequencing (Dixon and Verma 2013, Das Gupta et al. 2015, Dixon et al. 2017, Baucells and Zhao 2020, Li et al. 2022, Chen et al. 2022), activity duration (Das Gupta et al. 2015), information release (Ely et al. 2015, Buraimo et al. 2020), budget allocation or effort exertion (Soteriou and Hadjinicola 1999, Soteriou and Chase 2000, Aflaki and Popescu 2014), or allocation of work between a service provider and its customers (Bellos and Kavadias 2019, 2021); see Roels (2019) for a review. We focus here on activity selection and sequencing.

We contribute to this literature by not only considering the impact of affect infusion on service design, but also demonstrating the optimality of interior peaks, in contrast to the celebrated peak-end rule, and consistent with some preliminary evidence, based on aggregate and not individual data, by Dixon and Verma (2013). Li et al. (2022) and Chen et al. (2022) also develop theories for interior peaks, using, respectively, activity-specific memory decay rates or loss aversion. In contrast, we assume a constant discount factor and no specific sensitivity to losses, but our model can be extended to incorporate these factors. Our model is grounded on psychology to include affect infusion, for which we find empirical evidence. Moreover, our counterfactuals are based on empirically estimated parameters, bringing us closer to real-world applications, while validating the intuition of the aforementioned works. Finally, we introduce the notion of contingent scheduling, whereas the aforementioned works (except the ones on information release) ignore uncertainty.

Summary. Our contribution is original in multiple respects: We combine empirical and analytical methodologies; we introduce affect infusion within both the literatures on behavioral operations and service experience design; we analytically formalize affect infusion; we explore quality contrast and affect infusion in four contexts; and we derive service experience design principles demonstrating the optimality of interior peaks and contingent scheduling.

3. Model and Hypotheses Development

3.1. A Model of Experience with Intertemporal Spillovers

An individual consumer i experiences several activities in a sequence. Let $\mathbf{x}_{ij}$ be the *attributes* of consumer i's j^{th} activity, t_{ij} be the *time of its consumption*, and q_{ij} be its inherent *quality* (e.g., its rating by the entire consumer population). Consumer i is characterized by a certain degree of *agreeableness* c_i, representing a tendency to be easily pleased or not. Consumer i's utility from her j^{th} activity is defined as:

$$u_{ij} = \bar{u}_{ij} + \varepsilon_{ij} \tag{1}$$

with

$$\bar{u}_{ij} = \eta q_{ij} + \zeta c_i, \tag{2}$$

in which ε_{ij} is a random shock with zero mean, independent across all i and j.

Consumer i's utility from her j^{th} activity u_{ij} is compared to an outside option with utility u^0_{ij}. If u_{ij} is higher that u^0_{ij}, customer i's binary *rating* of her j^{th} activity, denoted as r_{ij}, is equal to 1; otherwise, $r_{ij} = 0$ (McFadden 1974, Train 2009). Denote the probability that the rating is equal to 1 as:

$$\Phi(\bar{u}_{ij}) := \mathbb{P}[r_{ij} = 1] = \mathbb{P}[u_{ij} \geq u^0_{ij}]. \tag{3}$$

For instance, $\Phi(\bar{u}_{ij})$ could denote the probability of individual i's giving a top-star rating to her j^{th} activity. With a probit specification, as in our main analysis, Φ is the cumulative distribution function (c.d.f.) of the normal distribution; under a logit specification, $\Phi(z) = z/(1+z)$.

We are interested in the intertemporal effects in customer experiences. As stated by Smith and Bolton (2002, p. 7), "consistent with previous research ..., Wirtz and Bateson (1999) have suggested that satisfaction is a partly cognitive and partly affective (emotional) evaluation of a consumption experience and that separating cognitive antecedents from emotional antecedents is both valuable and necessary for modeling consumer behavior in service settings." Following this call, we expand (2) to account for the consumer's affective and cognitive antecedents. Let $a_{i,j-1}$ be consumer i's level of *affect* prior to experiencing her j^{th} activity and let $b_{i,j-1}$ be her *baseline* (or reference) quality level prior to her j^{th} activity. Accordingly,

$$\bar{u}_{ij} = \eta q_{ij} + \zeta c_i + \alpha a_{i,j-1} + \beta b_{i,j-1}. \tag{4}$$

The two first terms in (4) are the same as those in (2). The third term, with coefficient α, captures the random (subjective) shock of past experiences on current satisfaction, through the consumer's affect level. Accordingly, parameter α is called the *affect infusion*. Higher affect can lead to either higher or lower utility, depending on whether there is assimilation or contrast (Schwarz and Clore 1983, 2003, Forgas 1995). Thus, α could *a priori* be positive or negative. In the absence of a well-defined affect scale in an observational setting (Watson et al. 1988), we measure individual i's affect as a function of her past ratings. A consumer who recently gave top-star ratings is most likely in a higher affective state than if she gave lower ratings. Hence, the reported satisfaction ratings of past activities are used as a proxy for an individual's affective state at the time of the focal activity. In order to allow for the possibility of long memories of affective states, following the specification in Wathieu (1997), we assume consumer i's affect prior to consuming her j^{th} activity is a weighted average of her past ratings. Specifically, for some rate $\lambda_a \in [0,1]$, we assume:

$$a_{ij} = \lambda_a r_{i,j-1} + (1-\lambda_a) a_{i,j-1}. \tag{5}$$

The fourth term in (4), with coefficient β, captures the deterministic (objective) effect of past choices on current satisfaction; parameter β is called the *quality contrast*. According to adaptation theory, past experiences that have high quality increase the reference point (Helson 1964) of a consumer, who then becomes more difficult to satisfy (Baucells and Sarin 2012), i.e., β is *a priori* negative. The process through which the reference point evolves is through adaptation (Wathieu 1997) with rate $\lambda_b \in [0,1]$:

$$b_{ij} = \lambda_b q_{i,j-1} + (1-\lambda_b) b_{i,j-1}. \tag{6}$$

We can further expand (4) to account for moderating factors, i.e.,

$$\bar{u}_{ij} = \eta q_{ij} + \zeta c_i + \boldsymbol{\chi}\mathbf{Z}_{ij} + (\alpha_0 + \boldsymbol{\alpha}_1\mathbf{Z}_{ij})a_{i,j-1} + (\beta_0 + \boldsymbol{\beta}_1\mathbf{Z}_{ij})b_{i,j-1}, \tag{7}$$

in which $\mathbf{Z}_{ij}$ are contextual factors influencing intertemporal spillovers, such as the dissimilarity in attributes of successive experienced activities $\Delta\mathbf{x}_{ij} := ||\mathbf{x}_{ij} - \mathbf{x}_{i,j-1}||$, in which $||\cdot||$ is a generic distance measure, to be specified by context, or the temporal distance between the experience of successive activities $\Delta t_{ij} := t_{ij} - t_{i,j-1}$. In our empirical specification in §4.2, we also control for the rank of the consumer's review, the age of the activity, and the total number of reviews for this activity.

3.2. Hypotheses Development

There is a rich literature in decision analysis, psychology, marketing, and information systems on the effects of affect and past quality on present experiences. Our theoretical exploration focuses on developing hypotheses about the sequential effects of consuming experiences and characterizing the valence of $\alpha_0, \alpha_1, \beta_0$, and β_1 in (7). Given that the formalization of quality contrast is more established, we start with characterizing the valence of β_0 and β_1.

3.2.1. Quality Contrast

Main Effects. According to the disconfirmation framework (Howard and Sheth 1969, Oliver 1980), consumer satisfaction is a function of expectation and expectancy disconfirmation. Expectations are dynamically shaped by past experiences according to adaptation theory (Helson 1948, Wathieu 1997), as captured in (6)' see, e.g., Baucells and Sarin (2012). Specifically, the baseline quality, or reference point, for a particular activity increases in the quality of past activities. For example, after an individual reads Bram Stoker's *Dracula*, a classic novel widely regarded to be excellent, her satisfaction from her subsequent book will be benchmarked, i.e., contrasted, against *Dracula*'s quality. Thus, the inherent quality of past activities has a negative spillover effect on the satisfaction from subsequent activities.

Hypothesis 1. The higher the quality baseline $b_{i,j-1}$, the lower the satisfaction from the focal activity, i.e., $\beta_0 < 0$.

Moderating Effect of Similarity. Naturally, quality-driven contrast is moderated by the degree of similarity between the focal activity and its reference point. Similarity can be measured in two ways: in terms of content (i.e., attributes) or in terms of time. Prevailing theories suggest that contrast is stronger if the focal item belongs to the same mental category as the reference as it is easier to recall a reference with higher similarity (Nosofsky 1986, Posner and Petersen 1990). Also, reference levels are often assumed to function at the attribute level (Bleichrodt et al. 2009, Baucells and Zhao 2021); thus, a higher number of common attributes increases the opportunities for contrast.

To illustrate this moderating effect of attribute dissimilarity, consider an individual reading Mary Shelley's *Frankenstein* after *Dracula*. Due to the thematic overlap between the two books (namely, classical Gothic novels), the consumer will most likely directly compare the two books much more than if she were reading a contemporary sci-fi novel after *Dracula*. In terms of time, longer times between experiences reduce the salience of the last experience (Croson and Donohue 2006, Aydogan 2021), and thus dampen contrast (Das Gupta et al. 2015, Chan et al. 2021, Deshmane et al. 2022). Hence, as in Cassar and Ko (2023), we expect the extent of quality contrast to be weaker when the distance in attributes and in time between the focal activity and the previous one is larger ($\beta_1 > 0$).

Hypothesis 2. As the attribute and time distance between the focal and the previous activities ($\Delta \mathbf{x}_{ij}, \Delta t_{ij}$) increases, the impact of quality contrast diminishes, i.e., $\beta_1/\beta_0 < 0$.

3.2.2. Affect Infusion

Main Effects. There is a large literature on whether and how affects may trigger different information processing mechanisms (Mackie and Worth 1989, Bless et al. 1996, Bless and Schwarz 2010), therefore influencing judgments (Schwarz and Clore 1983), memories (Parrott and Sabini 1990), and decisions (Forgas 1989). In particular, Forgas (1995) posits that affect infuses judgment when individuals adopt open-ended and constructive judgmental strategies (heuristic-driven or substantive)—as is likely be the case in our evaluative contexts, in which individuals learn and interpret unstructured information about an activity they experienced before rating it. Thus, we expect α_0 to be non-zero.

For the valence of α_0, the literature reports evidence that affects, whenever they are salient, may lead to either positive or negative spillovers depending on whether the information being processed is assimilated or contrasted to the object of evaluation (Podsakoff et al. 2003). This leads to a set of competing hypotheses. On the one hand, we may theorize that affect generates positive spillover, e.g., affect-congruent judgment of the focal activity: all else held equal, individuals in positive affective state may derive a higher satisfaction from an activity than individuals in a negative affective state. On the other hand, affects may generate negative spillovers, e.g., due to mood self-regulation. That is, people may wish to engage in pleasurable activities to try to repair negative emotions (Gross and Thompson 2007, Zillmann 2015). Also, Parrott and Sabini (1990) and Erber and Erber (1994) report that individuals, upon being primed by an experience inducing bad mood (e.g., gloomy weather), tend to recall positive memories of past experiences to neutralize the negative affect infusion on the focal activity. Thus, an individual's (low or high) satisfaction from reading *Dracula* may carry over to the evaluation of her next book through either positive (assimilation) or negative (contrast) spillovers. In order to study the dual character of affect infusion, we formulate the following two opposing hypotheses.

Hypothesis 3a. The higher the affect level $a_{i,j-1}$, the higher the satisfaction from the focal activity, i.e., $\alpha_0 > 0$.

HYPOTHESIS 3B. The higher the affect level $a_{i,j-1}$, the lower the satisfaction from the focal activity, i.e., $\alpha_0 < 0$.

Moderating Effect of Similarity. Thematic similarity between consecutive activities tends to strengthen affect infusion. In particular, perceptual and conceptual fluency facilitate the overall processing fluency (Reber et al. 1998, Schwarz and Clore 2003). In other words, individuals associate their affect with a theme rather than with a specific activity. Accordingly, there will be greater affect infusion if the focal and former activities share theme commonalities (e.g., classical Gothic novels) than if they are fundamentally dissimilar.

Likewise, time similarity strengthens affect infusion. Affects can be categorized as either emotions, which are "intense, short-lived, [with] usually a definite cause and clear cognitive content" or mood, which are "low-intensity, diffuse and relatively enduring affective states without a salient antecedent cause and therefore little cognitive content (e.g. feeling good or feeling bad)" (Forgas 1995, p. 41). Both emotions and moods are inherently dynamic (Kuppens and Verduyn 2017, Parkinson et al. 1996). Given that we only observe past satisfaction reports, we cannot identify the underlying driver of affect, between emotions and mood. However, given the short-lived nature of emotions, and the tendency of individuals to self-regulate their mood over time (Parrott and Sabini 1990), we expect the intensity of affect infusion to diminish as the time lapse between two consecutive activities increases.

HYPOTHESIS 4. As the attribute and time distance between the focal and the previous activities $(\Delta\mathbf{x}_{ij}, t_{ij})$ increases, the impact of affect infusion diminishes, i.e., $\alpha_1/\alpha_0 < 0$.

4. Empirical Specification with Retrospective Data

In this section, we first describe the four empirical contexts we study, then specify how the variables of our utility model presented in §3.1 are measured in these contexts, and finally identify and discuss empirical challenges.

4.1. Empirical Contexts

To empirically explore the intertemporal spillovers in experience consumption, we carry out reduced-form empirical analyses with large-scale retrospective data. For a wider external validity, we consider four distinct experiential contexts, which are economically and culturally relevant (Hardey 2011).

- **Watching movies.** IMDb.com ("IMDb") is an online platform where movie watchers can post reviews or read reviews by other users. We scraped review data for 4,259 consumers, who posted a total of 0.49 million reviews on a 1-10 scale in 1998-2022.
- **Reading books.** Goodreads.com ("GoodReads") is an online platform where readers review books, share what they are reading, explore what is new in the market, and, in general, participate in a worldwide community of avid readers. From data collected by Wan and McAuley (2018), we built reading histories of 85,201 consumers over 2006-2017, consisting of 4.06 million reviews on a 1-5 scale for 0.35 million books by 0.30 million authors.

- **Visiting tourist attractions.** TripAdvisor.com ("TripAdvisor") is an online platform in which travelers post reviews on various attractions or activities experienced on a trip (e.g., taking a bicycle tour, visiting a museum). We scraped review histories of 13,382 travelers who rated 0.17 million activities on a 1-5 scale in 2004-2022 (both within and across trips). This data amounts to 0.55 million reviews in total.
- **Eating Out.** In addition to tourist activities, TripAdvisor also allows travelers to rate their experiences at restaurants. We scraped the rating histories, again on a 1-5 scale, of 33,622 consumers across 0.55 million restaurants over 2004-2022, amounting to 1.5 million reviews.

One potential criticism of these datasets is that individuals may choose to rate an activity only if their experience is highly positive or negative. This censoring bias is partially mitigated by the social network nature of these platforms, where frequent contributors are rewarded with higher status positions; thus, individuals are incentivized to post reviews, irrespective of their satisfaction (Mallipeddi et al. 2022). We further address this concern by only considering users who have posted at least 15 reviews, i.e., our first observation for a given user is her 15^{th} review. A stricter robustness test is also carried out by only considering the top-quartile most active reviewers in our sample.

A second potential concern is that TripAdvisor is quite heterogeneous as it allows individuals to review tourist attractions, restaurants, and hotels. To focus on studying spillovers across different activities of the same type, we separate the reviews for tourist attractions from those for restaurants, and we ignore the hotel reviews. Although we hypothesize limited spillovers across categories (Hypotheses 2 and 4), they might still arise, thus raising caution in the interpretation of the results. Despite the limitations of the dataset, the context of tourist attractions is very relevant for service experience design.

4.2. Variables Specification

We next describe how we measure the variables in the utility model introduced in §3.1.

Ratings. To attain binary ratings (3), we translate the original ratings (see the histograms in Figure EC.1 in the electronic companion) into binary outcomes. Specifically, we set r_{ij} to 1 when the rating is 8-9-10 on IMDb, 4-5 on GoodReads, and 5 on TripAdvisor (similar to Godes and Silva 2012 or Carrera et al. 2020); and to zero otherwise. Across all datasets, the percentage of top ratings lies between 34.7% and 54.2%.

Quality and Agreeableness. Using these binary rating definitions, we estimate the inherent quality q_{ij} of consumer i's j^{th} activity as well as consumer i's agreeableness c_i. We proceed as follows. Let $\kappa(i,j)$ be consumer i's j^{th} activity. For instance, in Figure 1, $\kappa(1,2)$ is the Sagrada Familia. We measure the inherent quality of consumer i's j^{th} activity as the percentage of top ratings given to that activity, formally

$$q_{ij} := \frac{\sum_{i'} \sum_{j'} r_{i',j'} \mathbb{1}[\kappa(i',j') = \kappa(i,j)]}{\sum_{i'} \sum_{j'} \mathbb{1}[\kappa(i',j') = \kappa(i,j)]}$$

in which $\mathbb{1}[X]$ is the indicator function, equal to 1 if statement X is true and zero otherwise. While consumer i's rating is included in the numerator of this metric, the number of reviews for each activity is typically large, so $r_{ij} - \eta q_{ij}$ (with η defined as in (2)) should have a negligible correlation with q_{ij}.

We measure the consumer i's agreeableness as consumer i's average rating on her first $\bar{j}$ activities, for some fixed $\bar{j}$, i.e.,

$$c_i := \frac{\sum_{j \leq \bar{j}} r_{ij}}{\bar{j}} \tag{8}$$

In our analysis, we consider individuals with at least 15 reviews and only consider activities $j \geq 15$, as mentioned in §4.1 and set $\bar{j} = 10$. This should guarantee that $r_{ij} - \zeta c_i$ (with ζ defined as in (2)) is independent from c_i since any influence from early activities $j \leq \bar{j} = 10$ should have washed away in the rating of activities $j \geq 15$.

Moderators. We compute moderators $\mathbf{Z}_{ij}$ as follows. Let Δt_{ij} be the time gap between reviews, measured in weeks. The attribute dissimilarity measure, $\boldsymbol{\Delta}\mathbf{x}_{ij}$, is defined in different ways for every dataset, because of the distinct nature of the attribute characterization; see §EC.2 in the electronic companion for details on the specification of this variable.

Controls. We add the following controls to our model specification (7):

- the rank j of the consumer i's review;
- the age of the j^{th} activity experienced by consumer i, A_{ij}, which is defined as the logarithm of the time (in days) between the release date of the movie/book (on IMDb and GoodReads) or the first review of an activity (on TripAdvisor) and the date of consumer i's review; and
- the log-transformed total number of reviews garnered for the focal activity (i.e., consumer i's j^{th} activity), n_{ij}.

We present representative statistics for the key variables in Table 1, and other descriptive statistics in §EC.1 in the electronic companion (Tables EC.2-EC.5).

To identify the rate of adaptation of affect a_{ij} (λ_a) and of the baseline quality b_{ij} (λ_b) in (5)-(6), we carry out a grid search between 0 and 1 with a 0.1-increment as in Lattin and Bucklin (1989) and Tereyağoğlu et al. (2018) to maximize the likelihood (see Tables EC.23 to EC.30). The maximizing values are $\lambda_a = 0.3$ and $\lambda_b = 0.2$ for movies and books, $\lambda_a = 0.9$ and $\lambda_b = 0.2$ for tourist attractions, and $\lambda_a = 0.1$ and $\lambda_b = 0.2$ for restaurants. In §5.3 we replicate the analysis with $\lambda_a = \lambda_b = 1$ (full adaptation to the last activity) and find similar results compared to the main analysis, suggesting that the effects of affect infusion and quality contrast are robust to their speed of adaptation.

4.3. Empirical Challenges

Self-reported consumer reviews are rife with self-selection, data quality, and structural issues (Chen et al. 2021), which we discuss next.

Table 1 Representative statistics of the key variables across the four contexts, in the selected sample used for the analysis.

Variable		IMDb	GoodReads	TripAdvisor Attractions	TripAdvisor Restaurants
No. activities		48,659	324,221	92,678	398,002
No. users (i)		4,259	85,214	13,426	33,893
No. of reviews for an activity	Mean	8.2	9.5	3.8	2.5
	Min.	1	1	1	1
	Max.	914	6,390	1,556	400
Quality of an activity	Mean	0.40	0.35	0.59	0.49
	Min.	0	0	0	0
	Max.	1	1	1	1
Agreeableness of an individual	Mean	0.41	0.33	0.55	0.44
	Min.	0	0	0	0
	Max.	1	1	1	1
Age in days of an activity	Mean	4,537	2,092	1,221	778
	Min.	0	1	1	1
	Max.	52,530	366,873	6,417	6,211
Time lag in days between activities j and $j-1$	Mean	18.4	48.8	53.8	59.7
	Min.	0	7	0	0
	Max.	7,981	3,245	3,393	3,823
No. of reviews per individual (starting from the 15$^{\text{th}}$ review)	Mean	93.4	36.0	26.3	29.6
	Min.	1	1	3	4
	Max.	1,433	204	496	460

Self-Selection. Since individuals make conscious choices of consuming particular activities among other possible options, not controlling for such non-random selection may lead to biased estimates. To overcome this challenge, we carry out our analysis with *Heckprobit*, a variant of Heckman's selection model (Heckman 1979), consisting of two stages. In the first stage, we control for the likelihood of an individual to select a particular activity for consumption. In the second stage, we control for the inverse Mills ratio (denoted as IMR) to account for this potential selection bias. The first stage is challenged by data censoring since we do not observe the consumers' selection process. To tackle this challenge, we adopt the approach utilized in Singhvi and Singhvi (2022) to generate a distribution of first-stage activity options for the focal consumer. See details in §EC.3.1 in the electronic companion.

Data Issues. Individuals who have experienced multiple activities over a certain time window may be batching their reviews into a single session. While GoodReads' users often record the dates of their reading of a book, neither IMDb nor TripAdvisor keeps track of the activity consumption time. With batching, individuals may be posting their recalled satisfaction from an activity, which may differ from their true utility (Kahneman et al. 1997), though it is certainly correlated (Baucells and Bellezza 2017). To address this potential challenge, we drop, in one of the robustness tests, users who ever posted multiple reviews on the same date on IMDb and TripAdvisor. While this conservative approach prevents us from tracking within-day spillover effects, it diminishes the likelihood of batching, incorrect ordering, and delays in retrospective evaluations.

