How Fit-Revealing Interfaces Reshape Online Demand:

Product Values, Contextual Fit, and the Information Environment

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Abstract

Online retailers increasingly deploy technologies, such as augmented reality and generative virtual try-on, that enable consumers to simulate product experience within their own context prior to purchase. We introduce *fit-revealing interfaces* (FRI) to unify this class of tools under a common theoretical property: they resolve *contextual fit* uncertainty, a dimension of product fit that is idiosyncratic to each buyer's environment, unresolved by descriptive reviews, and only revealed through FRI experiences. We develop an analytical model that decompose the horizontal value (i.e. fit) into the non-contextual component, addressed by others' description, and the contextual component that results residual fit uncertainty even with informative product reviews. The derived propositions show that FRI engagement and its effect in product demand is not a monotonic solution but jointly determined by the information volume (i.e., informativeness level), the inferred product vertical value (i.e., quality), and the importance of contextual fit. FRI adoption increases demand only when vertical value falls below a threshold governed by contextual fit importance and informativeness level. Based on the theoretical model, we construct an empirical framework that can recover these key latent variables that sketch the informativeness level, the product's vertical position, and the categorical product type. Using item-week-level observations from five product categories on a leading retailing platform, we apply the framework and estimate these structural parameters for practical implications. Counterfactual simulation indicates FRI adoption increases market share by 3.94% on average, while the effect is shown heterogeneous along each of the three-layer product measures.

Keywords: fit-revealing interfaces, contextual fit uncertainty, online reviews, analytical modeling, structural estimation.

1 INTRODUCTION

When shopping online, consumers face substantial *ex ante* product uncertainty. This uncertainty arises along two distinct dimensions: *quality uncertainty*, concerning a product's objective performance shared across all consumers, and *fit uncertainty*, concerning the match between a product's attributes and a consumer's idiosyncratic preferences or context (Garvin, 1984; Chen et al., 2021). E-commerce platforms have long sought to bridge this information gap by providing tools that help consumers evaluate products before purchase. Online review systems, for instance, aggregate the post-purchase experiences of prior buyers, such as a product's durability, comfort, or aesthetic appeal, helping later consumers resolve much of both quality and fit uncertainty (Dimoka et al., 2012; Hong and Pavlou, 2014). However, such descriptive information from prior buyers cannot communicate some components of product fit. For example, how a cabinet looks in the corner of a particular room, how a foundation shade appears on one's own complexion, or how a shirt drapes on one's own body — these evaluation are determined jointly by the product's attributes and the consumer's own physical context, and thus requires consumers' own product experience to reveal the exact value. We term this component *contextual fit*. Contextual fit cannot be inferred from other buyers' reviews, no matter how numerous or detailed. It constitutes the *residual fit uncertainty* that remains after all shared product information has been fully absorbed.

A class of emerging technologies in e-commerce, which we term *fit-revealing interfaces* (FRI), directly targets this residual fit uncertainty. An FRI is an interface that enable consumers to simulate product experience within their own context prior to purchase. For example, augmented reality (AR) tools can project virtual objects into a consumer's physical space; AI-powered virtual try-on tools (VTO), including recent generative methods that synthesize photorealistic renderings on consumer-supplied images (Zhu et al., 2023), show apparel and cosmetics on the consumer's own photograph; size recommendation tools can predict fit from individual measurements (Gallino and Moreno, 2018). Despite differing in implementation, these interfaces are all capable to reveal contextual fit. [1]

These tools proliferate across major retailing platforms. For example, AR has already been

[1] The definition of FRI is rooted in the concept and strategy of fit revelation (Gu and Xie, 2013) but also draws a boundary: product videos and 3D presentation in a generic context, customer photographs in reviews present it in *other* consumers' contexts enrich consumer learning but none of these resolves contextual fit, and none is an FRI.

applied to online shopping platforms such as Sephora and IKEA, allowing consumers to virtually try on makeup or place furniture in their homes. However, deploying an FRI is not free for a retailer: activating the interface requires producing and maintaining digital assets such as 3-D product models, and the payoff of FRI is not clear. According to Tracxn, a research platform for investment decisions, there are 1,033 AR startups in the US as of 2022, and the AR software market is projected to reach a value of $137.14 billion by 2028; while according to the same survey, 52% of retailers reported not yet integrating AR into their retail strategy, indicating a lack of preparedness in this area. For these retailers, it is important to understand how FRI will affect the product sales and through what mechanisms (Tan et al., 2022). Particularly, the signals inferred from the descriptive information make the consequence of adopting FRI unclear, for the following two reasons.