Structural Issues. To obtain stable estimates of consumer agreeableness (8), we only consider users that have a long review history (namely, who have posted at least 15 reviews, as discussed in §4.1). Although our findings are robust to the choice of this minimum requirement, we may be introducing a selection bias. However, we found no significant demographics difference between the individuals who engage in frequent reviewing activity and the individuals we excluded.

Although we restrict our attention to "moderately heavy" users, we cannot rule out a form of endogenous reporting bias (Lee et al. 2015). Specifically, infrequent users may only rate activities that lead to extreme (dis)satisfaction. To address this issue, we include a variable that controls for the likelihood of individuals to register their reviews for a particular activity. Specifically, we control for the total number of reviews for the focal activity (n_{ij}), as described in §4.2, in case some activities are more susceptible to generate reviews as shown in Dellarocas et al. (2010). In addition, we carry out a more focused analysis on a sub-sample of "very heavy" users, namely consumers who are in the top-quartile of reviewing activity.

A potential downside of focusing on "moderately heavy" users is that they may review differently than the general population. There is indeed evidence that reviewers tend to get more critical as their tenure and status increase on a platform (Toubia and Stephen 2013, Goes et al. 2014, Caro and Martínez-de Albéniz 2020). To control for this negative review bias, we control for the activity's rank j in a consumer's experience, as described in §4.2.

5. Empirical Results

We now present the results for the empirical estimation of the model specified in Equations (4) and (7) across the four contexts, using a two-stage Heckprobit model to account for self-selection, as introduced in §4.3. A high-level overview of the first stage and its resulting estimation of the likelihood of an individual choosing the focal activity is discussed in §5.3. The details appear in §EC.3 in the electronic companion.

Table 2 presents the key results of the second stage of our estimations, across all four contexts. We discuss the main effects of quality control and affect infusion (Hypotheses 1 and 3a-3b) in §5.1, the moderating effects of content and time dissimilarity (Hypotheses 2 and 4) in §5.2, and the role of selection through the inverse Mills ratio and the robustness of our findings in §5.3.

A comparison of the log-likelihood of the models in Tables EC.8- EC.11 in the electronic companion reveals that, after controlling for individual agreeableness (c_i) and the quality of an activity (q_{ij}), the largest improvement in the log-likelihood values of the prediction models arises after the introduction of the key independent variables, namely, affect infusion ($a_{i,j-1}$) and quality contrast ($b_{i,j-1}$), indicating the significance of these effects in explaining the variation in the data.

Table 2 Estimation of Equations (4) and (7).

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.9$ & $\lambda_b = 0.2$		$\lambda_a = 0.1$ & $\lambda_b = 0.2$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	-2.284^{***}	-2.148^{***}	-2.371^{***}	-2.338^{***}	-2.406^{***}	-2.379^{***}	-2.065^{***}	-2.118^{***}
	(0.040)	(0.057)	(0.016)	(0.031)	(0.025)	(0.067)	(0.016)	(0.038)
c_i	2.835^{***}	2.833^{***}	2.677^{***}	2.683^{***}	2.864^{***}	2.865^{***}	3.104^{***}	3.093^{***}
	(0.028)	(0.028)	(0.011)	(0.011)	(0.018)	(0.018)	(0.015)	(0.015)
q_{ij}	3.038^{***}	3.062^{***}	2.679^{***}	2.690^{***}	2.351^{***}	2.346^{***}	1.850^{***}	1.839^{***}
	(0.025)	(0.027)	(0.011)	(0.011)	(0.021)	(0.021)	(0.015)	(0.015)
j	-0.023^{***}	-0.023^{***}	0.007^{***}	0.012^{***}	-0.010^{**}	-0.010^{**}	0.001	0.004
	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
n_{ij}	0.002	0.002	0.042^{***}	0.043^{***}	0.012^{***}	0.012^{***}	-0.012^{***}	-0.009^{***}
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	-0.013^{***}	-0.024^{***}	-0.026^{***}	-0.027^{***}	0.006^{***}	0.006^{***}	0.010^{***}	0.010^{***}
	(0.005)	(0.008)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$a_{i,j-1}$	0.318^{***}	0.687^{***}	0.549^{***}	0.772^{***}	0.120^{***}	0.290^{***}	-0.200^{***}	-0.139^{***}
	(0.021)	(0.049)	(0.008)	(0.026)	(0.007)	(0.025)	(0.010)	(0.027)
$b_{i,j-1}$	-1.330^{***}	-2.001^{***}	-1.611^{***}	-2.342^{***}	-0.957^{***}	-1.142^{***}	-0.681^{***}	-0.774^{***}
	(0.040)	(0.108)	(0.020)	(0.078)	(0.030)	(0.108)	(0.021)	(0.071)
$a_{i,j-1} \times \Delta t_{ij}$		-0.039^{***}		-0.040^{***}		-0.052^{***}		0.001
		(0.009)		(0.007)		(0.003)		(0.004)
$a_{i,j-1} \times \Delta \mathbf{x}_{ij}$		-0.410^{***}		-0.223^{***}		-0.098^{***}		-0.074^{**}
		(0.058)		(0.016)		(0.026)		(0.029)
$b_{i,j-1} \times \Delta t_{ij}$		0.120^{***}		0.123^{***}		0.063^{***}		0.023^{**}
		(0.022)		(0.022)		(0.013)		(0.010)
$b_{i,j-1} \times \Delta \mathbf{x}_{ij}$		0.625^{***}		0.852^{***}		0.098		0.058
		(0.133)		(0.051)		(0.113)		(0.079)
IMR	0.067^{***}	0.123^{***}	0.128^{***}	0.112^{***}	-0.771	-0.690	7.814^{***}	7.978^{***}
	(0.021)	(0.037)	(0.005)	(0.006)	(0.605)	(0.606)	(1.167)	(1.170)
AIC	118,214.7	118,129.2	754,266.2	753,385.5	214,047.4	213,761.9	394,088.3	393,601.6
Log Likelihood	−59098.3	−59049.6	−377124.1	−376,677.7	−107,014.7	−106,865.9	−197,035.1	−196,785.8
Pseudo R^2	0.295	0.296	0.284	0.285	0.206	0.207	0.189	0.190
No. obs.	124,027	124,027	774,235	774,235	195,407	195,407	350,744	350,744

Notes: Observations are at the individual-activity level. Standard errors are shown in parentheses. The table was shortened for brevity. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5.1. Main Effects

We first discuss the statistical significance and valence of the controls and then those of the main independent variables of interest.

Controls. Consider first individual i's agreeableness and the quality of her j^{th} activity. As expected, we see in Models (1), (3), (5), and (7) in Table 2 that both c_i and q_{ij} are positive and statistically significant predictors of the likelihood of a person to give a top-star rating. Specifically, an increase in a consumer's agreeableness by one standard deviation (SD, see values in §EC.1) increases the average likelihood of the consumer to give an activity a top rating from 22 percentage points (p.p.) for reading books to 26 p.p. for visiting restaurants (p-value < 0.01). To elaborate on these effect sizes, consider the case of reading books: the standard normal c.d.f. at the mean values of all the covariates (given in Table EC.3) is 0.32; and it increases to 0.54 upon increasing c_i by one SD and keeping everything else the same; giving us $(0.54 - 0.32) \times 100 = 22$ p.p. (Wooldridge 2010, §15.6). Similarly, a one-SD increase in the quality of the activity increases the likelihood of a consumer to enjoy it from 15 p.p. for visiting restaurants to 27 p.p. for watching movies (p-value < 0.01).

Consider next the effect of reviewers' tenure on ratings, measured through j (the activity's rank in a consumer's review history). We observe mixed effects. On the one hand, when watching movies (Model (1)) and visiting tourist attractions (Model (5)), individuals tend to be more demanding over time, consistent with Goes et al. (2014), since the covariate j has a negative and statistically significant estimate of -0.023 and -0.010, respectively. On the other hand, in the context of reading books, the opposite effect arises.

Finally, consider the effect of the age of the activity A_{ij} and the number of reviews it has received n_{ij}. Here again we have mixed effects. On the one hand, consumers tend to enjoy more recent movies and books, but they tend to enjoy more established tourist attractions and restaurants. Similarly, the greater the number of reviews for books and attractions, the more consumers like them; restaurants, however, suffer with an increase in the total number of reviews they garner.

Main Independent Variables of Interest. Controlling for these factors, we now turn our attention to the key independent variables of interest, $a_{i,j-1}$ and $b_{i,j-1}$. Across all contexts, both are statistically significant for determining consumer satisfaction. These results confirm the general patterns observed in Figure 2.

For affect infusion ($a_{i,j-1}$), we see in Models (1), (3), (5), and (7) that a recent history of higher positive ratings has a positive spillover in the assessment of a movie, book, or attraction (for a one-SD increment a change of 3.7, 6.1, and 2.2 p.p. in the respective probabilities, p-value < 0.01), but a negative spillover in the assessment of a restaurant (-2.4 p.p. for a similar increment, p-value < 0.01). Thus, in the former three contexts, we observe assimilation effects, resulting in affect-congruent judgments in line with Hypothesis 3a. For restaurants, we observe contrast effects, resulting in affect-incongruent assessments, in line with Hypothesis 3b. However, this contrasting effect disappears (and becomes a significant assimilation effect) when the sample is restricted to the top-quartile reviewers, as shown in Table EC.17 in the electronic companion. The difference in valence in the affect infusion effect for restaurants could be due to the censoring that may happen with the occasional reviewers.

For the baseline quality comparison ($b_{i,j-1}$), we consistently observe across all contexts that a recent history of higher-quality activities has a negative spillover in the assessment of an activity (change within a range of -3.2 p.p. for restaurants to -6.2 p.p. for movies for a one-SD increment). This signals the prevalence of quality-contrast effects, consistent with Hypothesis 1.

5.2. Moderating Effects

We next discuss the moderating effects of content dissimilarity and time lapse using Models (2), (4), (6), and (8) in Table 2. Consider first the moderating effect of time lapse Δt_{ij}. Since its interaction with $a_{i,j-1}$ has a negative and statistically significant estimate in all cases but the eating out experience, we conclude that affect infusion is reduced as the time gap between the focal and penultimate activities increases. Hence the positive spillover of affect infusion diminishes over time. In a similar vein, since the interaction between Δt_{ij} and $b_{i,j-1}$ is positive and statistically significant across all four contexts, we conclude that the effect of quality contrast diminishes over time. Both findings validate Hypothesis 2 and 4.

Consider next the moderating effect of content dissimilarity $\Delta \mathbf{x}_{ij}$. Since its interaction with $a_{i,j-1}$ has a negative and statistically significant estimate in all cases, we conclude that, in the first three contexts, affect assimilation is reduced as there is less content overlap between the focal and the penultimate activities, validating Hypothesis 4. In the context of eating out, we actually see an amplification of affect contrast as contents become more dissimilar, so our hypothesis does not seem to be validated. However, the more focused sample of the top-quartile reviewers in Table EC.16 suggests that this deviation from our expectation may be due to the censoring that happens with occasional reviewers since on this restricted sample, we observe that assimilation is reduced with greater dissimilarity. The interaction of $\Delta \mathbf{x}_{ij}$ with $b_{i,j-1}$ has a positive and statistically significant estimate in the contexts of watching movies and reading books, and is statistically insignificant on TripAdvisor. Hence, in the former two contexts, quality contrast is less salient when there is less content overlap between the focal and penultimate activities, consistent with Hypothesis 2.

In summary, these observations, with the exception of the interaction of content dissimilarity on affect contrast in the context of eating out on the full sample of users, validate Hypotheses 2 and 4.

5.3. Robustness

No Control for Selection. In the main model, we controlled for the self-selection bias of choosing a particular activity with the following two-stage Heckprobit specification: in the first stage, we track the likelihood of selecting a particular activity and in the second stage, we focus on the satisfaction derived from it. As in Arora et al. (2009), we use, as exclusion restriction, a variable measuring the size of the option set, i.e., "market thickness" at the time of selection, which only affects the likelihood of an activity being chosen without affecting the likelihood of the chosen activity to receive a top rating after its consumption, estimated in the second stage. For example, an individual, while considering reading *Dracula*, might also consider novels that overlap with the theme of the book; or while considering eating at a particular restaurant, she might consider all other restaurants in its vicinity (Aouad et al. 2021). We specify how we construct this market thickness variable in the four contexts under consideration in §EC.3.1 in the electronic companion. In addition, we control, in the first stage of the Heckprobit specification, for the activity's baseline quality q_{ij}, its rank in the customer's experience j, and its age A_{ij}. Table EC.7 in the electronic companion presents the results for the first stage.

As shown in Table 2, the inverse Mills ratio (IMR) in the second stage is significant and positively related with the dependent variable for watching movies (0.07, p-value < 0.01), reading books (0.13, p-value < 0.01), and eating out (7.82, p-value < 0.01). In other words, higher satisfaction comes from activities that are more likely to be chosen. To assess whether controlling for selection affects the estimation of coefficients $\alpha_0, \alpha_1, \beta_0$, and β_1, we replicate the analyses without the first-stage selection correction. As shown in Tables EC.12-EC.15 in the electronic companion, the significance and valence of the results without controlling for selection remain consistent with our two-stage estimation.

Review Batching. In our baseline specification (Table 2), we ignored the potential effects of batching of reviews. Table EC.16 in the electronic companion replicates the analyses by excluding users who ever posted multiple reviews on the same date on IMDb and TripAdvisor. Since the issue of batching does not arise on GoodReads, the column that corresponds to this context is identical to the one in Table 2. Overall, Table EC.16 reveals consistent results to Table 2.

Censoring. To consider the possible effects of a reporting bias, Table EC.17 in the electronic companion replicates the main analyses focusing on the top-quartile most active reviewers. Again, we find consistent results with Table 2.

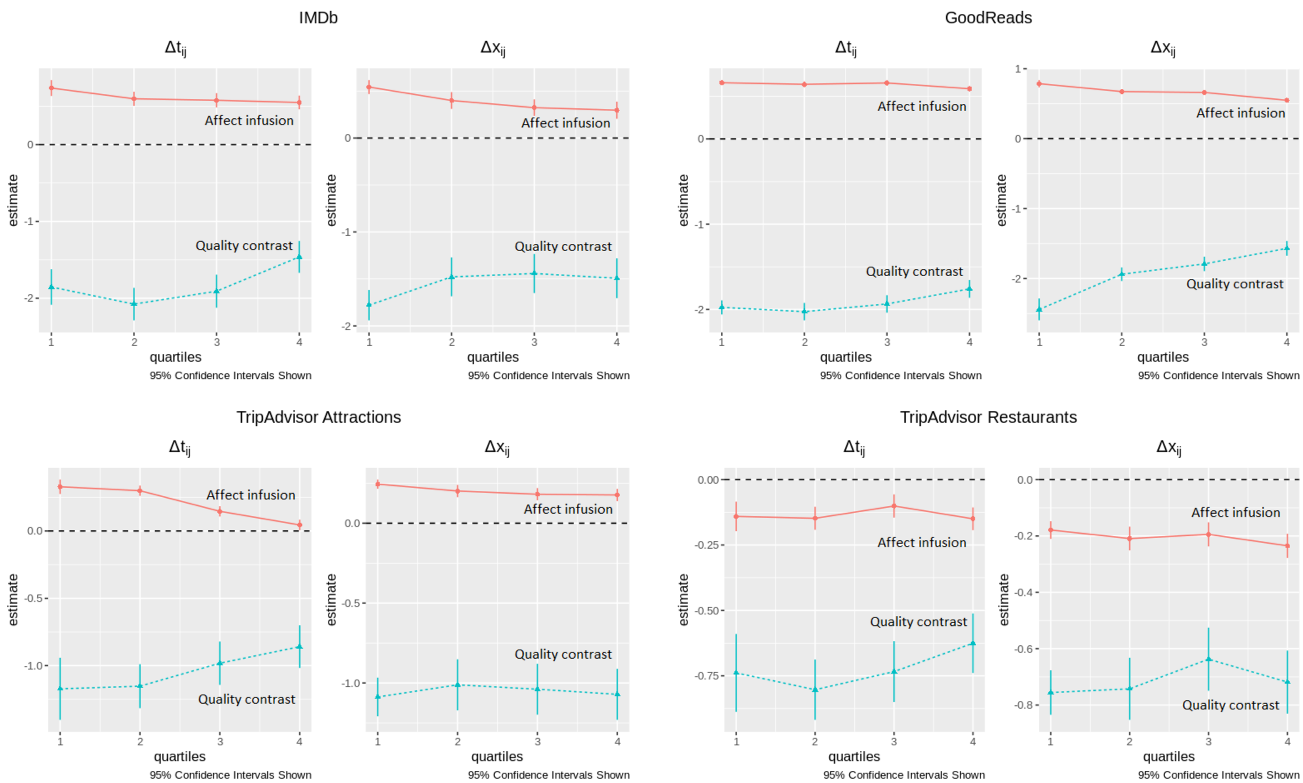
Genre Controls. We replicate the analyses by controlling for the most representative genre/tag of the activity to account for the underlying affinity of an individual towards a particular type of activity as in Tereyağoğlu et al. (2018). We see that this additional control does not change the estimates of the key variables from our main findings. See Table EC.18 in the electronic companion.

Geographical Distance Control. We consider, in the particular case of TripAdvisor, the geographical distance in locations between the focal and former activity, denoted as ΔL_{ij}, as an additional moderator. Table EC.19 in the electronic companion shows that, in the case of attractions, distance diminishes the effect of affect infusion, consistent with Hypothesis 4, while being insignificant in the case of restaurants. It both contexts, distance does not change the intensity of quality contrast, suggesting that quality reference is only affected by attribute similarity, and not geographical proximity.

Instantaneous Adaptation. To consider the sensitivity of our results to the fine-tuning of parameters λ_a and λ_b to maximize the log-likelihood, Table EC.20 in the electronic companion replicates the analyses when $\lambda_a = \lambda_b = 1$. In this case, the quality of the last activity fully determines the reference level and its rating by the focal consumer fully determines her affect. Overall, comparing Tables 2 and EC.20 suggests that affect infusion and quality contrast are robust to the speed of adaptation. Tables EC.23-EC.30 study one-dimensional comparative statics around the base values of λ_a and λ_b and demonstrate robustness of of our results.

Non-Linear Effects. To test the non-linearity of the effects of the main dependent variables and moderators, we divided their respective ranges into four quartiles. From Table EC.21 and as illustrated in Figure EC.2 in the electronic companion, we see that the effects of both affect infusion and quality contrast are monotonic, respectively increasing and decreasing, further validating our main findings. From Table EC.22 in the electronic companion and as illustrated in Figure 3, we observe that the moderating effects of content dissimilarity and time lapse on affect infusion and quality contrast are, by and large, also monotonic.

Figure 3 **Estimated coefficients α and β as a function of time and attribute distance, for IMDB (upper left), GoodReads (upper right), TripAdvisor-Attractions (lower left), and TripAdvisor-Restaurants (lower right).**



6. Optimal Activity Sequencing

We next turn to deriving the service experience design implications of both positive affect infusion ($\alpha > 0$) and quality contrasts ($\beta < 0$) for an "experience curator" (service provider) who seeks to sequence a set of activities to maximize customer utility or satisfaction from the experience. While the empirical contexts are settings where consumers do not necessarily plan their future consumption in advance and potentially have a universe of options to choose from at every epoch, this prescriptive part deals with how service providers can leverage this new learning to optimize the scheduling for a limited time horizon and options. We make this conscious switch to the setting where the decision-maker is the service provider, responsible for making active interventions to manage experiences, following works such as Das Gupta et al. (2015) or Li et al. (2022), in order to study the potential change in managerial implications for service design.

Here, we demonstrate the existence of interior peaks in the optimal sequence, absent loss aversion (Chen et al. 2022) and activity-specific discount rates (Li et al. 2022). Considering the inherent stochastic nature of experiential processes, we show that, to maximize *ex-post* customer satisfaction, a service provider should keep in reserve a "wild-card" activity to be played whenever the customer's affect level unluckily drops below a certain level and there is little time until the end of the horizon. We formulate the general optimization model in §6.1, characterize its optimal structure in a special (linear) case in §6.2, numerically investigate the structure of the optimal policy for the general case in §6.3, and apply it to a tourist trip design example, calibrated by our empirical study, in §6.4.

6.1. Decision Problem

Consistent with the literature on activity sequencing (Roels 2019), we consider a setting where a service provider seeks to maximize an individual consumer's (or a homogeneous group of consumers') total discounted expected utility over an experience lasting T (discrete) periods by selecting and scheduling activities from a set $\mathcal{J} = \{1, \ldots, J\}$. Each activity can be assigned at most once and each activity lasts one period only. This assumption can be relaxed by creating duplicates of activities in $\mathcal{J}$, in which case the proposed optimization problem would also optimize the activity durations. We denote j_t the activity scheduled in period t.

At the beginning of period t, let the state be (a_t, b_t), in which a_t denotes the consumer's affect and b_t denotes her quality baseline prior to experiencing activity j_t. Both a_t and b_t are updated over time as in (5)-(6); that is, $a_{t+1} = \lambda_a \cdot 1 + (1-\lambda_a)a_t$ if the consumer is satisfied from activity t and $a_{t+1} = (1-\lambda_a)a_t$ otherwise, and $b_{t+1} = \lambda_b q_{j_t} + (1-\lambda_b)b_t$, in which $0 \leq \lambda_a, \lambda_a \leq 1$.

To formulate the closed-loop optimization problem, in which activities are dynamically selected given the current state (a_t, b_t), we let $\mathcal{J}_t$ be the collection of activities that have not been assigned yet. Starting from a given initial affect level a_0 and a quality baseline level b_0, and $\mathcal{J}_0 = \mathcal{J}$, the discounted expected utility experienced by a consumer can be expressed as $V_0(a_0, b_0, \mathcal{J}_0)$, where V_t denotes the value function of the following dynamic program:

$$V_t(a_t, b_t, \mathcal{J}_t) = \max_{j \in \mathcal{J}_t} \left\{ \begin{array}{l} \quad q_j + \alpha a_t + \beta b_t \\ +\Phi(q_j + \alpha a_t + \beta b_t)\delta V_{t+1}(\lambda_a + (1-\lambda_a)a_t, \lambda_b q_j + (1-\lambda_b)b_t, \mathcal{J}_t \setminus \{j\}) \\ +\Big(1 - \Phi(q_j + \alpha a_t + \beta b_t)\Big)\delta V_{t+1}((1-\lambda_a)a_t, \lambda_b q_j + (1-\lambda_b)b_t, \mathcal{J}_t \setminus \{j\}) \end{array} \right\}$$
$$\text{for } t = 0, \ldots, T-1, \tag{9}$$

and

$$V_T(a_T, b_T, \mathcal{J}_T) = 0. \tag{10}$$

Similar to (3), $\Phi(\bar{u})$ denotes the probability of being satisfied from an activity if it is expected to generate utility $\bar{u}$; δ is the discount factor, with $\delta < 1$ if the goal is to maximize the consumer's discounted utility as in Baucells and Sarin (2007) and $\delta > 1$ if the goal is to maximize her remembered utility at time T as in Das Gupta et al. (2015).

In this formulation, utilities are assumed to be linear in $q_t + \alpha a_t + \beta b_t$, similar to (4), but the formulation can easily be extended to account for nonlinear relationships, e.g., to account for loss aversion or gain seeking (Aflaki and Popescu 2014, Chen et al. 2022). This formulation generalizes Das Gupta et al. (2015) who consider $\alpha = 0$ or $\lambda_a = 0$. Note that, in comparison with standard dynamic programs, the transition probabilities for b_{t+1} depend on q_{ij}, which introduces technical complexity.

We next characterize the structure of the optimal scheduling policy in the particular case where $\Phi(u) = u$ and then numerically illustrate the dynamic behavior of the optimal policy in the general case.

6.2. Structural Results for the Case of Linear Probabilities

While (9)-(10) is hard to solve in general, it turns out to be analytically tractable when $\Phi(u) = u$. This condition assumes that the probability of a high rating is linear in the expected utility derived from the choice; in other words, the error term is uniformly distributed. Note that this probability is well defined when $\max_{j\in\mathcal{J}} q_j + \alpha + \beta \min_{j\in\mathcal{J}} q_j \leq 1$ and $0 \leq \min_{j\in\mathcal{J}} q_j + \beta \max_{j\in\mathcal{J}} q_j$, which is without loss of generality given that q_{ij} can be rescaled and shifted.

We first show that when $\Phi(u) = u$, the value function $V_t(a_t, b_t, \mathcal{J}_t)$ is linear in (a_t, b_t). Moreover, only the constant term depends on the choice set $\mathcal{J}_t$. The proof of all results appear in §EC.5 in the electronic companion.

LEMMA 1. *Let $\gamma := \alpha\lambda_a + (1-\lambda_a)$. When $\Phi(u) = u$, then $V_t(a_t, b_t, \mathcal{J}_t) = A_t a_t + B_t b_t + C_t(\mathcal{J}_t)$ with*

$$\begin{aligned} A_t &= \alpha \tfrac{1-(\delta\gamma)^{T-t}}{1-\delta\gamma}, \\ B_t &= \tfrac{\beta}{1-\delta(1-\lambda_b)} \left(1 + \tfrac{\alpha\delta\lambda_a}{1-\delta\gamma}\right) + \tfrac{\beta}{1-\delta(1-\lambda_b)} \left(\tfrac{\alpha\lambda_a}{\gamma+\lambda_b-1} - 1\right) (\delta(1-\lambda_b))^{T-t} - \tfrac{\alpha\beta\lambda_a}{(1-\delta\gamma)(\gamma+\lambda_b-1)} (\delta\gamma)^{T-t}, \\ C_t(\mathcal{J}_t) &= \max_{j\in\mathcal{J}_t} \left\{\delta C_{t+1}(\mathcal{J}_t \setminus \{j\}) + \delta^{T-t} w_t q_j\right\} \end{aligned} \tag{11}$$

for $t < T$ and $A_T = B_T = C_T(\mathcal{J}_T) = 0$, where, for $t < T$,

$$\begin{aligned} w_t = &\tfrac{1-\delta(1-\lambda_a)}{1-\delta\gamma} \left(1 + \tfrac{\beta\delta\lambda_b}{1-\delta(1-\lambda_b)}\right) \delta^{-(T-t)} + \tfrac{\beta\lambda_b(\lambda_a-\lambda_b)}{(1-\lambda_b)(1-\delta(1-\lambda_b))(\gamma+\lambda_b-1)} (1-\lambda_b)^{T-t} \\ &- \tfrac{\alpha\lambda_a}{\gamma(1-\delta\gamma)} \left(1 + \tfrac{\beta\lambda_b}{\gamma+\lambda_b-1}\right) \gamma^{T-t}. \end{aligned} \tag{12}$$

Using this linear decomposition of the value function, we next show that, remarkably, the solution to the closed-loop problem (9)-(10) and that of the open-loop problem—in which the sequence is determined upfront—coincide when $\Phi(u) = u$.

THEOREM 1. *When $\Phi(u) = u$, the dynamic optimization problem (9)-(10) can be solved in open loop. Its optimal solution is independent of the initial state (a_0, b_0) and solves $\max_{\{j_0,\dots,j_{T-1}\}\subseteq\mathcal{J}} \sum_{t=0}^{T-1} w_t q_{j_t}$ with w_t given by (12) for $t < T$.*

Table 3 Examples of Optimal Sequences.

Parameters					Result	w_t						Optimal Sequence					
α	β	δ	λ_a	λ_b		w_0	w_1	w_2	w_3	w_4	w_5	q_{j_0}	q_{j_1}	q_{j_2}	q_{j_3}	q_{j_4}	q_{j_5}
1.27	-1.83	1.74	0.27	0.95	Lemma 2	-0.42	-0.41	-0.42	-0.45	-0.47	0.57	4	5	3	2	1	6
0.10	-0.90	0.92	0.90	0.13		1.17	1.15	1.14	1.15	1.15	1.09	6	4	2	3	5	1
0	-0.67	1.93	0.59	0.61	Lemma 3	-0.03	-0.04	-0.06	-0.05	0.06	0.52	4	3	1	2	5	6
0.67	0	1.60	0.79	0.17	Lemma 4	0.42	0.52	0.62	0.70	0.72	0.62	1	2	3	5	6	4
1.90	0	1.30	0.10	0.70		0.79	0.75	0.73	0.73	0.74	0.77	6	4	2	1	3	5
1.20	-0.90	1	0.27	0.40	Lemma 5	1.14	1.07	1.01	0.97	0.96	1.00	6	5	4	2	1	3
0.30	-0.30	1	0.80	0.50		1.02	1.04	1.06	1.08	1.09	1.00	2	3	4	5	6	1

Note: In all cases, $\mathbf{q} = (1,2,3,4,5,6)$.

Hence, the optimal sequence can be determined upfront. Although we assumed *a priori* that the service provider should customize the service experience design to each individual consumer, this is without loss of generality, *despite* the stochastic nature of the affect transitions. In particular, the optimal sequence is independent of the initial state (a_0, b_0).

Theorem 1 also characterizes the structure of the optimal solution, which is remarkably simple. Specifically, the optimal sequence consists in scheduling the highest-quality activity in the time period that is associated with the highest weight w_t, to schedule the second-highest-quality activity in the period associated with the second-highest weight w_t, and so on. Hence, the optimal sequencing policy can be identified in a greedy fashion, irrespective of the relative differences in quality; that is, an optimal sequence with activities of quality $\mathbf{q} = (1,2,3,4,5,6)$ will also be optimal with activities of quality $\mathbf{q} = (5, 5.1, 5.2, 5.3, 5.4, 20)$.

We next characterize the optimal sequences, first in general, and then by considering special cases when $\alpha = 0$, $\beta = 0$, and $\delta = 1$. To illustrate the different patterns, we consider an experience consisting of six activities ($T = 6$). Although this is irrelevant, as discussed above, let us assume that activities have qualities $\mathbf{q} = (1,2,3,4,5,6)$. Table 3 illustrates the optimal sequences that emerge under the conditions of the following lemmas.

Our first lemma presents a general characterization. It shows that w_t has at most two local maxima (and if so, one of which lies either when $t = 0$ or when $t = T-1$) and two local minima (and if so, one of which lies either when $t = 0$ or when $t = T-1$). Therefore, the optimal experience will have at most two local peaks and at most two local troughs—a departure from the aforementioned literature, which generally demonstrates the optimality of a U-shaped pattern in the simplest (linear) case.

LEMMA 2. *Suppose that $\alpha \geq 0 \geq \beta$. Then, w_t is first pseudo-concave and then pseudo-convex if $\gamma + \lambda_b - 1 > -\beta\lambda_b$, or first pseudo-convex and then pseudo-concave otherwise.*

We next consider particular cases of Lemma 2, namely when $\alpha = 0$ (Lemma 3), when $\beta = 0$ (Lemma 4), and when $\delta = 1$ (Lemma 5). Our first result confirms that, without affect infusion, the optimal sequence is U-shaped, as in Das Gupta et al. (2015). Moreover, if the goal is to maximize the remembered utility (at the end of the experience) of a consumer who is subject to memory decay (i.e., $\delta > 1$), it is optimal to finish with a positive gradient ("finish strong"), consistent with the peak-end rule (Kahneman et al. 1993).

LEMMA 3. *Suppose that $\alpha = 0 \geq \beta$. Then w_t is always pseudo-convex. Moreover, there exists a threshold $\hat{\delta} < 1$, such that $w_{T-1} \geq w_{T-2}$ if and only if $\delta \geq \hat{\delta}$.*

The next two lemmas consider two other particular cases, namely when there is no quality contrast ($\beta = 0$) and when there is no discounting ($\delta = 1$). In both cases, the optimal sequence may turn out to be an inverted U-shape. Without quality comparison ($\beta = 0$), the optimal sequence is an inverted U-shape if and only if $\alpha \leq 1$. Experiencing a high-quality activity boosts the affect level, which will have a positive effect on the utility the consumer derives in the future; accordingly, it may be optimal to place the peak activity early enough to impact utilities over a sufficiently large time window. Yet, placing the peak too early may not be desirable as it is always possible that the consumer may experience "tough luck", bringing her affect level down to zero, which may then negatively impact her utilities until the end of the horizon. When the consumer discounts the future ($\delta < 1$), the peak always appears at the beginning of the sequence; hence, an interior peak happens only when the consumer is subject to memory decay and maximizes her remembered utility ($\delta > 1$).

LEMMA 4. *Suppose that $\alpha \geq 0 = \beta$. Then w_t is pseudo-concave if and only if $\alpha \leq 1$.*

Our final result explores the trade-off between quality contrast and affect infusion, without discounting. In this case, the optimal sequence is an inverted U-shape when the affect adapts at a faster pace than the quality baseline, i.e., $\lambda_a > \lambda_b$, but it is a U-shape otherwise. We also obtain in closed form the period at which the peak (or through) is achieved, on which comparative statics can be established.

LEMMA 5. *Suppose that $\delta = 1$, and $\alpha \geq 0 \geq \beta$. Then w_t is pseudo-concave if $\lambda_a > \lambda_b$ and pseudo-convex otherwise. Its global optimum, if it lies in $(0, T)$, is attained at either $\lfloor t^* \rfloor$ or $\lceil t^* \rceil$, in which*

$$t^* = T - \frac{\ln\left(\frac{\ln(1-\lambda_b)}{\ln\gamma}\frac{\beta\gamma(\lambda_a-\lambda_b)(1-\gamma)}{\alpha(1-\lambda_b)\lambda_a(\gamma+\lambda_b-1+\beta\lambda_b)}\right)}{\ln\left(\frac{\gamma}{1-\lambda_b}\right)}.$$

Moreover, as $T \to \infty$, $w_0 \leq w_1$ if and only if $1 - \lambda_b - \gamma > \beta\lambda_b$.

Intuitively, quality contrast and affect infusion give rise to the following trade-off: Experiencing a high-quality activity has a higher likelihood to boost affect, which will increase future utility ("riding the wave"), but it also raises the quality baseline, which will negatively affect future utility. If affect adapts faster than the quality baseline (i.e., $\lambda_a > \lambda_b$), the former effect dominates the latter, and it is optimal to place the peak activity early enough to positively impact subsequent utilities over a sufficiently large time window. Yet, placing the peak too early may not be desirable as it increases the chances that the consumer faces "tough luck", bringing her affect level down to zero, which, combined with the high-quality baseline, may hurt her future utilities. As the time horizon increases, the expected duration of a high-affect "wave" will converge to a finite number, thus yielding decreasing marginal returns from scheduling early the peak activity.

Conversely, if affect adapts slower than the quality baseline (i.e., $\lambda_a < \lambda_b$), any benefit of a peak activity will be short-lived, i.e., the quality baseline will be very much influenced by the quality of the last activity. It then makes sense to schedule the peak activity either at the end of the sequence to avoid the negative consequences of a high quality baseline, or at the beginning of the experience, to gradually build up the affect level, which will then positively influence the consumer's evaluation of future activities.

6.3. Numerical Analysis for General Case

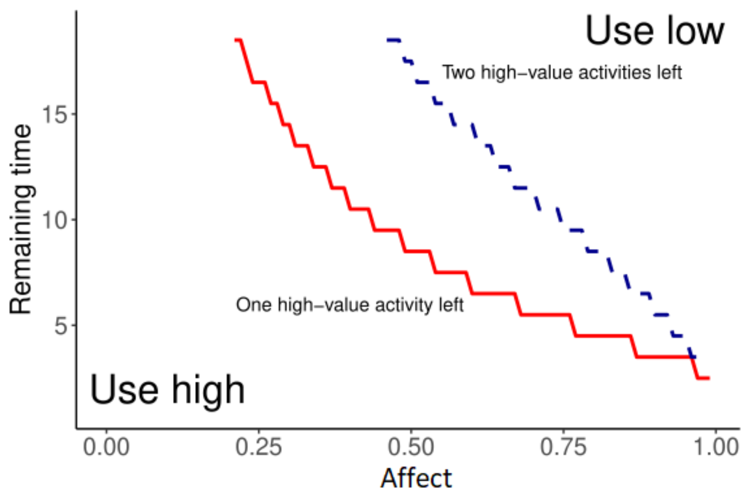
In the general case, the dynamic program in (9) is intractable. For this reason, here we numerically investigate the behavior of the dynamic (closed-loop) policy when $\Phi(u)$ is nonlinear; specifically, we assume that $\Phi(u) = F(10u - 4)$, in which $F(z)$ is the c.d.f. of the standard normal distribution, and the argument has been scaled to cover a wide range of probabilities.

To illustrate the nonlinear dynamics in this context, we consider a simple setting where $\mathcal{J}$ consists of two types of activities: many of low quality $q_L = 0.3$ and a few of high quality $q_H = 0.6$. Moreover, we focus on affect infusion $\alpha = 0.3$ with fast adaptation $\lambda_a = 1$, and assume that quality baseline remains constant at $b_t = 0.3$ (i.e., we set $b_0 = 0.3$ and no adaptation $\lambda_b = 0$). This scenario is representative of strong positive spillovers as those found in our empirical results. In this context, when should a service provider schedule a high-quality activity, as a function of a consumer's affect a_t, and time until the end of the experience?

Figure 4 illustrates the optimal policy as a function of the current affect level (horizontal axis), and the time until the end of the horizon (vertical axis). We observe that when there is a single high-value activity left, it should be reserved for circumstances in which the current affect level is low or the remaining time is short. In other words, scheduling the high-quality activity will allow the consumer to reach a high satisfaction with high probability (specifically, with probability $F\Big(10(0.6 + 0.3a - 0.03) - 4\Big) = F(1.7 + 3a) \geq 95.5\%$) regardless of the current affect level. In contrast, scheduling the low-quality activity will lead to high satisfaction with a probability $F\Big(10(0.3 + 0.3a - 0.03) - 4\Big) = F(-1.3 + 3a)$, and is much more sensitive to the current affect level: at low affect levels, it generates high satisfaction with only 9.7% probability, while at high affect levels, it generates high satisfaction with 95.5% probability. For this reason, it is best to use the high-quality activity to "recover" from a previous unsatisfying experience, i.e., when a_t is low, and save it for the future when the affect level is already high.

When more than one high-quality activity are available, the same intuition applies, but at even higher levels of affect and time left. Indeed, we see that the dashed line (which characterizes when to schedule a high-quality activity when two such activities are available) is above the solid line (which characterizes when to schedule a high-quality activity when only one such activity is available).

Figure 4 Optimal decisions when there are one or two high-quality activities available.



Note. Here, $\lambda_a = 1$, $\lambda_b = 0$, $a_0 = 0$, $b_t = 0.3$, $\alpha = 0.3$, $\beta = -0.1$, and $\delta = 1.01$.

Hence, in contrast to the linear case of §6.2 (Theorem 1), the optimal sequence depends on the current affect level and thus needs to be optimized in closed loop. In particular, the scheduling of high-quality activities is motivated by the goal of restoring the affect to a high level, similar to the playing of "wild cards" to recover from bad outcomes (Van Vaerenbergh et al. 2019). The notion behind this is well expressed in Hart et al. (1990, p. 148): "A good recovery can turn angry, frustrated customers into loyal ones. It can, in fact, create more goodwill than if things had gone smoothly in the first place." The service provider should thus use high-quality activities in a reactive, non pro-active manner, to restore the affect to a high level. Therefore, along a particular sample path we might observe numerous ups and down in quality, thereby departing from the optimal sequence with linear probabilities (Lemma 2).

6.4. Application: Design of a Tourist Trip

To demonstrate the applicability of our prescriptions, we conduct a counterfactual experiment around the design of a three-day trip to Barcelona. In this setting, we estimated in §5 that, when the time between visits is small ($\Delta t = 0$), $\alpha = 0.290$, $\beta = -1.142$, $\lambda_a = 0.9$ and $\lambda_b = 0.2$; see Model (6) in Table

2. We consider a tourist who has an intermediate level of agreeableness, i.e., $c_i = 0.5$. At the start of her trip we assume the tourist has a high affect and low quality baseline; specially, $a_1 = 1$ and $b_1 = 0.2$. She wants to schedule one activity per day, choosing among the Sagrada Familia ($q = 0.795$), the Gothic Quarter ($q = 0.671$), and Park Güell ($q = 0.469$), to maximize her (undiscounted) sum of utilities.

We solve problem (9) with these values and find the following optimal schedule. On her first day, she should visit Park Güell, the attraction with the lowest quality in the choice set. This increases her quality baseline to $b_2 = 0.24$ and results in two possible affect outcomes: $a_2 = 1$ if $r_1 = 1$ or $a_2 = 0.1$ if $r_1 = 0$. On the second day, she should choose the highest-quality attraction (the Sagrada Familia) if her affect is low ($a_2 = 0.1$), and the other one (the Gothic Quarter) otherwise ($a_2 = 1$). On her last day, there is only one attraction left, so there is no choice to be made.

This decision tree illustrates the following two insights. First, it may not necessarily be optimal to schedule the highest-quality activity at the beginning or at the end, thereby deviating from U-shaped designs. Second, contingent scheduling is strictly better than pre-arranged fixed sequences (which turns out to be in this case a crescendo: Park Güell - Gothic Quarter - Sagrada Familia).

Notably, the optimal sequence depends on the starting conditions (a_1, b_1): a visitor starting the visit with a low quality baseline ($b_1 = 0$) should choose a fixed sequence of increasing quality (Park Güell - Gothic Quarter - Sagrada Familia), while a visitor starting from a high quality baseline ($b_1 = 1$) should choose a fixed inverted U-shaped sequence with increasing then decreasing quality (Park Güell - Sagrada Familia - Gothic Quarter).

7. Conclusion

In experiences, which are dynamic and stochastic processes, the utility one derives from an activity depends on past consumptions through cognitive and affective spillovers (Wirtz and Bateson 1999). In this paper, we tackle the double challenge of (i) reporting observational evidence of both baseline quality contrast and affect infusion and identifying the salient valence of affect infusion (assimilation or contrast) and (ii) deriving implications of the joint effect of baseline quality contrast and affect assimilation on activity sequencing in experiential services.

For external validity, we consider four contexts of application drawn from three datasets, namely, watching movies (IMDb.com), reading books (Goodreads.com), visiting tourist attractions, and dining at restaurants (TripAdvisor.com). Across all four contexts, we find strong evidence for the presence of both baseline quality contrast and affect infusion, and the latter usually takes the form of assimilation, and not contrast. Thus, past experiences have both negative spillovers (through quality contrast) and positive spillovers (through affect assimilation) on the satisfaction derived from future activities. Remarkably, the magnitude of these effects is quite similar across all contexts (Table 2).

Both quality contrast and affect assimilation diminish with an increased dissimilarity between the focal activity and the previously experienced activity, in terms of both attributes and consumption times.

The salience of affect assimilation has profound implications for experiential service design. In particular, we show that, even in the simplest case of linear probabilities (i.e., when the probability of being satisfied from an activity is equal to the experienced utility), the optimal activity sequence may have two local minima and two local maxima (Lemma 2)—a stark contrast with the U-shape sequence that is optimal without affect assimilation (Lemma 3). The rationale for the optimality of placing the peak activity in the middle of an experience is to positively impact the consumer's affect level, which will impact the consumer's evaluation of her subsequent activities. Hence, by delivering this high-quality activity, the service provider is then able to "ride the wave" on subsequent activities while being cognizant that "tough luck" may happen, which requires not to play the wild cards early so as to be able to recover in case the consumer's affect level were to drop. This guideline still applies when the probability of making consumers satisfied is nonlinear in their utilities. In this case, the optimal policy is in general complex to solve, and must be solved in closed loop, i.e., dynamically adapted to the affect level and baseline quality level of the consumer. We show numerically that it is optimal for a service provider to hold a wild card in one's hand in case the consumer's affect level were to drop. A wild card is more likely to be played if the consumer's affect level is low, the time until the end of the experience is short, and the stock of similar cards in one's hand is abundant (Figure 4).

Although we focus on four domains of application, the principles outlined in this paper apply to other experiential services. Scheduling classes for executive education programs, programming artists and songs at music concerts, or planning the flow of dishes in multi-course fine dining are just a few of such potential application areas. Furthermore, the integration of AI-based tools (e.g., ChatGPT) in online platforms (e.g., Expedia) makes it easier to offer personalized recommendations.[1] Our research makes a strong call for tracking the affect level (mood) of consumers and dynamically adjusting the sequence of such experiences to their affect. In addition to improving consumer utility, it may also enable service providers to smooth their workload over time. To take a practical example, consider a tour operator offering weekend city trips. If the tour operator wants to adopt a U-shaped sequence of activities, and all its competitors do the same, this would inevitably lead to congestion in the most desirable activities at the beginning and end of the trip. In contrast, offering a flexible tour plan, customized based on how individual consumers "feel," offers an opportunity to alleviate peak times and enhance the experience of everyone.