First, given the matured paradigm of information provision in platforms, consumers have been used to using the existing descriptive information as important resources for their purchase decisions. Thus, an FRI embedded in a product page is an alternative option the consumer may or may not use. Established theories of information acquisition hold that search is motivated by the uncertainty that remains given what the consumer already knows (Murray, 1991). The intuition suggests that more uncertainty invites more usage, so FRI engagement should be highest wherever existing information are scarce. However, as we decompose product uncertainty to different components, among which FRI only resolves *contextual fit*, the search logic points somewhere sharper: what matters is not how much uncertainty remains, but whether the residual component, contextual fit uncertainty, is *decision-pivotal*. For a consumer has been convinced not to purchase due to the absence of quality or non-contextual fit information, FRI would not change her decision by resolving contextual fit; only a consumer whose purchase decision still hinges on the unrevealed contextual fit component has reason to engage.

Second, even if a consumer engage FRI and change her decision, it is not clear whether the change is positive or negative, because revealing fit could operate on two opposing ways. On the one hand, the FRI recruits consumers who would not have purchased under the residual uncertainty but discover a favorable contextual fit; on the other, it repels buyers who would have purchased on expected contextual fit but discover an unfavorable one. The purchase decisions, with or without FRI, are typically conditioned on the vertical value and the horizontal fit value decomposition.

Hence, the net effect on product demand depends on the quality and non-contextual fit value consumers infer from existing ratings, and on how important contextual fit is to the product's utility in the first place.

To understand how FRI reshape online retailing, we investigate it as an alternative information source that interplays with existing ones, and focus on how FRI and online reviews affect product sales synergistically. Formally, we answer two theoretical questions as follows.

RQ1: *How does the information consumers obtain from the existing review system, the product's vertical value and their own non-contextual fit, determine whether they engage the FRI before purchase?*

RQ2: *How does FRI integration change product demand, and how does this change depend on the review informativeness, the contextual fit importance, and the product's perceived value?*

Answering these two questions raises a third practical one. Any theoretical solution must be stated in terms of quantities that are latent: the vertical value consumers infer from ratings, the informativeness of the review stock, and the share of utility that rides on contextual fit in different product categories. While these latent variables represent and sketch an abstract product, none of them is directly observable. Product ratings correlate with perceived value, but a rating average is not the value itself (Sun, 2012a); and no archival field records how much fit uncertainty a category leaves unresolved from rich online reviews. Thus, we propose to build a theory-grounded measurement framework to understand the three-layers of product positions and information environment. Once these primitives can be recovered from observable data, the theory can be deployed to make outcome predictions and to offer actionable guidance. Formally, we ask:

RQ3: *How can the latent quantities that govern the interplay—review informativeness, inferred vertical value, and contextual fit importance—be measured from observable rating and sales data?*

This paper aims to analytically and empirically investigate how the introduction of FRI to an online retailing platform interplays with the existing information environment. To answer RQ1 and RQ2, we develop an analytical model that extends the literature on product ratings and consumer search (Chen and Xie, 2008; Sun, 2012b; Chen et al., 2021). The model separates horizontal product attributes into contextual and non-contextual components, and characterizes how the value of FRI engagement depends on the information already available to the consumer. A central result is that FRI engagement is non-monotonic in the product's vertical value inferred from existing ratings: consumers with very high or very low inferred quality have little incentive to use FRI, because their purchase decision is unlikely to change regardless of what contextual fit reveals. For the same reason, FRI integration smooths product demand function of the vertical values inferred from rating characteristics. It increases demand for low-vertical value products, but decrease demand for high-vertical value products. The model further shows that the relative importance of contextual fit, which varies across product categories, and the lack of informativeness, which varies on existing information volume, amplify FRI engagement and demand change.

To answer RQ3, we show that the model itself supplies the measurement strategy. Its closed-form demand and click-through expressions link latent primitives to observable sales and engagement data, so estimating the structure recovers a three-layer measurement of the information environment and perceived product positions: the informativeness of each product's reviews (α), the vertical value inferred by consumers (z), and the category's contextual fit importance (ω^C) in addition to a categorical value-to-fit measure defined by (Chen et al., 2021). Using item-week data spanning five product categories from a leading retailing platform that launched an AR "place and view" interface, we estimate the structural parameters using maximum likelihood. The estimates align with theoretical expectations: contextual fit importance is highest for cabinets, whose value depends heavily on spatial integration, and lowest for air conditioners, whose value is dominated by functional performance conveyed in reviews. Model-implied counterfacts then indicate that FRI adoption increases demand on average, by 3.94% relative lift, with the largest gains concentrated among products in high-ω^C categories. The cold-start cases with low informativeness benefits the most from the FRI adoption when the estimated expectations of net product value are at a moderate level, right below the thresholds of "blind purchase". The most informative cases benefit significantly only when the inferred product value are low, so FRI converts consumers who would otherwise not buy through contextual fit revelation.