[1] `https://www.nytimes.com/2023/06/13/travel/artificial-intelligence-travel-adviser-milan.html`

Indeed, an interesting avenue for future work can be to verify the validity of our prescriptions in these experiential settings through experimentation. In particular, a lab setting would be suitable to distinguish short-term affects (emotions) from long-term ones (mood), which may generate more elaborate prescriptions for activity scheduling. Another possible extension could be to adopt a multi-dimensional definition of quality and/or content dissimilarity to refine our prescriptions. As many B2C services increasingly compete on delivering outstanding service experiences to escape commoditization, our data-driven approach can help firms engineer better experiences (for example, Deezer, a music streaming platform, has already implemented a basic, feedback-based mood-dependent song recommendation system, see Bontempelli et al. (2022) and Moscato et al. (2020)). Finally, it may also be relevant to explore the prescriptions for scenarios where the end-consumers make their own decisions on scheduling their sequential consumption of experiential activities.

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Appendix: Empirical Specification and Proofs

EC.1. Descriptive Statistics

Figure EC.1 shows the histograms of ratings across all four contexts under consideration. As explained in §4.2, we carry out a binary transformation of the ratings to get r_{ij}, which descriptive statistics are shown in Table EC.1. Tables EC.2-EC.5 report the correlation matrix among the variables of interest, their mean, minimum and maximum values, and standard deviation. In the regressions, observations with missing values for any of these variables are dropped. Note that the mean values of the inverse Mills ratio, eventually used in the second stage of the Heckprobit estimation and necessary for estimating the percent point estimate values, are given in the corresponding section §EC.3.2.

Figure EC.1 Histograms for the ratings recorded by individuals across the different contexts under consideration.

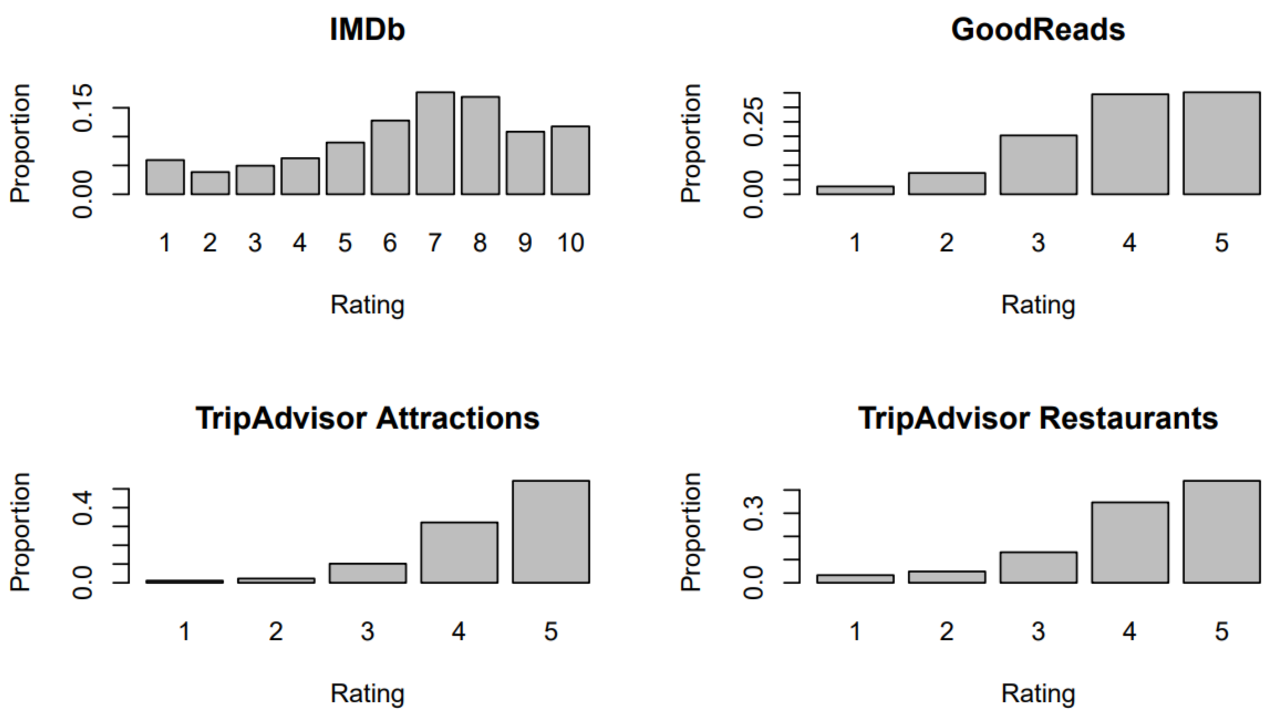

Table EC.1 Descriptive statistics for the binary transformed ratings r_{ij} across the four contexts.

r_{ij}	IMDb	GoodReads	TripAdvisor Attractions	TripAdvisor Restaurants
Mean	0.38	0.34	0.54	0.44
Min	0	0	0	0
Max	1	1	1	1
Std. dev.	0.48	0.47	0.49	0.49

Table EC.2 Descriptive statistics for IMDb.

	c_i	q_{ij}	j	n_{ij}	A_{ij}	$a_{i,j-1}$	$b_{i,j-1}$	Δt_{ij}	$\Delta \mathbf{x}_{ij}$
c_i	1.00	0.24	-0.18	0.20	0.01	0.74	0.42	-0.01	-0.08
q_{ij}	0.24	1.00	-0.03	0.50	0.21	0.20	0.32	-0.04	-0.06
j	-0.18	-0.03	1.00	0.01	0.12	-0.16	-0.04	-0.28	0.01
n_{ij}	0.20	0.50	0.01	1.00	0.01	0.17	0.26	-0.04	-0.08
A_{ij}	0.01	0.21	0.12	0.01	1.00	0.02	0.13	-0.23	-0.07
$a_{i,j-1}$	0.74	0.20	-0.16	0.17	0.02	1.00	0.53	-0.01	-0.07
$b_{i,j-1}$	0.42	0.32	-0.04	0.26	0.13	0.53	1.00	-0.06	-0.08
Δt_{ij}	-0.01	-0.04	-0.28	-0.04	-0.23	-0.01	-0.06	1.00	0.09
$\Delta \mathbf{x}_{ij}$	-0.08	-0.06	0.01	-0.08	-0.07	-0.07	-0.08	0.09	1.00
Mean	0.41	0.40	4.50	10.68	7.22	0.41	0.41	1.35	0.74
Min.	0.00	0.00	0.69	1.79	0.69	0.00	0.00	0.00	0.00
Max.	1.00	0.98	7.31	14.75	10.87	1.00	0.96	8.98	1.00
Std. dev.	0.22	0.24	1.50	2.12	1.68	0.30	0.13	1.42	0.28

Table EC.3 Descriptive statistics for GoodReads.

	c_i	q_{ij}	j	n_{ij}	A_{ij}	$a_{i,j-1}$	$b_{i,j-1}$	Δt_{ij}	$\Delta \mathbf{x}_{ij}$
c_i	1.00	0.22	-0.13	-0.12	-0.19	0.71	0.37	0.02	-0.11
q_{ij}	0.22	1.00	0.01	0.03	-0.12	0.17	0.31	0.01	-0.05
j	-0.13	0.01	1.00	-0.04	-0.01	-0.09	0.02	-0.13	0.04
n_{ij}	-0.12	0.03	-0.04	1.00	0.39	-0.10	-0.08	0.01	0.01
A_{ij}	-0.19	-0.12	-0.01	0.39	1.00	-0.15	-0.17	0.04	0.09
$a_{i,j-1}$	0.71	0.17	-0.09	-0.10	-0.15	1.00	0.41	0.03	-0.08
$b_{i,j-1}$	0.37	0.31	0.02	-0.08	-0.17	0.41	1.00	-0.02	-0.11
Δt_{ij}	0.02	0.01	-0.13	0.01	0.04	0.03	-0.02	1.00	0.04
$\Delta \mathbf{x}_{ij}$	-0.11	-0.05	0.04	0.01	0.09	-0.08	-0.11	0.04	1.00
Mean	0.33	0.35	2.93	7.87	6.27	0.35	0.35	3.41	0.46
Min.	0.00	0.01	0.69	1.10	0.69	0.00	0.01	2.08	0.00
Max.	1.00	0.97	5.32	12.72	12.81	1.00	0.95	8.09	1.00
Std. dev.	0.21	0.16	0.93	2.23	2.06	0.30	0.09	0.88	0.37

Table EC.4 Descriptive statistics for TripAdvisor attractions.

	c_i	q_{ij}	j	n_{ij}	A_{ij}	$a_{i,j-1}$	$b_{i,j-1}$	Δt_{ij}	$\Delta \mathbf{x}_{ij}$
c_i	1.00	0.14	-0.06	0.05	0.04	0.46	0.24	0.02	0.01
q_{ij}	0.14	1.00	-0.04	0.33	0.18	0.08	0.24	0.05	0.02
j	-0.06	-0.04	1.00	-0.06	0.10	-0.05	-0.13	-0.06	-0.01
n_{ij}	0.05	0.33	-0.06	1.00	0.55	0.04	0.12	-0.05	-0.03
A_{ij}	0.04	0.18	0.10	0.55	1.00	0.03	0.04	-0.03	-0.02
$a_{i,j-1}$	0.46	0.08	-0.05	0.04	0.03	1.00	0.22	-0.00	0.01
$b_{i,j-1}$	0.24	0.24	-0.13	0.12	0.04	0.22	1.00	-0.00	0.02
Δt_{ij}	0.02	0.05	-0.06	-0.05	-0.03	-0.00	-0.00	1.00	0.08
$\Delta \mathbf{x}_{ij}$	0.01	0.02	-0.01	-0.03	-0.02	0.01	0.02	0.08	1.00
Mean	0.55	0.59	2.72	4.77	5.89	0.54	0.60	1.58	0.92
Min.	0.00	0.00	0.69	0.69	0.69	0.00	0.00	0.00	0.00
Max.	0.98	1.00	6.30	10.34	8.77	1.00	1.00	8.13	1.00
Std. dev.	0.22	0.20	0.93	1.97	2.56	0.46	0.11	2.12	0.25

Table EC.5 Descriptive statistics for TripAdvisor restaurants.

	c_i	q_{ij}	j	n_{ij}	A_{ij}	$a_{i,j-1}$	$b_{i,j-1}$	Δt_{ij}	$\Delta\mathbf{x}_{ij}$
c_i	1.00	0.14	-0.07	0.09	0.07	0.66	0.24	0.05	-0.01
q_{ij}	0.14	1.00	0.02	0.34	0.15	0.09	0.23	0.03	-0.13
j	-0.07	0.02	1.00	-0.02	0.16	-0.10	-0.00	-0.04	-0.01
n_{ij}	0.09	0.34	-0.02	1.00	0.49	0.06	0.17	-0.04	-0.06
A_{ij}	0.07	0.15	0.16	0.49	1.00	0.04	0.08	-0.01	-0.05
$a_{i,j-1}$	0.66	0.09	-0.10	0.06	0.04	1.00	0.29	0.02	-0.01
$b_{i,j-1}$	0.24	0.23	-0.00	0.17	0.08	0.29	1.00	-0.00	-0.07
Δt_{ij}	0.05	0.03	-0.04	-0.04	-0.01	0.02	-0.00	1.00	0.07
$\Delta\mathbf{x}_{ij}$	-0.01	-0.13	-0.01	-0.06	-0.05	-0.01	-0.07	0.07	1.00
Mean	0.44	0.49	2.82	3.32	4.76	0.45	0.50	2.21	0.89
Min.	0.00	0.00	0.69	0.69	0.69	0.00	0.00	0.00	0.00
Max.	0.98	0.99	6.17	8.92	8.73	1.00	0.97	8.25	1.00
Std. dev.	0.22	0.21	0.95	1.28	2.92	0.30	0.12	2.08	0.23

EC.2. Specification of the Attribute Dissimilarity Variable

In this appendix, we explain how we measure attribute dissimilarity $\Delta\mathbf{x}_{ij}$ in the different contexts of interest.

- On IMDb, movie producers provide genre tags out of 28 possible distinct labels. For each movie, we construct a n-dimensional vector representing the different genres the movie belongs to, i.e., $\mathbf{x}_{ij} = (x_{ij,1}, \dots x_{ij,n})$, in which $x_{ij,k} = 1$ if individual i's j^{th} movie has been tagged the k^{th} genre and zero otherwise. We measure dissimilarity between individual i's j^{th} and $j-1^{\text{th}}$ movies as the fraction of the j^{th} movie's tagged genres that are distinct:

$$\Delta\mathbf{x}_{ij} = 1 - \frac{\mathbf{x}_{ij} \cdot \mathbf{x}_{i,j-1}}{\|\mathbf{x}_{ij}\|_0}, \tag{EC.1}$$

in which $\|\mathbf{x}\|_0$ denotes the cardinality, i.e., the number of nonzero elements, of $\mathbf{x}$.

- On GoodReads, readers vote on which genre category a particular book belongs to out of ten possible options (e.g., history, fiction, fantasy). For instance, *Dracula* by Bram Stoker is classified in our collected data as *Classics* by 43,839 readers, as *Fiction* by 25,932 readers, and as *Science-Fiction* by 11,551 readers. For each book, we construct a 10-dimensional vector representing the number of votes for each category, i.e., $\mathbf{x}_{ij} = (x_{ij,1}, \dots x_{ij,10})$, in which $x_{ij,k}$ denotes the number of votes individual i's j^{th} book received in the k^{th} category. To obtain a measure of dissimilarity between individual i's j^{th} and $j-1^{\text{th}}$ books, we use the concept of cosine dissimilarity:

$$\Delta\mathbf{x}_{ij} = 1 - \frac{\mathbf{x}_{ij} \cdot \mathbf{x}_{i,j-1}}{\|\mathbf{x}_{ij}\|\|\mathbf{x}_{i,j-1}\|}. \tag{EC.2}$$

- On TripAdvisor, attractions and restaurants are tagged according to their themes provided by the business owners. For example, the Sagrada Familia is tagged as *Points of Interest & Landmarks*, *Architectural Buildings*, and *Churches & Cathedrals*, among others. For each entry on TripAdvisor (attraction or restaurant), we construct a n-dimensional vector representing the different tags associated with the entry, i.e., $\mathbf{x}_{ij} = (x_{ij,1}, \dots x_{ij,n})$, in which $x_{ij,k} = 1$ if individual i's j^{th} activity has been tagged the k^{th} genre and zero otherwise. Note that if an attraction or restaurant has no tag specified, all the values in this vector are 0. We measure dissimilarity between individual i's j^{th} and $j-1^{\text{th}}$ attractions as the fraction of the total number of tags between the two activities that are distinct:

$$\Delta\mathbf{x}_{ij} = 1 - \frac{\mathbf{x}_{ij} \cdot \mathbf{x}_{i,j-1}}{\|\mathbf{x}_{ij} + \mathbf{x}_{i,j-1}\|_0}. \tag{EC.3}$$

EC.3. Additional Details on Two-Stage Estimation Procedure

We first develop the first-stage selection model outlined in §5.3 and then show its estimation results. We then derive a second-stage model by embedding the first-stage model into the second-stage estimation and then report its estimation results.

EC.3.1. First-Stage Selection Model

Similar to (1), define the utility consumer i derives from a focal activity to be consumed in the j^{th} position of her consumption stream as follows:

$$v_{ij} = \bar{v}_{ij} + \epsilon_{ij},$$

in which ϵ_{ij} is a random shock with zero mean, independent across all i and j.

Consumer i's utility from her the focal activity v_{ij} is compared to an outside option with utility v^0_{ij}. If v_{ij} is higher that v^0_{ij}, customer i selects the focal activity. Let s_{ij} denote a binary selection variable, equal to 1 if consumer i selects the focal activity in position j of her consumption stream, and zero otherwise. Similar to (3), we have

$$\Phi(\bar{v}_{ij}) := \mathbb{P}[s_{ij} = 1] = \mathbb{P}[v_{ij} \geq v^0_{ij}].$$

We consider a probit specification, so here, $\Phi(.)$ is the c.d.f. of a normal distribution.

Similar to (7), we specify the base utility from the focal activity as

$$\bar{v}_{ij} = \gamma q_{ij} + \nu A_{ij} + \delta D_{ij} + \mu M_{ij},$$

in which q_{ij} is the inherent quality of the focal activity, A_{ij} is its age as experienced by consumer i (as specified in §4.2), D_{ij} is a measure of dissimilarity in individual i in her consumption stream between the focal activity and individual i's $j-1^{\text{th}}$ activity, and M_{ij} is a measure of market thickness at the time of selection. For IMDb and GoodReads, we use $\Delta\mathbf{x}_{ij}$ for D_{ij} and we use the number of movies (resp., books) sharing at least 95% attribute similarity with the focal movie (resp., book) and released prior to the focal movie (resp., book) for M_{ij}. For TripAdvisor, we use the Euclidean distance (in km) between the focal activity and individual i's $j-1^{\text{th}}$ activity, denoted as ΔL_{ij} for D_{ij} and the number of activities (attractions or restaurants) within a 0.5km-radius of the focal activity for M_{ij}. Table EC.6 provides the descriptive statistics of the variables used in the first-stage selection procedure.

The purpose of M_{ij} is to track the relevant competition faced by the focal activity in individual i's choice set. The higher the competition, the lower the likelihood of that activity to be chosen. Note that M_{ij} affects only the individual's choice of activity, but not her evaluation of the activity (after it has been selected). Accordingly, it satisfies the exclusion restriction condition in our two-stage formulation.

Table EC.7 summarizes the estimation results for the first-stage selection model. We discuss, in turn, the effect of each variable. The inherent activity quality q_{ij} has a positive effect on its likelihood of selection in IMDb and TripAdvisor-Attractions, and null effect in TripAdvisor-Restaurants, and—surprisingly—a negative effect in GoodReads. In terms of age A_{ij}, newer movies, newer books, and older attractions are more likely to be selected; the effect of age on selection is thus directionally similar to its effect on ratings (Table 2). Considering now the effect of dissimilarity D_{ij}, the coefficients of both $\Delta\mathbf{x}_{ij}$ and ΔL_{ij} are negative

Table EC.6 Descriptive statistics of the variables in the first-stage selection procedure across the four contexts.

Variable			IMDb	GoodReads	TripAdvisor Attractions	TripAdvisor Restaurants
q_j		Mean	0.44	0.41	0.57	0.56
		Min.	0.02	0.01	0.01	0.03
		Max.	0.98	0.97	0.99	0.99
A_{ij}		Mean	1,655.2	380.2	784.7	717.8
		Min.	1.00	1.00	1.00	1.00
		Max.	4,999	4,998	6,482	6,454
D_{ij}	$\Delta\mathbf{x}_{ij}$	Mean	0.75	0.73		
		Min.	0.00	0.00		
		Max.	1.00	1.00		
	ΔL_{ij}	Mean			7,513.8	6,338.7
		Min.			0.00	0.00
		Max.			20,034.2	20,034.7
M_{ij}		Mean	2,968.1	8,511.0	30.6	9.2
		Min.	0	3	0	1
		Max.	30,729	41,513	650	65

and significant implying that individuals tend to select consecutive activities that are quite similar to each other (in attributes for movies and books and distance for attractions and restaurants). Finally, the exclusion restriction variable M_{ij} representing the market thickness has a significantly negative effect: The more options available, the less likely the focal activity will be chosen.

Table EC.7 Estimation results for first-stage activity selection stage.

	IMDb	GoodReads	TripAdvisor-Attractions	TripAdvisor-Restaurants
(Intercept)	0.898^{***}	-2.130^{***}	2.970^{***}	3.590^{***}
	(0.005)	(0.001)	(0.018)	(0.027)
q_{ij}	0.088^{***}	-0.074^{***}	0.037^{***}	0.001
	(0.001)	(0.000)	(0.008)	(0.011)
A_{ij}	-0.220^{***}	-0.059^{***}	0.023^{***}	0.002
	(0.001)	(0.000)	(0.003)	(0.004)
$\Delta\mathbf{x}_{ij}$	-0.701^{***}	-0.011^{***}		
	(0.003)	(0.000)		
ΔL_{ij}			-4.562^{***}	-4.584^{***}
			(0.023)	(0.035)
M_{ij}	-0.000^{***}	-0.000^{***}	-0.004^{***}	-0.022^{***}
	(0.000)	(0.000)	(0.000)	(0.001)
AIC	$2,349,426.1$	$7,882,980.6$	$12,947.0$	$6,073.0$
Log Likelihood	$-1,174,708.0$	$-3,941,485.3$	$-6,468.5$	$-3,031.5$
Num. obs.	$4,732,557$	$31,023,238$	$19,454,850$	$12,789,438$

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

EC.3.2. Second-Stage Estimation Model

In our second-stage estimation model, we use a modified version of (3) that accounts for the selection bias:

$$
\begin{aligned}
\mathbb{E}[r_{ij}=1|s_{ij}=1] &= \mathbb{E}[r_{ij}=1|v_{ij}>v_{ij}^0] \\
&= \mathbb{E}[\eta q_{ij}+\zeta c_i+\alpha a_{i,j-1}+\beta b_{i,j-1}+\varepsilon_{ij}|\bar{v}_{ij}+\epsilon_{ij}>v_{ij}^0] \\
&= \eta q_{ij}+\zeta c_i+\alpha a_{i,j-1}+\beta b_{i,j-1}+\mathbb{E}[\varepsilon_{ij}|\epsilon_{ij}>v_{ij}^0-\bar{v}_{ij}].
\end{aligned}
$$

Given that the errors ϵ_{ij} and v_{ij} are correlated, one needs the following Heckman correction (Heckman 1979).

$$
\mathbb{E}[\varepsilon_{ij}|\epsilon_{ij}>v_{ij}^0-\bar{v}_{ij}] = \rho\sigma_\varepsilon h(v_{ij}^0-\bar{v}_{ij}),
$$

in which ρ is the correlation between the unobserved determinants of individual i's selection of the focal activity (ϵ_{ij}) and the unobserved determinants of her rating of the focal activity (ε_{ij}), σ_ε is the standard deviation of ε_{ij}, and $h(x) := \frac{\phi(x)}{1-\Phi(x)}$ is the hazard rate of a normal distribution, also known as inverse Mills ratio.

Tables EC.8, EC.9, EC.10, and EC.11 report the second-stage estimation models with the sample selection correction for IMDb, GoodReads, TripAdvisor-Attractions, and TripAdvisor-Restaurants, respectively. Note that the mean values of the inverse Mills ratio IMR are 1.64, 2.03, 0.005, and 0.002 across the four contexts, respectively.

Table EC.8 Second-stage estimation results on IMDb with sample selection correction.

	IMDb								
	$\lambda_a=0.3$ & $\lambda_b=0.2$								
	1	2	3	4	5	6	7	8	9
(Intercept)	−1.467***	−1.341***	−2.641***	−2.460***	−2.468***	−2.284***	−2.184***	−2.229***	−2.148***
	(0.021)	(0.020)	(0.024)	(0.040)	(0.040)	(0.040)	(0.055)	(0.044)	(0.057)
c_i	2.946***		2.869***	2.851***	2.856***	2.835***	2.834***	2.834***	2.833***
	(0.018)		(0.020)	(0.020)	(0.020)	(0.028)	(0.028)	(0.028)	(0.028)
q_{ij}		2.925***	2.827***	2.852***	2.899***	3.038***	3.058***	3.043***	3.062***
		(0.020)	(0.022)	(0.023)	(0.025)	(0.025)	(0.027)	(0.025)	(0.027)
j				−0.028***	−0.027***	−0.023***	−0.024***	−0.023***	−0.023***
				(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
n_{ij}				−0.009***	−0.008***	0.002	0.002	0.002	0.002
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
A_{ij}					−0.026***	−0.013***	−0.024***	−0.013***	−0.024***
					(0.005)	(0.005)	(0.008)	(0.005)	(0.008)
$a_{i,j-1}$						0.318***	0.632***	0.402***	0.687***
						(0.021)	(0.047)	(0.027)	(0.049)
$b_{i,j-1}$						−1.330***	−1.838***	−1.566***	−2.001***
						(0.040)	(0.104)	(0.056)	(0.108)
$\Delta\mathbf{x}_{ij}$							−0.164***		−0.143**
							(0.058)		(0.059)
$a_{i,j-1}\times\Delta\mathbf{x}_{ij}$							−0.434***		−0.410***
							(0.057)		(0.058)
$b_{i,j-1}\times\Delta\mathbf{x}_{ij}$							0.702***		0.625***
							(0.132)		(0.133)
Δt_{ij}								−0.035***	−0.034***
								(0.008)	(0.008)
$a_{i,j-1}\times\Delta t_{ij}$								−0.045***	−0.039***
								(0.009)	(0.009)
$b_{i,j-1}\times\Delta t_{ij}$								0.130***	0.120***
								(0.021)	(0.022)
IMR	0.026**	−0.127***	−0.017	−0.009	0.080***	0.067***	0.120***	0.067***	0.123***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.020)	(0.021)	(0.037)	(0.021)	(0.037)
AIC	138,462.4	143,387.1	119,454.6	119,382.1	119,355.1	118,214.6	118,156.9	118,179.2	118,129.1
Log Likelihood	−69,228.2	−71,690.5	−59,723.3	−59,685.0	−59,670.5	−59,098.3	−59,066.4	−59,077.6	−59,049.5
No. obs.	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027

***$p<0.01$; **$p<0.05$; *$p<0.1$

Table EC.9 Second-stage estimation results on GoodReads with sample selection correction.

	GoodReads								
	$\lambda_a = 0.3$ & $\lambda_b = 0.2$								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.833^{***}	-1.075^{***}	-2.465^{***}	-2.837^{***}	-2.829^{***}	-2.371^{***}	-2.271^{***}	-2.412^{***}	-2.338^{***}
	(0.010)	(0.009)	(0.010)	(0.014)	(0.014)	(0.016)	(0.018)	(0.030)	(0.031)
c_i	3.253^{***}		2.928^{***}	2.977^{***}	2.962^{***}	2.677^{***}	2.679^{***}	2.681^{***}	2.683^{***}
	(0.008)		(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
q_{ij}		3.035^{***}	2.400^{***}	2.440^{***}	2.417^{***}	2.679^{***}	2.693^{***}	2.678^{***}	2.690^{***}
		(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
j				-0.003^{*}	-0.004^{**}	0.007^{***}	0.006^{***}	0.012^{***}	0.012^{***}
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
n_{ij}				0.040^{***}	0.044^{***}	0.042^{***}	0.042^{***}	0.043^{***}	0.043^{***}
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
A_{ij}					-0.022^{***}	-0.026^{***}	-0.026^{***}	-0.027^{***}	-0.027^{***}
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$						0.549^{***}	0.642^{***}	0.696^{***}	0.772^{***}
						(0.008)	(0.010)	(0.025)	(0.026)
$b_{i,j-1}$						-1.611^{***}	-1.945^{***}	-2.094^{***}	-2.342^{***}
						(0.020)	(0.028)	(0.077)	(0.078)
$\Delta\mathbf{x}_{ij}$							-0.206^{***}		-0.201^{***}
							(0.017)		(0.017)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$							-0.226^{***}		-0.223^{***}
							(0.016)		(0.016)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$							0.877^{***}		0.852^{***}
							(0.051)		(0.051)
Δt_{ij}								0.009	0.015^{**}
								(0.007)	(0.007)
$a_{i,j-1} \times \Delta t_{ij}$								-0.045^{***}	-0.040^{***}
								(0.007)	(0.007)
$b_{i,j-1} \times \Delta t_{ij}$								0.146^{***}	0.123^{***}
								(0.022)	(0.022)
IMR	0.176^{***}	-0.148^{***}	0.095^{***}	0.138^{***}	0.176^{***}	0.128^{***}	0.115^{***}	0.124^{***}	0.112^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
AIC	830, 665.4	924, 934.2	766, 897.9	764, 301.8	763, 670.2	754, 266.1	753, 901.7	753, 729.6	753, 385.4
Log Likelihood	−415, 329.7	−462464.1	−383, 444.9	−382, 144.9	−381, 828.1	−377, 124.0	−376, 938.8	−376, 852.8	−376, 677.7
No. obs.	774, 235	774, 235	774, 235	774, 235	774, 235	774, 235	774, 235	774, 235	774, 235

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.10 Second-stage estimation results on TripAdvisor-Attractions with sample selection correction.

	TripAdvisor - Attractions								
	$\lambda_a = 0.9$ & $\lambda_b = 0.2$								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.438^{***}	-1.285^{***}	-2.800^{***}	-2.854^{***}	-2.867^{***}	-2.406^{***}	-2.379^{***}	-2.400^{***}	-2.379^{***}
	(0.009)	(0.012)	(0.016)	(0.020)	(0.021)	(0.025)	(0.066)	(0.028)	(0.067)
c_i	2.893^{***}		2.868^{***}	2.868^{***}	2.867^{***}	2.864^{***}	2.864^{***}	2.865^{***}	2.865^{***}
	(0.015)		(0.016)	(0.016)	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)
q_{ij}		2.330^{***}	2.275^{***}	2.234^{***}	2.238^{***}	2.351^{***}	2.351^{***}	2.346^{***}	2.346^{***}
		(0.018)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
j				0.005	0.002	-0.010^{**}	-0.011^{**}	-0.010^{**}	-0.010^{**}
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
n_{ij}				0.013^{***}	0.009^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}					0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}
					(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$a_{i,j-1}$						0.120^{***}	0.241^{***}	0.203^{***}	0.290^{***}
						(0.007)	(0.025)	(0.009)	(0.025)
$b_{i,j-1}$						-0.957^{***}	-1.088^{***}	-1.055^{***}	-1.142^{***}
						(0.030)	(0.107)	(0.038)	(0.108)
$\Delta\mathbf{x}_{ij}$							-0.030		-0.024
							(0.067)		(0.067)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$							-0.133^{***}		-0.098^{***}
							(0.026)		(0.026)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$							0.145		0.098
							(0.112)		(0.113)
Δt_{ij}								-0.005	-0.005
								(0.008)	(0.008)
$a_{i,j-1} \times \Delta t_{ij}$								-0.053^{***}	-0.052^{***}
								(0.003)	(0.003)
$b_{i,j-1} \times \Delta t_{ij}$								0.064^{***}	0.063^{***}
								(0.013)	(0.013)
IMR	-6.296^{***}	0.006	-1.488^{**}	-1.634^{***}	-1.209^{**}	-0.771	-0.761	-0.705	-0.690
	(0.597)	(0.558)	(0.594)	(0.596)	(0.605)	(0.605)	(0.606)	(0.606)	(0.606)
AIC	229, 750.0	252, 163.3	215, 292.4	215, 237.4	215, 224.1	214, 047.3	214, 025.8	213, 772.3	213, 761.9
Log Likelihood	−114, 872.0	−126, 078.6	−107, 642.2	−107, 612.7	−107, 605.0	−107, 014.6	−107, 000.9	−106, 874.1	−106, 865.9
No. obs.	195, 407	195, 407	195, 407	195, 407	195, 407	195, 407	195, 407	195, 407	195, 407

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

EC.4. Robustness Checks

In this section, we present several robustness checks.

First, Table EC.12, EC.13, EC.14, and EC.15 present the estimation results when selection effects are ignored in the contexts of IMDb, GoodReads, TripAdvisor-Attractions, and TripAdvisor-Restaurants, respec-

Table EC.11 Second-stage estimation results on TripAdvisor-Restaurants with sample selection correction.

	TripAdvisor - Restaurants								
	$\lambda_a = 0.1$ & $\lambda_b = 0.2$								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.371^{***}	-1.080^{***}	-2.309^{***}	-2.310^{***}	-2.307^{***}	-2.065^{***}	-2.078^{***}	-2.104^{***}	-2.118^{***}
	(0.006)	(0.008)	(0.010)	(0.014)	(0.014)	(0.016)	(0.037)	(0.019)	(0.038)
c_i	2.881^{***}		2.828^{***}	2.833^{***}	2.828^{***}	3.104^{***}	3.103^{***}	3.093^{***}	3.093^{***}
	(0.011)		(0.012)	(0.012)	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)
q_{ij}		1.897^{***}	1.755^{***}	1.762^{***}	1.770^{***}	1.850^{***}	1.848^{***}	1.839^{***}	1.839^{***}
		(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
j				0.008^{***}	0.003	0.001	0.001	0.004	0.004
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n_{ij}				-0.008^{***}	-0.019^{***}	-0.012^{***}	-0.012^{***}	-0.009^{***}	-0.009^{***}
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}					0.009^{***}	0.010^{***}	0.010^{***}	0.009^{***}	0.010^{***}
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$						-0.200^{***}	-0.141^{***}	-0.197^{***}	-0.139^{***}
						(0.010)	(0.026)	(0.013)	(0.027)
$b_{i,j-1}$						-0.681^{***}	-0.759^{***}	-0.731^{***}	-0.774^{***}
						(0.021)	(0.069)	(0.031)	(0.071)
$\Delta\mathbf{x}_{ij}$							0.016		0.018
							(0.039)		(0.039)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$							-0.073^{**}		-0.074^{**}
							(0.029)		(0.029)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$							0.100		0.058
							(0.078)		(0.079)
Δt_{ij}								0.012^{**}	0.011^{**}
								(0.005)	(0.005)
$a_{i,j-1} \times \Delta t_{ij}$								0.000	0.001
								(0.004)	(0.004)
$b_{i,j-1} \times \Delta t_{ij}$								0.024^{**}	0.023^{**}
								(0.010)	(0.010)
IMR	24.450^{***}	9.478^{***}	6.283^{***}	7.579^{***}	7.695^{***}	7.814^{***}	7.564^{***}	8.078^{***}	7.978^{***}
	(1.096)	(1.041)	(1.111)	(1.165)	(1.165)	(1.167)	(1.169)	(1.169)	(1.170)
AIC	411,818.8	463,991.2	395,954.8	395,937.4	395,843.7	394,088.2	394,073.8	393,603.9	393,601.6
Log Likelihood	−205,906.4	−231,992.6	−197,973.4	−197,962.7	−197,914.8	−197,035.1	−197,024.9	−196,789.9	−196,785.8
No. obs.	350,744	350,744	3507,44	350,744	350,744	350,744	350,744	350,744	350,744

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

tively. Second, Table EC.16 shows the second-stage estimation results after excluding users who posted multiple reviews on the same day. Third, Table EC.17 presents the second-stage estimation results after excluding the least active reviewers, i.e., by considering only the top-quartile most active users, which should address the issue of censoring with infrequent users. Fourth, Table EC.18 presents results for when the analyses are carried out by controlling for the most representative genre/tag of the given activity, which we consider to be the first listed genre/tag in the case of movies, attractions, and restaurants, and the one that received the highest votes by readers on GoodReads in the case of books.

Fifth, Table EC.19 presents the second-stage estimation results controling for the geographical distance in locations between the focal and former activity, ΔL_{ij}. Sixth, Table EC.20 presents the second-stage estimation results when $\lambda_a = \lambda_b = 1$. Next, Tables EC.21 and EC.22 present the second-stage estimation results in the presence of nonlinearities in (i) affect and baseline quality reference (Table EC.21) and (ii) time and attribute dissimilarity (Table EC.22), considering different quartiles of these variables. Figure EC.2 plots the nonlinear coefficients of affect and baseline quality and Figure 3 plots the nonlinear interaction coefficients with respect to time and attribute dissimilarity.

Finally, Tables EC.23 and EC.24 present the second-stage estimation results for a fixed λ_b (resp., λ_a) and variable λ_a (resp., λ_b). Tables EC.25 and EC.26 do the same for GoodReads, Tables EC.27 and EC.28 do the same for TripAdvisor-Attractions, and Tables EC.29 and EC.30 do the same for TripAdvisor-Restaurants.

Table EC.12 Estimation results on IMDb without selection correction.

	IMDb								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.492^{***}	-1.640^{***}	-2.758^{***}	-2.713^{***}	-2.622^{***}	-2.440^{***}	-2.371^{***}	-2.386^{***}	-2.334^{***}
	(0.008)	(0.009)	(0.013)	(0.031)	(0.035)	(0.035)	(0.052)	(0.039)	(0.054)
c_i	2.984^{***}		2.869^{***}	2.841^{***}	2.841^{***}	2.807^{***}	2.809^{***}	2.805^{***}	2.807^{***}
	(0.017)		(0.019)	(0.019)	(0.019)	(0.027)	(0.027)	(0.027)	(0.027)
q_{ij}		3.089^{***}	2.988^{***}	2.973^{***}	3.003^{***}	3.143^{***}	3.145^{***}	3.147^{***}	3.149^{***}
		(0.018)	(0.020)	(0.022)	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)
j				-0.028^{***}	-0.026^{***}	-0.022^{***}	-0.023^{***}	-0.022^{***}	-0.023^{***}
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n_{ij}				0.006^{**}	0.005^{*}	0.014^{***}	0.014^{***}	0.014^{***}	0.014^{***}
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
A_{ij}					-0.014^{***}	-0.004	-0.004	-0.004	-0.004
					(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$a_{i,j-1}$						0.329^{***}	0.642^{***}	0.405^{***}	0.691^{***}
						(0.020)	(0.045)	(0.026)	(0.047)
$b_{i,j-1}$						-1.312^{***}	-1.828^{***}	-1.521^{***}	-1.968^{***}
						(0.038)	(0.100)	(0.053)	(0.103)
$\Delta \mathbf{x}_{ij}$							-0.099^{**}		-0.079
							(0.050)		(0.050)
$a_{i,j-1} \times \Delta \mathbf{x}_{ij}$							-0.430^{***}		-0.409^{***}
							(0.055)		(0.056)
$b_{i,j-1} \times \Delta \mathbf{x}_{ij}$							0.715^{***}		0.648^{***}
							(0.126)		(0.127)
Δt_{ij}								-0.032^{***}	-0.030^{***}
								(0.008)	(0.008)
$a_{i,j-1} \times \Delta t_{ij}$								-0.041^{***}	-0.035^{***}
								(0.009)	(0.009)
$b_{i,j-1} \times \Delta t_{ij}$								0.115^{***}	0.104^{***}
								(0.020)	(0.020)
AIC	155,656.7	155,304.3	129,334.6	129,260.0	129,232.9	128,002.9	127,940.6	127,972.3	127,917.8
Log Likelihood	−77,826.3	−77,650.1	−64,664.3	−64,625.0	−64,610.4	−63,993.4	−63,959.3	−63,975.1	−63,944.9
No. obs.	142,360	142,360	142,360	142,360	142,360	142,360	142,360	142,360	142,360

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.13 Estimation results on GoodReads without selection correction.

	GoodReads								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.480^{***}	-1.461^{***}	-2.360^{***}	-2.521^{***}	-2.507^{***}	-2.152^{***}	-2.083^{***}	-2.148^{***}	-2.097^{***}
	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.006)	(0.008)	(0.015)	(0.016)
c_i	3.121^{***}		2.942^{***}	2.969^{***}	2.965^{***}	2.734^{***}	2.740^{***}	2.735^{***}	2.741^{***}
	(0.004)		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
q_{ij}		2.975^{***}	2.625^{***}	2.614^{***}	2.609^{***}	2.799^{***}	2.808^{***}	2.798^{***}	2.806^{***}
		(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
j				0.003^{**}	0.003^{**}	0.011^{***}	0.011^{***}	0.015^{***}	0.015^{***}
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
n_{ij}				0.019^{***}	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A_{ij}					-0.003^{***}	-0.007^{***}	-0.009^{***}	-0.008^{***}	-0.009^{***}
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$a_{i,j-1}$						0.430^{***}	0.518^{***}	0.621^{***}	0.694^{***}
						(0.004)	(0.006)	(0.013)	(0.014)
$b_{i,j-1}$						-1.443^{***}	-1.775^{***}	-1.997^{***}	-2.247^{***}
						(0.011)	(0.017)	(0.044)	(0.045)
$\Delta \mathbf{x}_{ij}$							-0.169^{***}		-0.166^{***}
							(0.010)		(0.010)
$a_{i,j-1} \times \Delta \mathbf{x}_{ij}$							-0.200^{***}		-0.195^{***}
							(0.009)		(0.009)
$b_{i,j-1} \times \Delta \mathbf{x}_{ij}$							0.801^{***}		0.778^{***}
							(0.029)		(0.029)
Δt_{ij}								-0.004	0.001
								(0.004)	(0.004)
$a_{i,j-1} \times \Delta t_{ij}$								-0.056^{***}	-0.053^{***}
								(0.004)	(0.004)
$b_{i,j-1} \times \Delta t_{ij}$								0.164^{***}	0.143^{***}
								(0.012)	(0.012)
AIC	2,957,878.2	3,220,924.1	2,735,757.6	2,733,467.4	2,733,416.8	2,711,239.1	2,710,083.6	2709981.5	2,708,918.7
Log Likelihood	−1,478,937.1	−1,610,460.0	−1,367,875.8	−1,366,728.7	−1,366,702.4	−1,355,611.5	−1,355,030.8	−1,354,979.7	−1,354,445.3
No. obs.	2,756,413	2,756,413	2,756,413	2,756,413	2,756,413	2,756,413	2,756,413	2,756,413	2,756,413

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.14 Estimation results on TripAdvisor-Attractions without selection correction.

	TripAdvisor-Attractions								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.464^{***}	-1.158^{***}	-2.662^{***}	-2.689^{***}	-2.693^{***}	-2.251^{***}	-2.247^{***}	-2.259^{***}	-2.257^{***}
	(0.008)	(0.009)	(0.013)	(0.018)	(0.018)	(0.023)	(0.064)	(0.026)	(0.064)
c_i	2.889^{***}		2.846^{***}	2.847^{***}	2.846^{***}	2.844^{***}	2.844^{***}	2.844^{***}	2.845^{***}
	(0.014)		(0.015)	(0.015)	(0.015)	(0.017)	(0.017)	(0.017)	(0.017)
q_{ij}		2.140^{***}	2.065^{***}	2.055^{***}	2.055^{***}	2.157^{***}	2.157^{***}	2.149^{***}	2.149^{***}
		(0.015)	(0.016)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
j				0.006	0.005	-0.008^{**}	-0.008^{**}	-0.007	-0.007
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
n_{ij}				0.003^{**}	0.001	0.004^{**}	0.004^{**}	0.005^{**}	0.005^{**}
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}					0.003^{**}	0.002	0.002	0.002	0.002
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$						0.114^{***}	0.239^{***}	0.196^{***}	0.287^{***}
						(0.007)	(0.024)	(0.009)	(0.025)
$b_{i,j-1}$						-0.894^{***}	-0.996^{***}	-0.977^{***}	-1.039^{***}
						(0.028)	(0.105)	(0.035)	(0.106)
$\Delta\mathbf{x}_{ij}$							-0.004		-0.002
							(0.065)		(0.065)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$							-0.136^{***}		-0.102^{***}
							(0.025)		(0.026)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$							0.113		0.070
							(0.109)		(0.109)
Δt_{ij}								0.002	0.002
								(0.007)	(0.007)
$a_{i,j-1} \times \Delta t_{ij}$								-0.051^{***}	-0.050^{***}
								(0.003)	(0.003)
$b_{i,j-1} \times \Delta t_{ij}$								0.054^{***}	0.054^{***}
								(0.012)	(0.012)
AIC	261,188.4	284,885.1	243,778.9	243,776.3	243,773.7	242,581.8	242,558.5	242,271.3	242,259.9
Log Likelihood	−130,592.2	−142,440.5	−121,886.4	−121,883.1	−121,880.8	−121,282.9	−121,268.2	−121,124.6	−121,115.9
No. obs.	222,225	222,225	222,225	222,225	222,225	222,225	222,225	222,225	222,225

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.15 Estimation results on TripAdvisor-Restaurants without selection correction.

	TripAdvisor-Restaurants								
	1	2	3	4	5	6	7	8	9
(Intercept)	-1.476^{***}	-1.012^{***}	-2.263^{***}	-2.249^{***}	-2.239^{***}	-2.024^{***}	-1.928^{***}	-2.070^{***}	-1.974^{***}
	(0.004)	(0.004)	(0.006)	(0.010)	(0.010)	(0.011)	(0.033)	(0.014)	(0.034)
c_i	2.895^{***}		2.830^{***}	2.839^{***}	2.834^{***}	3.068^{***}	3.070^{***}	3.058^{***}	3.060^{***}
	(0.009)		(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
q_{ij}		1.747^{***}	1.625^{***}	1.660^{***}	1.665^{***}	1.724^{***}	1.716^{***}	1.717^{***}	1.707^{***}
		(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
j				0.012^{***}	0.005^{**}	0.003	0.003	0.006^{**}	0.006^{**}
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
n_{ij}				-0.019^{***}	-0.030^{***}	-0.024^{***}	-0.024^{***}	-0.022^{***}	-0.021^{***}
				(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}					0.009^{***}	0.009^{***}	0.009^{***}	0.009^{***}	0.008^{***}
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$						-0.172^{***}	-0.136^{***}	-0.150^{***}	-0.119^{***}
						(0.007)	(0.024)	(0.010)	(0.024)
$b_{i,j-1}$						-0.575^{***}	-0.671^{***}	-0.612^{***}	-0.680^{***}
						(0.016)	(0.064)	(0.023)	(0.065)
$\Delta\mathbf{x}_{ij}$							-0.100^{***}		-0.100^{***}
							(0.035)		(0.035)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$							-0.041		-0.035
							(0.025)		(0.026)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$							0.100		0.066
							(0.069)		(0.069)
Δt_{ij}								0.016^{***}	0.017^{***}
								(0.004)	(0.004)
$a_{i,j-1} \times \Delta t_{ij}$								-0.008^{***}	-0.008^{***}
								(0.003)	(0.003)
$b_{i,j-1} \times \Delta t_{ij}$								0.017^{**}	0.018^{**}
								(0.007)	(0.007)
AIC	714,781.1	796,444.2	679,044.2	678,850.5	678,683.4	676,399.0	676,321.9	675,732.3	675,619.4
Log Likelihood	−357,388.5	−398,220.1	−339,519.1	−339,420.2	−339,335.7	−338,191.5	−338,149.9	−337,855.1	−337,795.7
No. obs.	614,279	614,279	614,279	614,279	614,279	614,279	614,279	614,279	614,279

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.16 Results by only considering users who never posted more than one review on a given day.