We highlight both theoretical contributions and practical implications in this paper. The analytical model we built contributes to the stream of literature on information provision and online retailing. In particular, our model provides a perspective of information acquisition and insights into the intertwined relationship between the effect of the adoption of a new information tool, existing information, and product categories. The endogenized engagement of FRI explains the low click-rate observed in practice – not as a failure of the technology, but as a rational response by consumers who are already sufficiently informed. The findings from theoretical modeling offer actionable guidance for practice: retailers should expect the greatest payoffs from FRI adoption when products information is cold-start, contextual fit is important, when review-inferred product value is low or when cold-start product has moderate expected value. Our empirical model allows the inference of these latent product information characteristics from observable data, offering theory-driven and insightful estimation.

2 LITERATURE REVIEW

2.1 Product Fit Uncertainty and Information Provision in Online Markets

Online markets expose consumers to substantially greater ex-ante uncertainty than offline settings, where physical inspection is available prior to purchase (Dimoka et al., 2012). A foundational distinction in this literature separates uncertainty with respect to *vertical* values, over quality attributes perceived homogeneously across consumers, and *horizontal* values, over idiosyncratic fit attributes whose value depends on the match between the product and the individual consumer's tastes and use context (Garvin, 1984; Hotelling, 1929; Gu and Chen, 2020; Chen et al., 2021). While vertical quality can often be signaled through reputation or certification, horizontal fit is inherently personal and resists conventional disclosure. The consequences of unresolved fit uncertainty for purchase decisions, product returns, and post-purchase satisfaction are well documented in both analytical and empirical IS research (Wang et al., 2021a; Hong and Pavlou, 2014; Mudambi and Schuff, 2010a).

Prior work identifies two broad strategies for mitigating fit uncertainty. The first is seller-provided disclosure, including versioning of information goods (Lahiri and Dey, 2018), structured fit information that combines valence and reference cues (Wang et al., 2021b), and fit information provision within distribution channels (Sun and Tyagi, 2020). Such disclosures are most effective for attributes that can be objectively described and uniformly interpreted. The second is peer-generated reviews that aggregate the post-purchase experiences of prior buyers and help later consumers resolve both quality and fit uncertainty (Li and Hitt, 2008; Forman et al., 2008; Ghose and Ipeirotis, 2011; Kwark et al., 2014). The informational value of reviews is greater for experience goods whose fit is difficult to evaluate ex ante (Mudambi and Schuff, 2010b; Forman et al., 2008), and their influence on demand operates through not only the mean valence but also the variance (Sun, 2012a). A parallel literature in information economics studies the market consequences of information that reveals idiosyncratic fit value. Johnson and Myatt (2006) show that such information rotates the demand curve, raising demand for products with low mass appeal while reducing demand for products that would otherwise be purchased broadly. Related analyses examine firms' incentives to provide fit relevant information and how much to provide (Lewis and Sappington, 1994; Anderson and Renault, 2006).

This paper departs from the previous literature by focusing on the residual part of product fit unresolved in conveyed information. Both seller disclosures and peer reviews share a fundamental limitation: they convey information about product attributes as experienced or described by *others*, but cannot resolve the uncertainty a consumer faces about how a product will perform in her own specific use context. Thus, we discuss the potential and necessity of additional information for idiosyncratic fit revelation based on product characteristics and information environment.

2.2 Online Rating Systems

The online reviews system has been a well-established research stream in the field of E-commerce and digital marketing (Dellarocas, 2003). A large body of work links rating characteristics, including volume, valence, and variance, to product demand (Zablocki et al., 2019). The empirical evidence is notably mixed: Chevalier and Mayzlin (2006) find that valence drives book sales; Liu (2006) finds that volume, not valence, predicts box office revenue, Amblee and Bui (2011) find that volume rather than valence is associated with sales rank for digital books; Xie et al. (2014) find both volume and valence matter for hotel reservation performance. The emerging consensus is that the effects of rating characteristics are contingent on product and market characteristics: they are stronger for niche products (Zhu and Zhang, 2010), vary across product categories (Cui et al., 2012), and depend on the design of the rating system itself (Chen et al., 2018). Our framework speaks directly to this contingency: in our model, the rating characteristics synergistically affect product demand and moderates the effect of residual fit revelation, depends on the product's categorical nature.