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.1$ & $\lambda_b = 0.2$		$\lambda_a = 0.1$ & $\lambda_b = 0.2$	
	1	2	3	4	5	6	7	8
(Intercept)	-2.190^{***}	-1.911^{***}	-2.371^{***}	-2.338^{***}	-2.538^{***}	-2.652^{***}	-2.120^{***}	-2.138^{***}
	(0.047)	(0.073)	(0.016)	(0.031)	(0.037)	(0.119)	(0.019)	(0.053)
c_i	3.021^{***}	3.026^{***}	2.677^{***}	2.683^{***}	3.177^{***}	3.171^{***}	3.158^{***}	3.148^{***}
	(0.034)	(0.034)	(0.011)	(0.011)	(0.030)	(0.030)	(0.018)	(0.019)
q_{ij}	2.960^{***}	2.978^{***}	2.679^{***}	2.690^{***}	2.379^{***}	2.376^{***}	1.878^{***}	1.874^{***}
	(0.029)	(0.032)	(0.011)	(0.011)	(0.030)	(0.030)	(0.018)	(0.018)
j	-0.021^{***}	-0.025^{***}	0.007^{***}	0.012^{***}	-0.002	0.001	0.015^{***}	0.021^{***}
	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.007)	(0.004)	(0.004)
n_{ij}	-0.007^{**}	-0.006^{*}	0.042^{***}	0.043^{***}	0.007^{**}	0.007^{**}	-0.013^{***}	-0.011^{***}
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
A_{ij}	-0.012^{**}	-0.018^{**}	-0.026^{***}	-0.027^{***}	0.005^{**}	0.005^{**}	0.010^{***}	0.010^{***}
	(0.006)	(0.009)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
a_{ij-1}	0.169^{***}	0.502^{***}	0.549^{***}	0.772^{***}	-0.257^{***}	-0.101	-0.213^{***}	-0.067^{*}
	(0.025)	(0.067)	(0.008)	(0.026)	(0.020)	(0.074)	(0.012)	(0.039)
$b_{i,j-1}$	-1.270^{***}	-2.218^{***}	-1.611^{***}	-2.342^{***}	-0.697^{***}	-0.683^{***}	-0.657^{***}	-0.899^{***}
	(0.047)	(0.151)	(0.020)	(0.078)	(0.044)	(0.204)	(0.026)	(0.101)
Δt_{ij}		-0.077^{***}		0.015^{**}		0.002		0.013^{*}
		(0.011)		(0.007)		(0.013)		(0.008)
$\Delta \mathbf{x}_{ij}$		-0.136^{*}		-0.201^{***}		0.112		-0.040
		(0.073)		(0.017)		(0.112)		(0.050)
$a_{i,j-1} \times \Delta t_{ij}$		-0.020		-0.040^{***}		-0.031^{***}		-0.003
		(0.012)		(0.007)		(0.009)		(0.006)
$a_{i,j-1} \times \Delta \mathbf{x}_{ij}$		-0.378^{***}		-0.223^{***}		-0.044		-0.158^{***}
		(0.073)		(0.016)		(0.070)		(0.038)
$b_{i,j-1} \times \Delta t_{ij}$		0.190^{***}		0.123^{***}		0.049^{**}		0.028^{*}
		(0.028)		(0.022)		(0.023)		(0.015)
$b_{i,j-1} \times \Delta \mathbf{x}_{ij}$		0.626^{***}		0.852^{***}		-0.208		0.159
		(0.170)		(0.051)		(0.196)		(0.100)
IMR	0.063^{**}	0.094^{**}	0.128^{***}	0.112^{***}	0.556	0.606	6.674^{***}	6.977^{***}
	(0.025)	(0.044)	(0.005)	(0.006)	(0.891)	(0.892)	(1.454)	(1.457)
AIC	85,042.6	84,970.2	754,266.1	753,385.4	94,554.6	94,516.2	260,045.3	259,809.7
Log Likelihood	−42,512.3	−42,470.1	−377,124.0	−376,677.7	−47,268.3	−47,243.1	−130,013.6	−129,889.8
No. obs.	89,180	89,180	774,235	774,235	86,891	86,891	233,811	233,811

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.17 Results by only considering the top-quartile most active reviewers.

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	$\lambda_a = 0.1$ & $\lambda_b = 0.1$		$\lambda_a = 0.3$ & $\lambda_b = 0.1$		$\lambda_a = 0.6$ & $\lambda_b = 0.2$		$\lambda_a = 0.4$ & $\lambda_b = 0.2$	
	1	2	3	4	5	6	7	8
(Intercept)	−2.515***	−2.388***	−2.347***	−2.162***	−2.293***	−2.300***	−2.005***	−2.012***
	(0.060)	(0.085)	(0.023)	(0.049)	(0.040)	(0.107)	(0.025)	(0.061)
c_i	2.346***	2.333***	2.566***	2.579***	2.603***	2.602***	2.754***	2.752***
	(0.045)	(0.045)	(0.017)	(0.017)	(0.030)	(0.030)	(0.023)	(0.023)
q_{ij}	3.242***	3.268***	2.740***	2.757***	2.340***	2.337***	1.856***	1.849***
	(0.036)	(0.039)	(0.015)	(0.015)	(0.032)	(0.032)	(0.023)	(0.023)
j	−0.033***	−0.032***	0.013***	0.013***	−0.025***	−0.024***	−0.018***	−0.015***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)
n_{ij}	0.040***	0.040***	0.044***	0.045***	0.020***	0.020***	−0.003	−0.000
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)
A_{ij}	−0.027***	−0.040***	−0.025***	−0.025***	0.004*	0.004*	0.010***	0.010***
	(0.007)	(0.011)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$a_{i,j-1}$	0.934***	1.150***	0.759***	0.948***	0.324***	0.561***	0.167***	0.293***
	(0.039)	(0.082)	(0.013)	(0.044)	(0.015)	(0.049)	(0.015)	(0.040)
$b_{i,j-1}$	−1.926***	−2.421***	−1.975***	−2.992***	−1.044***	−1.228***	−0.802***	−1.009***
	(0.065)	(0.164)	(0.032)	(0.136)	(0.050)	(0.179)	(0.035)	(0.117)
Δt_{ij}		−0.021		−0.018		−0.003		0.012
		(0.016)		(0.013)		(0.014)		(0.009)
$\Delta \mathbf{x}_{ij}$		−0.190**		−0.257***		0.009		−0.036
		(0.087)		(0.026)		(0.109)		(0.065)
$a_{i,j-1} \times \Delta t_{ij}$		−0.057***		−0.039***		−0.073***		−0.004
		(0.020)		(0.013)		(0.007)		(0.006)
$a_{i,j-1} \times \Delta \mathbf{x}_{ij}$		−0.193**		−0.166***		−0.152***		−0.145***
		(0.095)		(0.025)		(0.051)		(0.045)
$b_{i,j-1} \times \Delta t_{ij}$		0.119***		0.205***		0.080***		0.026
		(0.044)		(0.041)		(0.024)		(0.017)
$b_{i,j-1} \times \Delta \mathbf{x}_{ij}$		0.484**		1.005***		0.094		0.193
		(0.205)		(0.080)		(0.187)		(0.130)
IMR	0.093***	0.160***	0.123***	0.100***	−0.774	−0.729	9.936***	10.223***
	(0.029)	(0.053)	(0.007)	(0.008)	(0.887)	(0.887)	(1.876)	(1.880)
AIC	59,741.3	59,731.5	387,811.1	387,474.2	88,112.6	87,993.7	162,788.2	162,631.1
Log Likelihood	−29,861.6	−29,850.7	−193,896.5	−193,722.1	−44,047.3	−43,981.8	−81,385.1	−81,300.5
No. obs.	64,237	64,237	403,505	403,505	79,045	79,045	143,145	143,145

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.18 Second-stage estimation results with genre- and tag-level controls.

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.9$ & $\lambda_b = 0.2$		$\lambda_a = 0.1$ & $\lambda_b = 0.2$	
	1	2	3	4	5	6	7	8
c_i	2.770***	2.765***	2.757***	2.758***	2.891***	2.893***	3.143***	3.131***
	(0.031)	(0.033)	(0.035)	(0.035)	(0.026)	(0.026)	(0.025)	(0.025)
q_{ij}	3.011***	3.037***	2.765***	2.761***	2.304***	2.298***	1.812***	1.800***
	(0.048)	(0.062)	(0.060)	(0.061)	(0.045)	(0.045)	(0.040)	(0.040)
j	−0.033***	−0.032***	−0.000	0.005	−0.012***	−0.012***	0.003	0.006
	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
n_{ij}	0.004	0.004	0.050***	0.050***	0.011***	0.012***	−0.003	−0.001
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
A_{ij}	−0.000	−0.012*	−0.031***	−0.032***	0.007***	0.006***	0.008***	0.008***
	(0.008)	(0.007)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)
$a_{i,j-1}$	0.358***	0.720***	0.531***	0.735***	0.128***	0.279***	−0.202***	−0.142***
	(0.022)	(0.066)	(0.057)	(0.057)	(0.010)	(0.038)	(0.014)	(0.028)
$b_{i,j-1}$	−1.271***	−1.919***	−1.342***	−1.931***	−0.979***	−1.169***	−0.612***	−0.678***
	(0.100)	(0.105)	(0.089)	(0.101)	(0.035)	(0.115)	(0.033)	(0.087)
$\Delta\mathbf{x}_{ij}$		−0.147**		−0.148***		−0.045		0.043
		(0.058)		(0.041)		(0.070)		(0.031)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$		−0.384***		−0.198***		−0.081**		−0.076***
		(0.058)		(0.030)		(0.036)		(0.025)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$		0.589***		0.579***		0.100		0.029
		(0.098)		(0.099)		(0.121)		(0.077)
Δt_{ij}		−0.031***		0.017**		−0.007		0.011***
		(0.005)		(0.009)		(0.009)		(0.004)
$a_{i,j-1} \times \Delta t_{ij}$		−0.045***		−0.037***		−0.052***		0.002
		(0.012)		(0.007)		(0.004)		(0.004)
$b_{i,j-1} \times \Delta t_{ij}$		0.126***		0.107***		0.066***		0.023***
		(0.025)		(0.023)		(0.013)		(0.008)
IMR	0.021	0.084*	0.033***	0.043***	−0.489	−0.416	5.512***	5.632***
	(0.014)	(0.045)	(0.012)	(0.011)	(0.678)	(0.671)	(1.770)	(1.854)
Genre/Tag FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	93,419.9	93,356.1	749,801.8	749,149.6	188,147.8	187,907.0	387,742.8	387,267.2
Log Likelihood	−46,676.9	−46,639.0	−374,882.9	−374,550.8	−93,878.8	−93,752.5	−193,663.4	−193,419.6
No. obs.	98,486	98,486	774,235	774,235	171,773	171,773	345,724	345,724

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table EC.19 Second-stage estimation results on TripAdvisor controlling for the geographical distance between locations.

	TripAdvisor-Attractions $\lambda_a = 0.9$ & $\lambda_b = 0.2$	TripAdvisor-Restaurants $\lambda_a = 0.1$ & $\lambda_b = 0.2$
(Intercept)	0.176^{***}	-0.238^{***}
	(0.013)	(0.010)
c_i	0.646^{***}	0.698^{***}
	(0.004)	(0.005)
q_{ij}	0.489^{***}	0.421^{***}
	(0.005)	(0.004)
j	-0.009^{*}	0.005
	(0.005)	(0.004)
n_{ij}	0.018^{***}	-0.019^{***}
	(0.005)	(0.005)
A_{ij}	0.013^{**}	0.028^{***}
	(0.005)	(0.004)
$a_{i,j-1}$	0.166^{***}	-0.050^{***}
	(0.013)	(0.010)
$b_{i,j-1}$	-0.243^{***}	-0.193^{***}
	(0.025)	(0.019)
$\Delta\mathbf{x}_{ij}$	-0.034^{***}	-0.046^{***}
	(0.013)	(0.012)
Δt_{ij}	-0.004^{*}	0.019^{***}
	(0.002)	(0.002)
ΔL_{ij}	0.009^{***}	0.014^{***}
	(0.002)	(0.001)
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$	-0.035^{***}	-0.033^{***}
	(0.013)	(0.012)
$a_{i,j-1} \times \Delta t_{ij}$	-0.011^{***}	0.002
	(0.002)	(0.002)
$a_{i,j-1} \times \Delta L_{ij}$	-0.016^{***}	-0.000
	(0.002)	(0.001)
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$	0.022	0.041^{*}
	(0.025)	(0.023)
$b_{i,j-1} \times \Delta t_{ij}$	0.011^{***}	-0.001
	(0.004)	(0.004)
$b_{i,j-1} \times \Delta L_{ij}$	0.001	0.002
	(0.003)	(0.003)
IMR	-1.006	8.566^{***}
	(0.677)	(1.547)
AIC	170,880.7	212,583.0
Log Likelihood	$-85,422.3$	$-106,273.5$
No. obs.	156,755	190,181

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.20 Second-stage estimation results with $\lambda_a = \lambda_b = 1$.

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	-2.414^{***}	-2.406^{***}	-2.683^{***}	-2.736^{***}	-2.722^{***}	-2.691^{***}	-2.231^{***}	-2.332^{***}
	(0.040)	(0.048)	(0.015)	(0.023)	(0.022)	(0.044)	(0.015)	(0.027)
c_i	2.837^{***}	2.837^{***}	2.861^{***}	2.868^{***}	2.784^{***}	2.786^{***}	2.850^{***}	2.846^{***}
	(0.022)	(0.022)	(0.009)	(0.009)	(0.017)	(0.017)	(0.013)	(0.013)
q_{ij}	2.948^{***}	2.958^{***}	2.506^{***}	2.523^{***}	2.295^{***}	2.293^{***}	1.808^{***}	1.798^{***}
	(0.025)	(0.027)	(0.010)	(0.010)	(0.021)	(0.021)	(0.015)	(0.015)
j	-0.026^{***}	-0.026^{***}	-0.002	0.004^{*}	0.001	0.002	0.005^{*}	0.009^{***}
	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
n_{ij}	-0.005	-0.004	0.043^{***}	0.043^{***}	0.011^{***}	0.011^{***}	-0.015^{***}	-0.012^{***}
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	-0.021^{***}	-0.025^{***}	-0.024^{***}	-0.024^{***}	0.006^{***}	0.006^{***}	0.009^{***}	0.009^{***}
	(0.005)	(0.008)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$a_{i,j-1}$	0.107^{***}	0.395^{***}	0.186^{***}	0.253^{***}	0.123^{***}	0.292^{***}	0.012^{**}	0.126^{***}
	(0.010)	(0.028)	(0.004)	(0.015)	(0.007)	(0.024)	(0.005)	(0.016)
$b_{i,j-1}$	-0.409^{***}	-0.723^{***}	-0.506^{***}	-0.828^{***}	-0.347^{***}	-0.538^{***}	-0.262^{***}	-0.310^{***}
	(0.021)	(0.063)	(0.011)	(0.044)	(0.018)	(0.068)	(0.012)	(0.043)
Δt_{ij}		-0.004		0.033^{***}		0.011^{**}		0.015^{***}
		(0.006)		(0.005)		(0.005)		(0.003)
$\Delta \mathbf{x}_{ij}$		-0.025		-0.077^{***}		-0.056		0.062^{**}
		(0.041)		(0.011)		(0.042)		(0.026)
$a_{i,j-1} \times \Delta t_{ij}$		-0.013^{**}		-0.003		-0.049^{***}		-0.009^{***}
		(0.006)		(0.004)		(0.003)		(0.002)
$a_{i,j-1} \times \Delta \mathbf{x}_{ij}$		-0.367^{***}		-0.142^{***}		-0.103^{***}		-0.117^{***}
		(0.034)		(0.009)		(0.025)		(0.018)
$b_{i,j-1} \times \Delta t_{ij}$		0.027^{**}		0.040^{***}		0.036^{***}		0.027^{***}
		(0.013)		(0.012)		(0.008)		(0.006)
$b_{i,j-1} \times \Delta \mathbf{x}_{ij}$		0.370^{***}		0.455^{***}		0.150^{**}		-0.006
		(0.076)		(0.028)		(0.071)		(0.047)
IMR	0.069^{***}	0.093^{**}	0.161^{***}	0.134^{***}	-1.046^{*}	-0.953	7.817^{***}	8.036^{***}
	(0.020)	(0.037)	(0.005)	(0.006)	(0.605)	(0.605)	(1.166)	(1.169)
AIC	118,981.6	118,860.5	760,160.8	759,170.3	214,692.3	214,406.3	395,336.1	394,753.3
Log Likelihood	−59,481.8	−59,415.2	−380,071.4	−379,570.1	−107,337.1	−107,188.1	−197,659.0	−197,361.6
No. obs.	124,027	124,027	774,235	774,235	195,407	195,407	350,744	350,744

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.21 Second-stage estimation results with nonlinear affect and baseline quality effects.

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.9$ & $\lambda_b = 0.2$		$\lambda_a = 0.1$ & $\lambda_b = 0.2$	
	1	2	3	4	5	6	7	8
(Intercept)	-2.322^{***}	-2.577^{***}	-2.405^{***}	-2.765^{***}	-2.395^{***}	-2.829^{***}	-2.075^{***}	-2.290^{***}
	(0.041)	(0.040)	(0.016)	(0.015)	(0.025)	(0.021)	(0.016)	(0.014)
c_i	2.861^{***}	2.839^{***}	2.790^{***}	2.646^{***}	2.863^{***}	2.864^{***}	3.098^{***}	3.113^{***}
	(0.027)	(0.028)	(0.011)	(0.011)	(0.019)	(0.018)	(0.015)	(0.015)
q_{ij}	3.037^{***}	3.020^{***}	2.668^{***}	2.627^{***}	2.353^{***}	2.351^{***}	1.850^{***}	1.852^{***}
	(0.025)	(0.025)	(0.011)	(0.010)	(0.021)	(0.021)	(0.015)	(0.015)
j	-0.027^{***}	-0.024^{***}	-0.002	0.003	-0.011^{**}	-0.011^{**}	-0.002	-0.000
	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)
n_{ij}	0.001	0.000	0.042^{***}	0.043^{***}	0.012^{***}	0.012^{***}	-0.012^{***}	-0.012^{***}
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	-0.012^{**}	-0.015^{***}	-0.026^{***}	-0.025^{***}	0.006^{***}	0.006^{***}	0.010^{***}	0.010^{***}
	(0.005)	(0.005)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$a_{i,j-1}$		0.273^{***}		0.518^{***}		0.118^{***}		-0.208^{***}
		(0.021)		(0.008)		(0.007)		(0.010)
$Quart\_a_{i,j-1} = 2$	0.145^{***}		0.138^{***}		0.020^{**}		-0.022^{***}	
	(0.013)		(0.005)		(0.009)		(0.007)	
$Quart\_a_{i,j-1} = 3$	0.214^{***}		0.222^{***}		0.093^{***}		-0.096^{***}	
	(0.014)		(0.005)		(0.009)		(0.008)	
$Quart\_a_{i,j-1} = 4$	0.263^{***}		0.386^{***}		0.112^{***}		-0.159^{***}	
	(0.017)		(0.006)		(0.011)		(0.009)	
$b_{i,j-1}$	-1.306^{***}		-1.529^{***}		-0.959^{***}		-0.689^{***}	
	(0.039)		(0.020)		(0.030)		(0.021)	
$Quart\_b_{i,j-1} = 2$		-0.137^{***}		-0.072^{***}		-0.109^{***}		-0.081^{***}
		(0.012)		(0.005)		(0.009)		(0.007)
$Quart\_b_{i,j-1} = 3$		-0.257^{***}		-0.147^{***}		-0.206^{***}		-0.142^{***}
		(0.013)		(0.005)		(0.009)		(0.007)
$Quart\_b_{i,j-1} = 4$		-0.425^{***}		-0.341^{***}		-0.286^{***}		-0.224^{***}
		(0.014)		(0.005)		(0.009)		(0.007)
IMR	0.064^{***}	0.069^{***}	0.130^{***}	0.138^{***}	-0.781	-0.809	7.812^{***}	7.869^{***}
	(0.021)	(0.021)	(0.005)	(0.005)	(0.605)	(0.606)	(1.167)	(1.167)
AIC	118,180.5	118,362.7	755,440.8	755,618.1	214,141.7	214,063.7	394,074.3	394,045.8
Log Likelihood	−59,079.2	−59,170.3	−377,709.4	−377,798.0	−107,059.9	−107,020.9	−197,026.2	−197,011.9
No. obs.	124,027	124,027	774,235	774,235	195,407	195,407	350,744	350,744

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure EC.2 **Estimated non-linear coefficients for $a_{i,j-1}$ and $b_{i,j-1}$ for IMDb (row 1), GoodReads (row 2), TripAdvisor-Attractions (row 3) and TripAdvisor-Restaurants (row 4) based on Table EC.21.**

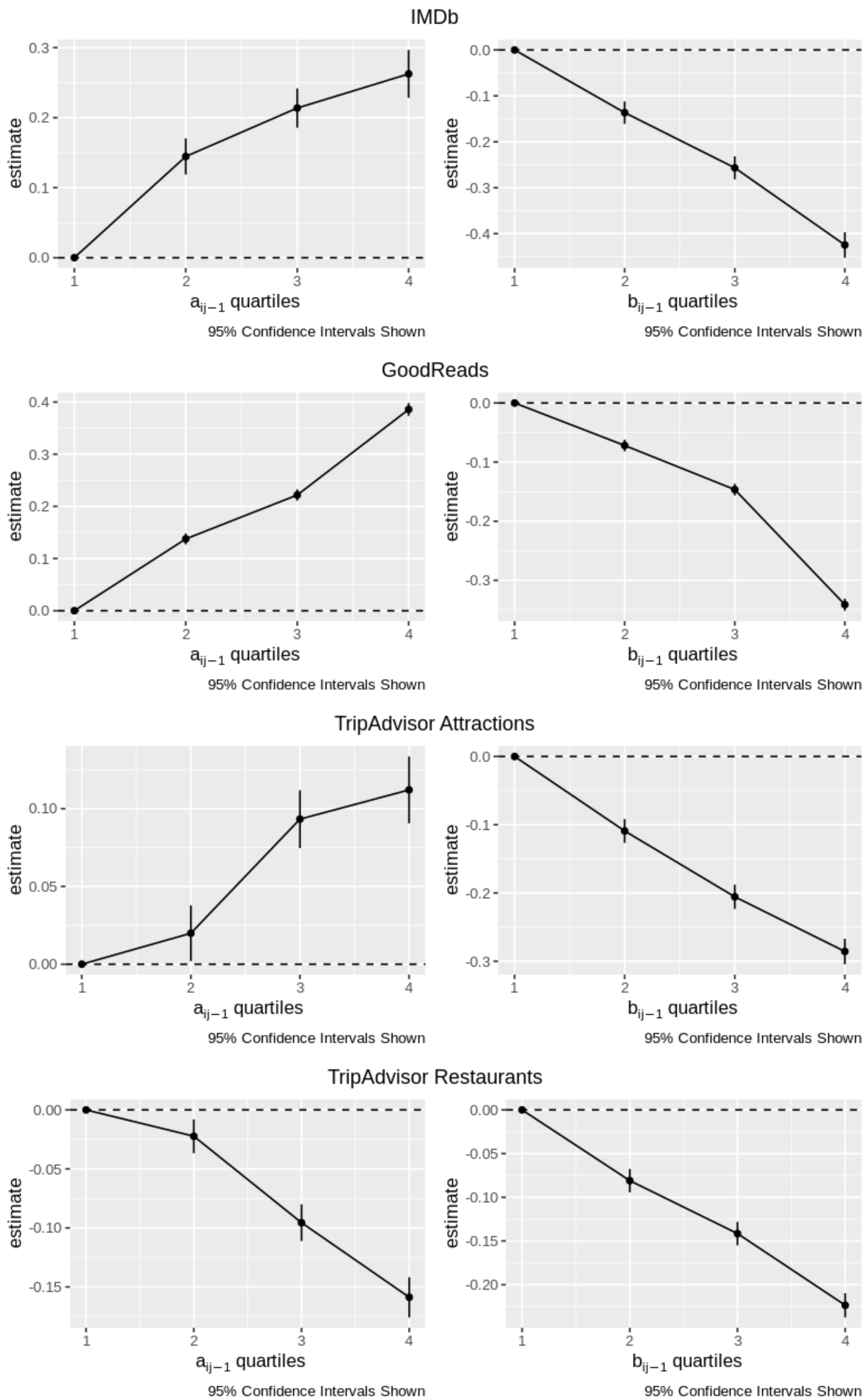

Table EC.22 Second-stage estimation results with time and attribute dissimilarity nonlinearities.

	IMDb		GoodReads		TripAdvisor-Attractions		TripAdvisor-Restaurants	
	$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.3$ & $\lambda_b = 0.2$		$\lambda_a = 0.9$ & $\lambda_b = 0.2$		$\lambda_a = 0.1$ & $\lambda_b = 0.2$	
	1	2	3	4	5	6	7	8
(Intercept)	-2.253^{***}	-2.216^{***}	-2.302^{***}	-2.304^{***}	-2.379^{***}	-2.395^{***}	-2.132^{***}	-2.106^{***}
	(0.060)	(0.050)	(0.021)	(0.031)	(0.072)	(0.041)	(0.040)	(0.024)
c_i	2.841^{***}	2.833^{***}	2.683^{***}	2.685^{***}	2.865^{***}	2.865^{***}	3.092^{***}	3.093^{***}
	(0.028)	(0.028)	(0.011)	(0.011)	(0.018)	(0.018)	(0.015)	(0.015)
q_{ij}	3.061^{***}	3.060^{***}	2.691^{***}	2.691^{***}	2.346^{***}	2.346^{***}	1.840^{***}	1.838^{***}
	(0.027)	(0.027)	(0.011)	(0.011)	(0.021)	(0.021)	(0.015)	(0.015)
j	-0.024^{***}	-0.023^{***}	0.011^{***}	0.012^{***}	-0.010^{**}	-0.010^{**}	0.004	0.004
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
n_{ij}	0.002	0.003	0.042^{***}	0.043^{***}	0.012^{***}	0.012^{***}	-0.010^{***}	-0.009^{***}
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	-0.023^{***}	-0.025^{***}	-0.027^{***}	-0.027^{***}	0.005^{***}	0.006^{***}	0.010^{***}	0.010^{***}
	(0.008)	(0.007)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$a_{i,j-1}$	0.736^{***}	0.543^{***}	0.660^{***}	0.786^{***}	0.328^{***}	0.244^{***}	-0.141^{***}	-0.179^{***}
	(0.053)	(0.038)	(0.015)	(0.026)	(0.027)	(0.015)	(0.029)	(0.016)
$b_{i,j-1}$	-1.854^{***}	-1.779^{***}	-1.976^{***}	-2.442^{***}	-1.172^{***}	-1.088^{***}	-0.739^{***}	-0.756^{***}
	(0.118)	(0.082)	(0.042)	(0.080)	(0.118)	(0.062)	(0.076)	(0.040)
$Quart\_\Delta t_{ij} = 2$	0.171^{***}		0.025		0.018		0.058^{*}	
	(0.042)		(0.018)		(0.050)		(0.030)	
$Quart\_\Delta t_{ij} = 3$	0.127^{***}		0.006		-0.031		0.038	
	(0.042)		(0.018)		(0.049)		(0.030)	
$Quart\_\Delta t_{ij} = 4$	-0.076^{*}		0.036^{**}		-0.006		0.072^{**}	
	(0.041)		(0.018)		(0.049)		(0.029)	
$\Delta\mathbf{x}_{ij}$	-0.163^{***}		-0.201^{***}		-0.024		0.019	
	(0.059)		(0.017)		(0.067)		(0.039)	
$b_{i,j-1} \times Quart\_\Delta t_{ij} = 2$	-0.223^{**}		-0.050		0.020		-0.064	
	(0.108)		(0.052)		(0.083)		(0.059)	
$b_{i,j-1} \times Quart\_\Delta t_{ij} = 3$	-0.054		0.040		0.190^{**}		0.005	
	(0.110)		(0.052)		(0.082)		(0.059)	
$b_{i,j-1} \times Quart\_\Delta t_{ij} = 4$	0.391^{***}		0.217^{***}		0.313^{***}		0.113^{*}	
	(0.106)		(0.053)		(0.081)		(0.058)	
$b_{i,j-1} \times \Delta\mathbf{x}_{ij}$	0.664^{***}		0.853^{***}		0.101		0.061	
	(0.133)		(0.051)		(0.113)		(0.079)	
$a_{i,j-1} \times Quart\_\Delta t_{ij} = 2$	-0.140^{***}		-0.019		-0.029		-0.007	
	(0.047)		(0.017)		(0.019)		(0.022)	
$a_{i,j-1} \times Quart\_\Delta t_{ij} = 3$	-0.159^{***}		-0.003		-0.182^{***}		0.040^{*}	
	(0.047)		(0.017)		(0.020)		(0.023)	
$a_{i,j-1} \times Quart\_\Delta t_{ij} = 4$	-0.187^{***}		-0.071^{***}		-0.283^{***}		-0.009	
	(0.045)		(0.017)		(0.020)		(0.022)	
$a_{i,j-1} \times \Delta\mathbf{x}_{ij}$	-0.407^{***}		-0.224^{***}		-0.097^{***}		-0.075^{**}	
	(0.058)		(0.016)		(0.026)		(0.029)	
Δt_{ij}		-0.035^{***}		0.015^{**}		-0.005		0.012^{**}
		(0.008)		(0.007)		(0.008)		(0.005)
a$Quart_\Delta\mathbf{x}_{ij} = 2$		-0.059		-0.131^{***}		-0.034		0.025
		(0.041)		(0.017)		(0.049)		(0.028)
$Quart\_\Delta\mathbf{x}_{ij} = 3$		-0.068		-0.191^{***}		-0.001		-0.039
		(0.042)		(0.018)		(0.049)		(0.028)
$Quart\_\Delta\mathbf{x}_{ij} = 4$		-0.061		-0.198^{***}		0.016		0.016
		(0.044)		(0.018)		(0.049)		(0.028)
$b_{i,j-1} \times \Delta t_{ij}$		0.123^{***}		0.122^{***}		0.063^{***}		0.023^{**}
		(0.022)		(0.022)		(0.013)		(0.010)
$b_{i,j-1} \times Quart\_\Delta\mathbf{x}_{ij} = 2$		0.301^{***}		0.503^{***}		0.076		0.013
		(0.106)		(0.050)		(0.082)		(0.056)
$b_{i,j-1} \times Quart\_\Delta\mathbf{x}_{ij} = 3$		0.337^{***}		0.651^{***}		0.048		0.118^{**}
		(0.106)		(0.053)		(0.081)		(0.057)
$b_{i,j-1} \times Quart\_\Delta\mathbf{x}_{ij} = 4$		0.286^{***}		0.873^{***}		0.016		0.037
		(0.108)		(0.054)		(0.081)		(0.057)
$a_{i,j-1} \times \Delta t_{ij}$		-0.041^{***}		-0.040^{***}		-0.052^{***}		0.001
		(0.009)		(0.007)		(0.003)		(0.004)
$a_{i,j-1} \times Quart\_\Delta\mathbf{x}_{ij} = 2$		-0.143^{***}		-0.112^{***}		-0.043^{**}		-0.030
		(0.046)		(0.016)		(0.020)		(0.021)
$a_{i,j-1} \times Quart\_\Delta\mathbf{x}_{ij} = 3$		-0.220^{***}		-0.125^{***}		-0.063^{***}		-0.015
		(0.045)		(0.017)		(0.019)		(0.022)
$a_{i,j-1} \times Quart\_\Delta\mathbf{x}_{ij} = 4$		-0.247^{***}		-0.237^{***}		-0.068^{***}		-0.056^{**}
		(0.047)		(0.017)		(0.020)		(0.022)
IMR	0.122^{***}	0.127^{***}	0.113^{***}	0.111^{***}	-0.718	-0.707	7.915^{***}	7.879^{***}
	(0.037)	(0.035)	(0.006)	(0.006)	(0.606)	(0.606)	(1.170)	(1.170)
AIC	118,099.3	118,147.4	753,455.0	753,329.8	213,743.4	213,772.0	393,661.4	393,600.1
Log Likelihood	−59,028.6	−59,052.7	−376,706.5	−376,643.9	−106,850.7	−106,865.0	−196,809.7	−196,779.0
No. obs.	124,027	124,027	774,235	774,235	195,407	195,407	350,744	350,744

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.23 Second-stage estimation results on IMDb with $\lambda_b = 0.2$ and a variable λ_a.

	IMDb									
	$\lambda_a = 0.1$	$\lambda_a = 0.2$	$\lambda_a = 0.3$	$\lambda_a = 0.4$	$\lambda_a = 0.5$	$\lambda_a = 0.6$	$\lambda_a = 0.7$	$\lambda_a = 0.8$	$\lambda_a = 0.9$	$\lambda_a = 1.0$
(Intercept)	-2.300^{***}	-2.285^{***}	-2.284^{***}	-2.287^{***}	-2.292^{***}	-2.296^{***}	-2.299^{***}	-2.302^{***}	-2.305^{***}	-2.307^{***}
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
c_i	2.892^{***}	2.807^{***}	2.835^{***}	2.881^{***}	2.922^{***}	2.955^{***}	2.981^{***}	3.002^{***}	3.018^{***}	3.032^{***}
	(0.030)	(0.030)	(0.028)	(0.027)	(0.026)	(0.025)	(0.024)	(0.024)	(0.024)	(0.023)
q_{ij}	3.031^{***}	3.039^{***}	3.038^{***}	3.035^{***}	3.032^{***}	3.030^{***}	3.028^{***}	3.026^{***}	3.024^{***}	3.023^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
j	-0.023^{***}	-0.022^{***}	-0.023^{***}	-0.023^{***}	-0.024^{***}	-0.024^{***}	-0.024^{***}	-0.025^{***}	-0.025^{***}	-0.025^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n_{ij}	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
A_{ij}	-0.013^{***}	-0.013^{***}	-0.013^{***}	-0.013^{***}	-0.014^{***}	-0.014^{***}	-0.014^{***}	-0.014^{***}	-0.014^{***}	-0.014^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$a_{i,j-1}$	0.242^{***}	0.349^{***}	0.318^{***}	0.264^{***}	0.215^{***}	0.175^{***}	0.143^{***}	0.118^{***}	0.098^{***}	0.081^{***}
	(0.024)	(0.024)	(0.021)	(0.018)	(0.016)	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)
$b_{i,j-1}$	-1.257^{***}	-1.340^{***}	-1.330^{***}	-1.297^{***}	-1.265^{***}	-1.238^{***}	-1.215^{***}	-1.197^{***}	-1.182^{***}	-1.170^{***}
	(0.040)	(0.040)	(0.040)	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)
IMR	0.066^{***}	0.066^{***}	0.067^{***}	0.067^{***}	0.067^{***}	0.067^{***}	0.067^{***}	0.067^{***}	0.067^{***}	0.067^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
AIC	118,337.3	118,227.5	118,214.6	118,237.7	118,267.8	118,296.0	118,320.3	118,340.6	118,357.4	118,371.4
Log Likelihood	−59,159.6	−59,104.7	−59098.3	−59,109.8	−59,124.9	−59139.0	−59,151.1	−59,161.3	−59169.7	−59,176.7
No. obs.	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.24 Second-stage estimation results on IMDb with $\lambda_a = 0.3$ and a variable λ_b.

	IMDb									
	$\lambda_b = 0.1$	$\lambda_b = 0.2$	$\lambda_b = 0.3$	$\lambda_b = 0.4$	$\lambda_b = 0.5$	$\lambda_b = 0.6$	$\lambda_b = 0.7$	$\lambda_b = 0.8$	$\lambda_b = 0.9$	$\lambda_b = 1.0$
(Intercept)	-2.290^{***}	-2.284^{***}	-2.306^{***}	-2.331^{***}	-2.354^{***}	-2.373^{***}	-2.388^{***}	-2.401^{***}	-2.412^{***}	-2.421^{***}
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
c_i	2.886^{***}	2.835^{***}	2.796^{***}	2.773^{***}	2.763^{***}	2.758^{***}	2.758^{***}	2.760^{***}	2.763^{***}	2.767^{***}
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
q_{ij}	3.022^{***}	3.038^{***}	3.029^{***}	3.014^{***}	2.999^{***}	2.985^{***}	2.973^{***}	2.962^{***}	2.952^{***}	2.943^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
j	-0.023^{***}	-0.023^{***}	-0.023^{***}	-0.024^{***}	-0.024^{***}	-0.024^{***}	-0.025^{***}	-0.025^{***}	-0.025^{***}	-0.025^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n_{ij}	0.000	0.002	0.001	0.000	−0.001	−0.002	−0.003	−0.004	−0.005	-0.005^{*}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
A_{ij}	-0.015^{***}	-0.013^{***}	-0.014^{***}	-0.015^{***}	-0.016^{***}	-0.018^{***}	-0.019^{***}	-0.020^{***}	-0.020^{***}	-0.021^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$a_{i,j-1}$	0.250^{***}	0.318^{***}	0.327^{***}	0.311^{***}	0.287^{***}	0.260^{***}	0.234^{***}	0.210^{***}	0.188^{***}	0.169^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
$b_{i,j-1}$	-1.231^{***}	-1.330^{***}	-1.205^{***}	-1.039^{***}	-0.882^{***}	-0.744^{***}	-0.626^{***}	-0.526^{***}	-0.440^{***}	-0.367^{***}
	(0.039)	(0.040)	(0.038)	(0.035)	(0.032)	(0.029)	(0.027)	(0.024)	(0.022)	(0.020)
IMR	0.071^{***}	0.067^{***}	0.065^{***}	0.065^{***}	0.066^{***}	0.067^{***}	0.067^{***}	0.068^{***}	0.070^{***}	0.071^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)
AIC	118,308.5	118,214.6	118,309.7	118,442.6	118,572.2	118,688.4	118,790.0	118,878.3	118,955.0	119,021.6
Log Likelihood	−59,145.2	−59,098.3	−59,145.8	−59,212.3	−59,277.1	−59,335.2	−59,386.0	−59,430.1	−59,468.5	−59,501.8
No. obs.	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027	124,027

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.25 Second-stage estimation results on GoodReads with $\lambda_b = 0.2$ and a variable λ_a.

	GoodReads									
	$\lambda_a = 0.1$	$\lambda_a = 0.2$	$\lambda_a = 0.3$	$\lambda_a = 0.4$	$\lambda_a = 0.5$	$\lambda_a = 0.6$	$\lambda_a = 0.7$	$\lambda_a = 0.8$	$\lambda_a = 0.9$	$\lambda_a = 1.0$
(Intercept)	-2.404^{***}	-2.375^{***}	-2.371^{***}	-2.376^{***}	-2.383^{***}	-2.390^{***}	-2.397^{***}	-2.402^{***}	-2.407^{***}	-2.411^{***}
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
c_i	2.785^{***}	2.638^{***}	2.677^{***}	2.749^{***}	2.816^{***}	2.873^{***}	2.919^{***}	2.958^{***}	2.991^{***}	3.018^{***}
	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
q_{ij}	2.662^{***}	2.680^{***}	2.679^{***}	2.674^{***}	2.667^{***}	2.662^{***}	2.657^{***}	2.653^{***}	2.649^{***}	2.646^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
j	0.008^{***}	0.008^{***}	0.007^{***}	0.006^{***}	0.005^{***}	0.005^{**}	0.005^{**}	0.005^{**}	0.004^{**}	0.004^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
n_{ij}	0.042^{***}	0.042^{***}	0.042^{***}	0.042^{***}	0.042^{***}	0.042^{***}	0.042^{***}	0.041^{***}	0.041^{***}	0.041^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
A_{ij}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$	0.432^{***}	0.593^{***}	0.549^{***}	0.469^{***}	0.394^{***}	0.331^{***}	0.278^{***}	0.235^{***}	0.198^{***}	0.167^{***}
	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
$b_{i,j-1}$	-1.511^{***}	-1.621^{***}	-1.611^{***}	-1.572^{***}	-1.531^{***}	-1.494^{***}	-1.462^{***}	-1.436^{***}	-1.413^{***}	-1.393^{***}
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
IMR	0.132^{***}	0.129^{***}	0.128^{***}	0.129^{***}	0.130^{***}	0.131^{***}	0.132^{***}	0.133^{***}	0.133^{***}	0.134^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
AIC	756,660.5	754,472.4	754,266.1	754,698.1	755,255.7	755,794.2	756,278.3	756,704.6	757,078.6	757,407.5
Log Likelihood	−378,321.2	−377,227.2	−377,124.0	−377,340.0	−377,618.8	−377,888.1	−378,130.1	−378,343.3	−378,530.3	−378,694.7
No. obs.	774,235	774,235	774,235	774,235	774,235	774,235	774,235	774,235	774,235	774,235

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.26 Second-stage estimation results on GoodReads with $\lambda_a = 0.3$ and a variable λ_b.

	GoodReads									
	$\lambda_b = 0.1$	$\lambda_b = 0.2$	$\lambda_b = 0.3$	$\lambda_b = 0.4$	$\lambda_b = 0.5$	$\lambda_b = 0.6$	$\lambda_b = 0.7$	$\lambda_b = 0.8$	$\lambda_b = 0.9$	$\lambda_b = 1.0$
(Intercept)	-2.390^{***}	-2.371^{***}	-2.420^{***}	-2.478^{***}	-2.531^{***}	-2.578^{***}	-2.619^{***}	-2.653^{***}	-2.683^{***}	-2.710^{***}
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
c_i	2.692^{***}	2.677^{***}	2.648^{***}	2.625^{***}	2.608^{***}	2.595^{***}	2.585^{***}	2.578^{***}	2.573^{***}	2.569^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
q_{ij}	2.655^{***}	2.679^{***}	2.658^{***}	2.629^{***}	2.601^{***}	2.575^{***}	2.553^{***}	2.533^{***}	2.516^{***}	2.501^{***}
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
j	0.004^{**}	0.007^{***}	0.006^{***}	0.005^{**}	0.003^{*}	0.002	0.001	0.001	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
n_{ij}	0.042^{***}	0.042^{***}	0.042^{***}	0.043^{***}	0.043^{***}	0.043^{***}	0.043^{***}	0.044^{***}	0.044^{***}	0.044^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
A_{ij}	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.025^{***}	-0.025^{***}	-0.024^{***}	-0.024^{***}	-0.024^{***}	-0.023^{***}	-0.023^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$	0.514^{***}	0.549^{***}	0.555^{***}	0.548^{***}	0.537^{***}	0.525^{***}	0.512^{***}	0.500^{***}	0.489^{***}	0.479^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$b_{i,j-1}$	-1.542^{***}	-1.611^{***}	-1.448^{***}	-1.256^{***}	-1.079^{***}	-0.923^{***}	-0.789^{***}	-0.674^{***}	-0.574^{***}	-0.487^{***}
	(0.020)	(0.020)	(0.019)	(0.018)	(0.016)	(0.015)	(0.014)	(0.013)	(0.012)	(0.011)
IMR	0.133^{***}	0.128^{***}	0.133^{***}	0.138^{***}	0.144^{***}	0.149^{***}	0.153^{***}	0.156^{***}	0.160^{***}	0.162^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
AIC	754,767.4	754,266.1	754,765.1	755,444.3	756,110.4	756714.8	757,249.4	757,718.5	758130.1	758,492.3
Log Likelihood	$-377,374.7$	$-377,124.0$	$-377,373.5$	$-377,713.1$	$-378,046.2$	$-378,348.4$	$-378,615.7$	$-378,850.2$	$-379,056.0$	$-379,237.1$
No. obs.	774,235	774,235	774,235	774,235	774,235	774,235	774,235	774,235	774,235	774,235

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.27 Second-stage estimation results on TripAdvisor-Attractions with $\lambda_b = 0.2$ and a variable λ_a.