A second stream examines the temporal dynamics of ratings and what they reveal about consumer learning. Early reviews are subject to self-selection, so rating trajectories carry information beyond contemporaneous averages (Li and Hitt, 2008). Subsequent work characterizes the sequential dynamics of opinion (Godes and Silva, 2012) and the incidence and evolution of posted ratings (Moe and Schweidel, 2012), and Zhao et al. (2013) structurally model consumers' learning from review content in purchase decisions. Collectively, these studies establish that the informativeness of a review stock is not static: it accumulates with volume and depends on how well reviews communicate the attributes consumers care about. This insight motivates us to consider varying information environment and to model review informativeness.

A third and most recent development uses rating data as a *measurement instrument* for latent product characteristics. Since Nelson (1970, 1981), scholars have sought to classify products by the mode through which consumers learn their utility, but empirical implementation long relied on coarse dichotomies or expert judgment (Mudambi and Schuff, 2010b). Chen et al. (2021) propose a innovative approach to derive theory-grounded, continuous measures of product type from archival rating statistics, recovering the degree of horizontal differentiation, the degree of experience versus search, and quality uncertainty from the means, variances, and temporal evolution of product ratings. This paper extends this literature, demonstrating a three layer measure framework for product characteristics and informativeness level.

2.3 Fit-Revealing Interfaces and Their Market Consequences

Research on FRI technologies has established several consistent findings. First, FRI adoption positively affects consumer decision-making by increasing contextual processing fluency — consumers' ability to mentally simulate how a product performs in their own context — and by reducing perceived purchase risk (Heller et al., 2019; Kowalczuk et al., 2021). Second, these effects translate into measurable market outcomes: Tan et al. (2022) provide field evidence that AR adoption increases product sales, with the effect strongest for less popular products, narrower-appeal items, and higher-priced goods — consistent with the view that FRI is most valuable when pre-purchase uncertainty is high. Pfaff and Spann (2025) corroborate this in a home interior retailing context, showing that spatial placement tools reduce fit uncertainty and increase sales with systematic variation across product categories. Third, the mechanism through which FRI affects outcomes is primarily informational rather than hedonic: Kowalczuk et al. (2021) show that the informational channel drives purchase intention for utilitarian products, while the hedonic channel dominates for experiential goods, suggesting that FRI's value depends on the nature of the uncertainty consumers face.

A parallel stream of research identifies important boundary conditions under which FRI effects attenuate or reverse. For example, AR's perceived usefulness is influenced by user characteristics, such as their approach to information processing (Hilken et al., 2017) and their need for self-referencing (Yim and Park, 2019). Additionally, AR's effectiveness is linked to product characteristics, including material properties (Brengman et al., 2019) and the perceived completeness of the product information displayed (Hoffmann et al., 2022). Therefore, this work aims to investigate the effects when AR interplays with other information such as online ratings.

3 THE THEORETICAL MODEL

3.1 Model Set-Up

We build our model by extending the product market framework for goods with both horizontal and vertical attributes (Chen and Xie, 2008; Sun, 2012a; Chen et al., 2021). Our model contributes to this literature in two respects. First, we refine the representation of horizontal attributes to distinguish between those whose fit can be inferred from conventional information sources, such as product descriptions and peer reviews, and those whose fit can only be assessed through direct contextual experience, which we term *contextual fit*. This distinction is theoretically motivated by the nature of fit-revealing interfaces (FRI): unlike product descriptions that convey objective specifications or reviews that aggregate prior purchasers' non-contextual experiences, FRI technologies such as augmented reality enable consumers to evaluate how a product integrates into their own physical environment, resolving a category of uncertainty that conventional information cannot address (Hilken et al., 2017; Tan et al., 2022). Second, we treat consumers' decision to engage with the FRI as an endogenous choice embedded within a sequential information search process (Branco et al., 2012), rather than assuming full or universal adoption. Together, these features allow us to derive predictions about both FRI usage and its downstream effects on demand under different information environments. For better readability, we provide a table of nomenclature that summarizes the key notations used in the model (see Table 1).