	TripAdvisor - Attractions									
	$\lambda_a = 0.1$	$\lambda_a = 0.2$	$\lambda_a = 0.3$	$\lambda_a = 0.4$	$\lambda_a = 0.5$	$\lambda_a = 0.6$	$\lambda_a = 0.7$	$\lambda_a = 0.8$	$\lambda_a = 0.9$	$\lambda_a = 1.0$
(Intercept)	-2.460^{***}	-2.443^{***}	-2.422^{***}	-2.409^{***}	-2.404^{***}	-2.402^{***}	-2.402^{***}	-2.404^{***}	-2.406^{***}	-2.409^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
c_i	3.106^{***}	3.012^{***}	2.918^{***}	2.868^{***}	2.848^{***}	2.843^{***}	2.847^{***}	2.854^{***}	2.864^{***}	2.874^{***}
	(0.020)	(0.021)	(0.021)	(0.020)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
q_{ij}	2.339^{***}	2.346^{***}	2.352^{***}	2.354^{***}	2.355^{***}	2.354^{***}	2.353^{***}	2.352^{***}	2.351^{***}	2.351^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
j	-0.014^{***}	-0.012^{***}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.011^{**}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
n_{ij}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$a_{i,j-1}$	-0.150^{***}	-0.043^{***}	0.061^{***}	0.115^{***}	0.137^{***}	0.142^{***}	0.138^{***}	0.130^{***}	0.120^{***}	0.109^{***}
	(0.013)	(0.015)	(0.014)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)
$b_{i,j-1}$	-0.813^{***}	-0.872^{***}	-0.929^{***}	-0.958^{***}	-0.969^{***}	-0.970^{***}	-0.968^{***}	-0.963^{***}	-0.957^{***}	-0.950^{***}
	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
IMR	-0.824	-0.809	-0.792	-0.780	-0.774	-0.770	-0.769	-0.770	-0.771	-0.773
	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)
AIC	214,174.8	214,294.8	214,284.1	214,217.4	214,151.5	214,102.3	214,070.5	214,053.2	214,047.3	214,050.1
Log Likelihood	$-107,078.4$	$-107,138.4$	$-107,133.0$	$-107,099.7$	$-107,066.7$	$-107,042.1$	$-107,026.2$	$-107,017.6$	$-107,014.6$	$-107,016.0$
No. obs.	195,407	195,407	195,407	195,407	195,407	195,407	195,407	195,407	195,407	195,407

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.28 Second-stage estimation results on TripAdvisor-Attractions with $\lambda_a = 0.9$ and a variable λ_b.

	TripAdvisor - Attractions									
	$\lambda_b = 0.1$	$\lambda_b = 0.2$	$\lambda_b = 0.3$	$\lambda_b = 0.4$	$\lambda_b = 0.5$	$\lambda_b = 0.6$	$\lambda_b = 0.7$	$\lambda_b = 0.8$	$\lambda_b = 0.9$	$\lambda_b = 1.0$
(Intercept)	-2.461^{***}	-2.406^{***}	-2.442^{***}	-2.495^{***}	-2.546^{***}	-2.592^{***}	-2.631^{***}	-2.666^{***}	-2.696^{***}	-2.723^{***}
	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)
c_i	2.869^{***}	2.864^{***}	2.844^{***}	2.826^{***}	2.811^{***}	2.799^{***}	2.790^{***}	2.783^{***}	2.778^{***}	2.775^{***}
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
q_{ij}	2.325^{***}	2.351^{***}	2.354^{***}	2.349^{***}	2.340^{***}	2.331^{***}	2.322^{***}	2.312^{***}	2.303^{***}	2.295^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
j	-0.009^{**}	-0.010^{**}	-0.008^{*}	-0.006	-0.004	-0.002	-0.001	-0.000	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
n_{ij}	0.011^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.012^{***}	0.011^{***}	0.011^{***}	0.011^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$a_{i,j-1}$	0.104^{***}	0.120^{***}	0.131^{***}	0.137^{***}	0.140^{***}	0.140^{***}	0.140^{***}	0.138^{***}	0.135^{***}	0.132^{***}
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$b_{i,j-1}$	-0.822^{***}	-0.957^{***}	-0.907^{***}	-0.813^{***}	-0.716^{***}	-0.626^{***}	-0.545^{***}	-0.471^{***}	-0.405^{***}	-0.345^{***}
	(0.028)	(0.030)	(0.029)	(0.027)	(0.026)	(0.024)	(0.022)	(0.021)	(0.019)	(0.018)
IMR	-0.805	-0.771	-0.800	-0.839	-0.880	-0.919	-0.955	-0.989	-1.020^{*}	-1.048^{*}
	(0.606)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)	(0.605)
AIC	214,187.5	214,047.3	214,102.2	214,200.9	214,302.0	214,396.5	214,483.2	214,562.9	214,636.2	214,703.5
Log Likelihood	$-107,084.7$	$-107,014.6$	$-107,042.1$	$-107,091.4$	$-107,142.0$	$-107,189.2$	$-107,232.6$	$-107,272.4$	$-107,309.1$	$-107,342.7$
No. obs.	195,407	195,407	195,407	195,407	195,407	195,407	195,407	195,407	195,407	195,407

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.29 Second-stage estimation results on TripAdvisor-Restaurants with $\lambda_b = 0.2$ and a variable λ_a.

	TripAdvisor - Restaurants									
	$\lambda_a = 0.1$	$\lambda_a = 0.2$	$\lambda_a = 0.3$	$\lambda_a = 0.4$	$\lambda_a = 0.5$	$\lambda_a = 0.6$	$\lambda_a = 0.7$	$\lambda_a = 0.8$	$\lambda_a = 0.9$	$\lambda_a = 1.0$
(Intercept)	-2.065^{***}	-2.069^{***}	-2.066^{***}	-2.063^{***}	-2.059^{***}	-2.057^{***}	-2.055^{***}	-2.054^{***}	-2.053^{***}	-2.053^{***}
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
c_i	3.104^{***}	3.087^{***}	3.033^{***}	2.992^{***}	2.965^{***}	2.948^{***}	2.936^{***}	2.929^{***}	2.924^{***}	2.921^{***}
	(0.015)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
q_{ij}	1.850^{***}	1.851^{***}	1.854^{***}	1.856^{***}	1.857^{***}	1.857^{***}	1.858^{***}	1.858^{***}	1.858^{***}	1.858^{***}
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
j	0.001	0.002	0.004	0.005	0.005	0.005^{*}	0.005^{*}	0.005^{*}	0.006^{*}	0.006^{*}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n_{ij}	-0.012^{***}	-0.012^{***}	-0.012^{***}	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.009^{***}	0.009^{***}	0.009^{***}	0.009^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$	-0.200^{***}	-0.179^{***}	-0.119^{***}	-0.074^{***}	-0.045^{***}	-0.027^{***}	-0.015^{**}	-0.007	-0.002	0.002
	(0.010)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)
$b_{i,j-1}$	-0.681^{***}	-0.689^{***}	-0.713^{***}	-0.732^{***}	-0.744^{***}	-0.752^{***}	-0.757^{***}	-0.760^{***}	-0.762^{***}	-0.763^{***}
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
IMR	7.814^{***}	7.906^{***}	7.985^{***}	8.022^{***}	8.036^{***}	8.040^{***}	8.039^{***}	8.037^{***}	8.034^{***}	8.031^{***}
	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)
AIC	394,088.2	394,233.8	394,362.5	394,431.4	394,465.5	394,482.1	394,490.0	394,493.4	394,494.5	394,494.5
Log Likelihood	−197,035.1	−197,107.9	−197,172.2	−197,206.7	−197,223.7	−197,232.0	−197,236.0	−197,237.7	−197,238.2	−197,238.2
No. obs.	350,744	350,744	350,744	350,744	350,744	350,744	350,744	350,744	350,744	350,744

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table EC.30 Second-stage estimation results on TripAdvisor-Restaurants with $\lambda_a = 0.1$ and a variable λ_b.

	TripAdvisor - Restaurants									
	$\lambda_b = 0.1$	$\lambda_b = 0.2$	$\lambda_b = 0.3$	$\lambda_b = 0.4$	$\lambda_b = 0.5$	$\lambda_b = 0.6$	$\lambda_b = 0.7$	$\lambda_b = 0.8$	$\lambda_b = 0.9$	$\lambda_b = 1.0$
(Intercept)	-2.094^{***}	-2.065^{***}	-2.082^{***}	-2.109^{***}	-2.134^{***}	-2.157^{***}	-2.176^{***}	-2.192^{***}	-2.207^{***}	-2.219^{***}
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
c_i	3.087^{***}	3.104^{***}	3.110^{***}	3.111^{***}	3.109^{***}	3.107^{***}	3.104^{***}	3.101^{***}	3.098^{***}	3.095^{***}
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
q_{ij}	1.833^{***}	1.850^{***}	1.850^{***}	1.844^{***}	1.837^{***}	1.830^{***}	1.823^{***}	1.817^{***}	1.811^{***}	1.806^{***}
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
j	-0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
n_{ij}	-0.013^{***}	-0.012^{***}	-0.012^{***}	-0.012^{***}	-0.013^{***}	-0.014^{***}	-0.014^{***}	-0.015^{***}	-0.016^{***}	-0.016^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
A_{ij}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}	0.010^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$a_{i,j-1}$	-0.198^{***}	-0.200^{***}	-0.211^{***}	-0.220^{***}	-0.228^{***}	-0.234^{***}	-0.239^{***}	-0.243^{***}	-0.246^{***}	-0.248^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$b_{i,j-1}$	-0.571^{***}	-0.681^{***}	-0.646^{***}	-0.575^{***}	-0.502^{***}	-0.435^{***}	-0.375^{***}	-0.324^{***}	-0.278^{***}	-0.238^{***}
	(0.020)	(0.021)	(0.020)	(0.019)	(0.017)	(0.016)	(0.015)	(0.013)	(0.012)	(0.011)
IMR	7.727^{***}	7.814^{***}	7.811^{***}	7.780^{***}	7.743^{***}	7.705^{***}	7.670^{***}	7.639^{***}	7.612^{***}	7.588^{***}
	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)	(1.167)
AIC	394,318.6	394,088.2	394,094.5	394,176.9	394,277.0	394,375.4	394,466.7	394,549.7	394,625.1	394,693.6
Log Likelihood	−197,150.3	−197,035.1	−197,038.2	−197,079.4	−197,129.5	−197,178.7	−197,224.3	−197,265.8	−197,303.5	−197,337.8
No. obs.	350,744	350,744	350,744	350,744	350,744	350,744	350,744	350,744	350,744	350,744

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

EC.5. Proofs

Proof of Lemma 1. The proof proceeds by backward induction of (11). To initialize the induction, note that by (10), $V_T = 0$ is linear in a_T and b_T, so that $A_T = B_T = C_T(\mathcal{J}_T) = 0$. We can set $w_T = 0$.

Suppose now that $V_{t+1}(a_{t+1}, b_{t+1}, \mathcal{J}_{t+1}) = A_{t+1}a_{t+1} + B_{t+1}b_{t+1} + C_{t+1}(\mathcal{J}_{t+1})$. Letting j be the maximizer of (9) and using the assumption that $\Phi(u) = u$ and the update dynamics of a_{t+1} and b_{t+1}, we can write (9) as:

$$\begin{aligned}
V_t(b_t, a_t, \mathcal{J}_t) = {} & q_j + \alpha a_t + \beta b_t \\
& + (q_j + \alpha a_t + \beta b_t)\delta A_{t+1}\lambda_a \\
& + \delta A_{t+1}(1-\lambda_a)a_t \\
& + \delta B_{t+1}(\lambda_b q_j + (1-\lambda_b)b_t) \\
& + \delta C_{t+1}(\mathcal{J}_t \setminus \{j\}) \\
= {} & q_j(1 + \delta\lambda_a A_{t+1} + \delta\lambda_b B_{t+1}) \\
& + \Big[\alpha + \delta\gamma A_{t+1}\Big]a_t + [\beta + \delta\beta\lambda_a A_{t+1} + \delta(1-\lambda_b)B_{t+1}]b_t \\
& + \delta C_{t+1}(\mathcal{J}_t \setminus \{j\})
\end{aligned}$$

in which $\gamma := \alpha\lambda_a + (1-\lambda_a)$. We thus have that the recursion is satisfied when, for $t < T$,

$$A_t = \alpha + \delta\gamma A_{t+1} \text{ hence } A_t = \alpha\frac{1-(\delta\gamma)^{T-t}}{1-\delta\gamma},$$

and when

$$B_t = \beta + \delta\beta\lambda_a A_{t+1} + \delta(1-\lambda_b)B_{t+1}$$

hence, for $t < T$, B_t is as defined in (11). Finally, letting $w_t := \delta^{-(T-t)}[1 + \delta\lambda_a A_{t+1} + \delta\lambda_b B_{t+1}]$, i.e., for $t < T$, w_t is as defined in (12). The recursion goes through when

$$C_t(\mathcal{J}_t) = \max_{j\in\mathcal{J}_t}\left\{\delta C_{t+1}(\mathcal{J}_t\setminus\{j\}) + \delta^{T-t}w_t q_j\right\}.$$

This completes the induction. $\square$

Proof of Theorem 1. By Lemma 1, $V_t(a_t, b_t, \mathcal{J}_t)$ can be expressed as $A_t a_t + B_t b_t + C_t(\mathcal{J}_t)$. Because only the constant term $C_t(\mathcal{J}_t)$ depends on the choice set, the optimal sequence is independent of the state (a_t, b_t) for all t, including the initial state (a_0, b_0). Furthermore, by (11), $C_0(\mathcal{J})$ can be expressed directly as a linear function of the qualities of the selected activities. In particular,

$$C_0(\mathcal{J}) = \delta^T \max_{\{j_0,\ldots,j_{T-1}\}\subseteq\mathcal{J}} \sum_{t=0}^{T-1} w_t q_{j_t}. \tag{EC.4}$$

$\square$

Proof of Lemma 2. We express (12) as $w_t = F\delta^{-(T-t)} + G(1-\lambda_b)^{T-t} - H\gamma^{T-t}$, for some F and G, and with $H := \frac{\alpha\lambda_a}{\gamma(1-\delta\gamma)}\left(1 + \frac{\beta\lambda_b}{\gamma+\lambda_b-1}\right)$. For any interior stationary point ($dw_t/dt = 0$), the second derivative equals

$$\begin{aligned}\left.\frac{d^2w_t}{dt^2}\right|_{dw_t/dt=0} &= F\delta^{-(T-t)}(\ln\delta)^2 + G(1-\lambda_b)^{T-t}(\ln(1-\lambda_b))^2 - H\gamma^{T-t}(\ln\gamma)^2\Big|_{dw_t/dt=0}\\ &= G(1-\lambda_b)^{T-t}\ln(1-\lambda_b)\ln(\delta(1-\lambda_b)) - H\gamma^{T-t}\ln\gamma\ln(\delta\gamma) := K(t).\end{aligned}$$

We next show that $K(t)$ switches sign at most once as t increases. Indeed, when $K(t) = 0$, $K'(t)|_{K(t)=0} = -G(1-\lambda_b)^{T-t}(\ln(1-\lambda_b))^2\ln(\delta(1-\lambda_b)) + H\gamma^{T-t}(\ln\gamma)^2\ln(\delta\gamma)|_{K(t)=0} = H\gamma^{T-t}\ln\gamma\ln(\delta\gamma)\ln(\gamma/(1-\lambda_b))$, which is positive if and only if $\gamma + \lambda_b - 1 > -\beta\lambda_b$. Hence, $K(t)$ crosses zero at most once, i.e., $\left.\frac{d^2w_t}{dt^2}\right|_{dw_t/dt=0}$ changes sign at most once. $\square$

Proof of Lemma 3. When $\alpha = 0$, we have $\gamma = (1-\lambda_a)$ and affect a_t does not enter the value function. We can express (12) as $w_t = F\delta^{-(T-t)} + G(1-\lambda_b)^{T-t}$, where $F := 1 + \frac{\beta\delta\lambda_b}{1-\delta(1-\lambda_b)}$ and $G := -\frac{\beta\lambda_b}{(1-\lambda_b)(1-\delta(1-\lambda_b))}$. When $dw_t/dt = 0$,

$$\begin{aligned}\left.\frac{d^2w_t}{dt^2}\right|_{dw_t/dt=0} &= F\delta^{-(T-t)}(\ln\delta)^2 + G(1-\lambda_b)^{T-t}(\ln(1-\lambda_b))^2\Big|_{dw_t/dt=0}\\ &= G(1-\lambda_b)^{T-t}\ln(1-\lambda_b)[\ln(\delta(1-\lambda_b))]\\ &= (1-\lambda_b)^{T-t}\frac{\beta\lambda_b\ln(1-\lambda_b)}{(1-\lambda_b)}\left(\frac{-\ln(\delta(1-\lambda_b))}{1-\delta(1-\lambda_b)}\right) \geq 0.\end{aligned}$$

Finally, note that $dw_{T-1}/dt = F\ln\delta/\delta - G(1-\lambda_b)\ln(1-\lambda_b) = \ln\delta/\delta + \beta\lambda_b\ln(\delta(1-\lambda_b))/(1-\delta(1-\lambda_b)) := f(\delta)$. When $\delta \geq 1$, $f(\delta) \geq 0$. Moreover, when $f(\delta)=0$,

$$\begin{aligned} f'(\delta)\Big|_{f(\delta)=0} &= \left(\tfrac{1-\ln\delta}{\delta^2} + \tfrac{\beta\lambda_b}{\delta(1-\delta(1-\lambda_b))} + \tfrac{\beta\lambda_b(1-\lambda_b)}{(1-\delta(1-\lambda_b))^2}\ln(\delta(1-\lambda_b))\right)|_{f(\delta)=0} \\ &= \tfrac{1}{\delta^2} + \tfrac{\beta\lambda_b}{\delta(1-\delta(1-\lambda_b))} + \tfrac{\beta\lambda_b}{\delta(1-\delta(1-\lambda_b))^2}\ln(\delta(1-\lambda_b)) \\ &\geq \tfrac{1}{\delta^2} + \tfrac{\beta\lambda_b}{\delta(1-\delta(1-\lambda_b))} - \tfrac{\beta\lambda_b}{\delta(1-\delta(1-\lambda_b))} \\ &= \tfrac{1}{\delta^2} > 0, \end{aligned}$$

in which the inequality follows by applying the logarithm inequality $\ln x \leq x-1$. Consequently, $f(\delta)$ crosses zero at most once, and the crossing is from below. In fact, it crosses zero only once since $\lim_{\delta\to 0} f(\delta) < 0$ and $f(1) > 0$. As a result, there exists a threshold $\hat{\delta} < 1$ such that $dw_{T-1}/dt \geq 0$ if and only if $\delta \geq \hat{\delta}$. $\square$

Proof of Lemma 4. When $\beta = 0$, we can express (12) as $w_t = F\delta^{-(T-t)} - H\gamma^{T-t}$, where $F := \frac{1-\delta(1-\lambda_a)}{1-\delta\gamma}$ and $H := \frac{\alpha\lambda_a}{\gamma(1-\delta\gamma)}$. When $dw_t/dt = 0$,

$$\begin{aligned} \frac{d^2w_t}{dt^2}\Big|_{dw_t/dt=0} &= F\delta^{-(T-t)}(\ln\delta)^2 - H\gamma^{T-t}(\ln\gamma)^2\Big|_{dw_t/dt=0} = -H\gamma^{T-t}\ln\gamma[\ln(\delta\gamma)] \\ &= \gamma^{T-t}\tfrac{\alpha\lambda_a\ln\gamma}{\gamma}\left(\tfrac{-\ln(\delta\gamma)}{1-\delta\gamma}\right), \end{aligned}$$

which is nonpositive if and only if $\gamma \leq 1$, i.e., if and only if $\alpha \leq 1$. $\square$

Proof of Lemma 5. When $\delta = 1$, we express (12) as $w_t = F + G(1-\lambda_b)^{T-t} - H\gamma^{T-t}$, where $F := \frac{1-(1-\lambda_a)}{1-\gamma}(1+\beta)$, $G := \frac{\beta(\lambda_a-\lambda_b)}{(1-\lambda_b)(\gamma+\lambda_b-1)}$, and $H := \frac{\alpha\lambda_a}{\gamma(1-\gamma)}\left(1+\frac{\beta\lambda_b}{\gamma+\lambda_b-1}\right)$. When $dw_t/dt = 0$,

$$\begin{aligned} \frac{d^2w_t}{dt^2}\Big|_{dw_t/dt=0} &= G(1-\lambda_b)^{T-t}(\ln(1-\lambda_b))^2 - H\gamma^{T-t}(\ln\gamma)^2\Big|_{dw_t/dt=0} \\ &= G(1-\lambda_b)^{T-t}\ln(1-\lambda_b)[\ln(1-\lambda_b) - \ln\gamma] \\ &= (1-\lambda_b)^{T-t}\tfrac{\beta\ln(1-\lambda_b)}{(1-\lambda_b)}\left(\tfrac{\ln(1-\lambda_b)-\ln\gamma}{1-\lambda_b-\gamma}\right)(\lambda_b-\lambda_a), \end{aligned}$$

which is nonnegative if and only if $\lambda_b \geq \lambda_a$. Hence, w_t is pseudo-concave when $\lambda_a > \lambda_b$ and peudo-convex otherwise.

Because w_t is pseudo-concave or pseudo-convex, it attains its maximum or minimum in the period that is either the integer below or the integer above the solution to the first-order optimality condition: $H\gamma^{T-t^*}\ln\gamma = G(1-\lambda_b)^{T-t^*}\ln(1-\lambda_b)$.

Consider next dw_0/dt as $T\to\infty$. If $1-\lambda_b > \gamma$, the dominating term in dw_0/dt is $-\ln(1-\lambda_b)G(1-\lambda_b)^T$, which is positive given that $1-\lambda_b > \gamma \geq 1-\lambda_a$ and $\beta \leq 0$. Conversely, if $(1-\lambda_b) < \gamma$, the dominating term in dw_0/dt is $\ln\gamma H\gamma^T$, which, given that $\alpha \geq 0$, has the same sign as $-1-\beta\lambda_b/(\gamma+\lambda_b-1)$ and is thus positive if and only if $1-\lambda_b-\gamma > \beta\lambda_b$. Combining both cases leads to the desired condition. $\square$