Consider a market of a single product characterized by both vertical and horizontal attributes. The vertical attribute captures objective product quality (q), of which the value is perceived homo-

Table 1: Key Notations in the Model

Notation	Definition
v	The common utility shared by all consumers (e.g., the product quality substract price)
t	The cost of per unit misfit distance
x_i^N	The non-contextual fit that consumers can discover through online reviews.
x_i^C	The contextual fit that consumers can discover only through AR.
ω ω^C ω^N	The relative importance of contextual fit in product utility (intrinsic to product category). The importance weight of contextual fit in product horizontal utility. The importance weight of non-contextual fit in product horizontal utility. ($\omega^N + \omega^C = 1$)
L	Click-through rate to the AR page.
D	Demand of the product (i.e., sales quantity).

geneously across consumers. The horizontal attributes, by contrast, are idiosyncratic: they capture the extent to which the product fits a given consumer's tastes and use context. We parameterize horizontal misfit as the distance between the product's attribute profile and the consumer's ideal point, weighted by a per-unit misfit cost $t > 0$.

We decompose the horizontal dimension into two orthogonal components: *non-contextual (mis)fit* distance x_i^N, which reflects aspects of product-consumer alignment that are observable through conventional information sources such as reviews and descriptions (e.g., aesthetic style, material feel, general sizing), and *contextual (mis)fit* distance x_i^C, which reflects alignment that depends on the consumer's specific physical environment and can only be assessed through direct experiential evaluation or through FRI (e.g., how a piece of furniture occupies a particular room, or how a cosmetic product appears on one's own face). The respective importance weights ω^N and ω^C are strictly positive, intrinsic to the product category.

Accordingly, the utility of a product with quality q and price p for a consumer i with a taste of (x_i^N, x_i^C) is

$$U_i = q - p - t \times (\omega^C x_i^C + \omega^N x_i^N) \tag{1}$$

We assume $\omega^C + \omega^N = 1$ to ensure the utility has a lower bound. If ω^C approaches zero, contextual fit plays a negligible role in consumer valuation, and the FRI conveys little additional information. Whereas ω^C is large for some certain product categories, contextual fit becomes an important source of purchase uncertainty, sharpening the value of FRI engagement. The higher the values of x_i^N or x_i^C are, the more misfit consumer i perceives on the product, and per unit increase in the total misfit (i.e., $\omega^C x_i^C + \omega^N x_i^N$) lowers the utility level by t. For a consumer i with misfit $x_i^N = 0$

and $x_i^C = 0$, the product perfectly fits her tastes or needs, and her utility if purchasing the product will be $q - p$, denoted as v, which capture a net vertical value to all consumers. Note that within the same product category, v is the common utility for every consumer, and it indicates the highest value a consumer can obtain from purchasing the product.

To facilitate analytical tractability and sharpen economic intuition, we simplify the notation by normalizing the vertical value. Let $v = q - p$ denote the net surplus at zero misfit, which is the maximum utility any consumer can obtain fraom the product.[2] Then the ratio $\frac{v}{t}$ denote the normalized net vertical value, which scales v by the misfit cost. The utility function simplifies to:

$$U_i = \frac{v}{t} - \omega^C x_i^C - \omega^N x_i^N, \qquad \omega^C + \omega^N = 1 \tag{2}$$

3.2 Consumer Decisions on Technology Usage and Product Purchase

Following the Hotelling (1929)spatial competition framework as adapted to product differentiation (Chen et al., 2021), we model consumers as uniformly distributed over the unit square $[0, 1]^2$ in the taste space (x_i^N, x_i^C). A consumer located at (x_i^N, x_i^C) experiences a total misfit of $\omega^N x_i^N + \omega^C x_i^C$; consumers with lower values of both components are better matched to the product and obtain higher utility from purchase. For given values of $\frac{v}{t}$ and ω^C, the boundary $\frac{v}{t} - (\omega^N x_i^N + \omega^C x_i^C) = 0$ partitions the consumer space into a positive-utility region (shaded) and a negative-utility region. The slope and the intersect of the zero-utility boundary vary systematically with $\frac{v}{t}$ and ω^C, generating the demand heterogeneity that drives our subsequent analysis. We assume that $0 < \frac{v}{t} < 1$ to ensure that positive-utility and negative-utility consumers both exist in this market.[3]

Under ex-ante uncertainty, consumers cannot directly observe their idiosyncratic misfit values or the product's vertical attribute prior to purchase. Instead, they form conditional expectations over utility based on whatever information is available and consulted, and then decide whether to make a purchase. Without enough information, consumer i only knows the distributions $\tilde{x_i}^N, \tilde{x_i}^C, \tilde{v}$ from descriptive information provided by the seller, while the exact values of common utility v and misfit x_i^N and x_i^C are uncertain. The online review systems aggregate post-purchase experiences of prior buyers and thus convey more about the vertical value and the potential misfit. The FRI

[2] We regard p and q as exogenous variables when considering the consumer's problem

[3] With this condition, the utility of the nearest misfit distance is always positive and the utility of the furthest misfit is always negative. Chen et al. (2021) illustrate the intuition of $\frac{v}{t}$.

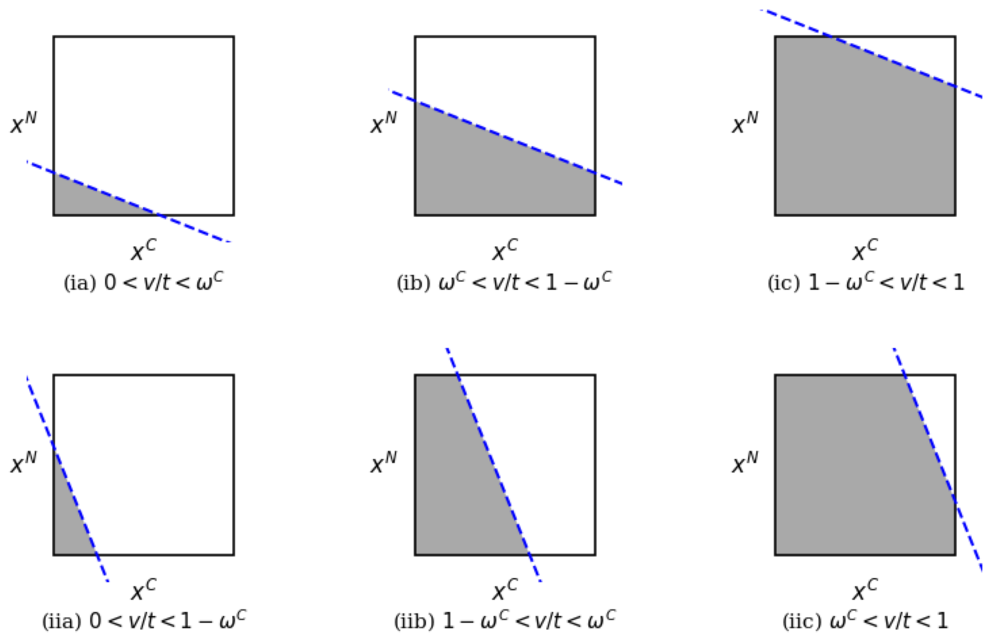

Figure 1: A Market with One-Unit Mass of Consumers Uniformly Distributed

resolves contextual fit x_i^C by enabling consumers to simulate the product within their own context, eliminating the residual uncertainty that neither descriptions nor reviews can address.

We first adopt the standard assumption that each information source, when consulted, perfectly reveals its associated attribute (Chen et al., 2021; Sun and Tyagi, 2020): consumers who engage with the online rating system learn the exact values of v and x_i^N, and consumers who engage the FRI learn the exact value of x_i^C. We will discuss the transparency level of online reviews to understand the effect of online review volumes.

3.2.1 Purchase Decision

Consumers purchase the product if and only if their expected utility, conditional on the information they have acquired, meets or exceeds their reservation utility. For notational simplicity, we normalize the reservation utility to zero. Because consumers may enter the purchase decision under qualitatively different information states — fully informed by online reviews and FRI, partially informed, or entirely uninformed in the cold-start case — the purchase threshold takes different forms depending on the information environment. Decision Rule 1 formalizes these cases.

Decision Rule 1 (purchasing): Consumer i's purchase decision depends on the information available at the time of choice:

- No information: purchase if and only if

$$E[U_i] = \frac{\overline{v}}{t} - \frac{1}{2} \geq 0 \tag{3}$$

- Reviews and descriptions only (no FRI): purchase if and only if

$$E[U|x_i^N, v] = \frac{v}{t} - (\frac{1}{2}\omega^C + (1-\omega^C)x_i^N) \geq 0 \tag{4}$$

- FRI only (no prior reviews): purchase if and only if

$$E[U_i] = \frac{\overline{v}}{t} - (\omega^C x_i^C + \frac{1}{2}(1-\omega^C)) \geq 0 \tag{5}$$

- Fully Informed (reviews, descriptions, and FRI): purchase if and only if

$$E[U|x_i^C, x_i^N, v] = \frac{v}{t} - (\omega^C x_i^C + (1-\omega^C)x_i^N) \geq 0 \tag{6}$$

3.2.2 FRI Engagement Decision

The decision to engage the FRI is voluntary and endogenous. Consumers weigh the expected benefit of resolving contextual fit uncertainty against the cognitive and time costs of using the interface. Following the sequential search framework of (Branco et al., 2012) and the stopping rule formalization of (Greminger, 2022), we model FRI engagement as a binary decision taken prior to the purchase choice: a consumer engages the FRI if and only if she expects the additional information to improve her expected utility outcome. For tractability, we normalize the search cost to zero, so that any positive expected gain from engagement is sufficient to motivate usage. This assumption is consistent with the low marginal cost of FRI interactions in contemporary e-commerce settings, where the interface is embedded directly in the product page and requires no additional navigation.

The value of FRI engagement derives exclusively from its potential to alter the consumer's purchase decision. A consumer who would purchase regardless of the contextual fit revelation — because her non-contextual misfit is sufficiently low relative to the product net value — gains nothing from engaging the FRI. Symmetrically, a consumer who would not purchase even under the most favorable contextual fit outcome — because her non-contextual misfit is already too high relative to the product net value — also gains nothing. Only consumers who occupy an intermediate range of non-contextual misfit, where the purchase decision remains contingent on the unknown x_i^C, have a positive expected gain from engagement. Formally, the gain from FRI engagement for consumer i, conditional on existing information $\mathcal{I}$, is:

$$\Delta EU(x_i^C) = E[U_i|\mathcal{I}, x_i^C]\mathbf{1}_{E\left[U|\mathcal{I}, x_i^C\right]\geq 0} - E[U_i|\mathcal{I}]\mathbf{1}_{E[U|\mathcal{I}]\geq 0} \tag{7}$$

Since x_i^C is unknown prior to FRI engagement, the consumer decides based on the expectation of this gain over the distribution of x_i^C:

Decision Rule 2 (FRI Engagement): *The consumers engage FRI if and only if they expect to have a positive gain in expected utility (*$E_{x_i^C}[\Delta EU] > 0$*).*

- Informed product reviews and descriptions: consumer i engages FRI if

$$E_{x_i^C}\left[E\left[U_i|x_i^C, x_i^N, \frac{v}{t}\right]\mathbf{1}_{E\left[U|x_i^C, x_i^N, \frac{v}{t}\right]\geq 0}\right] - E_{x_i^C}\left[E[U|x_i^N, \frac{v}{t}]\mathbf{1}_{E[U|x_i^N, \frac{v}{t}]\geq 0}\right] \geq 0$$

- No prior reviews: consumer i engages FRI if

$$E_{x_i^C}\left[E\left[U|x_i^C\right]\mathbf{1}_{E\left[U|x_i^C\right]\geq 0}\right] - E_{x_i^C}\left[E[U]\mathbf{1}_{E[U]\geq 0}\right] \geq 0$$

Note that if the consumers expect that they won't have a decision flip after using the AR interface, which means $\mathbf{1}_{E[U|\cdot]\geq 0} = \mathbf{1}_{E\left[U|\cdot, x_i^C\right]\geq 0}$ for any x^C, then $E_{x^C}[\Delta EU] = 0$. The following two sections characterize consumer decisions and derive FRI click-through rate and product demands under these two polar information regimes, before Section 1.5 develops a unified framework that nests both as special cases.

3.3 The Case of Fully Informative Online Reviews

3.3.1 Interface Click-Through Rate

With the online review system fully informative, a consumer i located at (x_i^N, x_i^C) know the exact value of x_i^N and v and make decisions based on the inferred information. Based on Decision Rule 2, we derived the condition of $E_{x_i^C}[\Delta EU] > 0$ (i.e., the consumer has an incentive to use AR) as following:

Lemma 1. *With fully informative online reviews, consumer i has an incentive to engage the FRI if and only if* $x_i^N \in [0,1] \cap (\frac{v}{t\omega^N} - \frac{\omega^C}{\omega^N}, \frac{v}{t\omega^N})$.

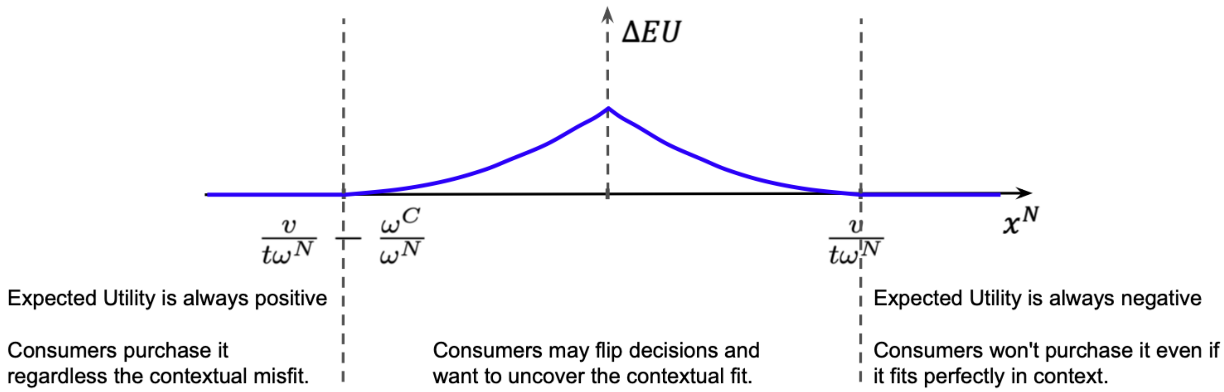

Figure 2: Expected Utility Gain

Figure 2 illustrates the intuition of Proposition 1. On one hand, when consumers perceive high non-contextual misfit and relatively low value ($\omega^N x_i^N \geq \frac{v}{t}$), they expect no benefit from using AR because they don't purchase it even if the revealed contextual attributes perfectly fit ($x_i^C = 0$). On the other hand, when the perceived non-contextual misfit is low and the relative value is high enough ($\omega^N x_i^N \leq \frac{v}{t} - \omega^C$), they will make a purchase even if the revealed contextual misfit is at the maximum ($x_i^C = 1$). Thus, only consumers who infer that $\frac{v}{t\omega^N} - \frac{\omega^C}{\omega^N} < x_i^N < \frac{v}{t\omega^N}$ may change their decision after AR usage and expect to benefit from that.

Since consumers are uniformly distributed over $x_i^N \in [0,1]$, the aggregate FRI click-through rate $L(\frac{v}{t}, \omega^C)$ equals the length of the interval $\{x_i^N | x_i^N \in [0,1] \cap (\frac{v}{t\omega^N} - \frac{\omega^C}{\omega^N}, \frac{v}{t\omega^N})\}$. This length depends jointly on $\frac{v}{t}$ and ω^C in an entangled, non-monotonic fashion, as formally characterized in Proposition 1.

Proposition 1 (Click-Through Rate). The FRI click-through rate under fully informative reviews is:

$$L(\frac{v}{t}, \omega^C) = \begin{cases} \frac{1}{1-\omega^C}\frac{v}{t} & \text{if } \frac{v}{t} \in (0, min\{\omega^C, 1-\omega^C\}]; \\ \frac{1}{1-\omega^C} min\{\omega^C, 1-\omega^C\} & \text{if } \frac{v}{t} \in (min\{\omega^C, 1-\omega^C\}, max\{\omega^C, 1-\omega^C\}]; \\ \frac{1}{1-\omega^C}(1-\frac{v}{t}) & \text{if } \frac{v}{t} \in (max\{\omega^C, 1-\omega^C\}, 1); \end{cases} \tag{8}$$

3.3.2 Product Demand Estimation

We derive aggregate demand by integrating the purchase indicator $\mathbf{1}_{E[U]>0}$, where $E[U]$ depends on Decision Rule 1, over the uniformly distributed x_i^N and x_i^C, separately for the cases with and without FRI adoption. We denote the product demand after AR adoption adoption as D_1^{info}, and the product demand without AR adoption as D_0^{info}. Lemma 2 characterizes the resulting demand functions.

Lemma 2 (Demand under Fully Informative Reviews). When online reviews are fully informative:

- Without FRI (i.e., the benchmark),

$$D_0^{info} = \begin{cases} 0 & \text{if } \frac{v}{t} \in (0, \frac{\omega^C}{2}]; \\ \frac{1}{1-\omega^C}(\frac{v}{t} - \frac{\omega^C}{2}) & \text{if } \frac{v}{t} \in (\frac{\omega^C}{2}, 1 - \frac{\omega^C}{2}]; \\ 1 & \text{if } \frac{v}{t} \in (1 - \frac{\omega^C}{2}, 1) \end{cases} \tag{9}$$

- With FRI,

$$D_1^{info} = \begin{cases} \frac{1}{2\omega^C(1-\omega^C)}(\frac{v}{t})^2 & \text{if } \frac{v}{t} \in (0, min\{\omega^C, 1-\omega^C\}]; \\ \frac{2\frac{v}{t} - min\{\omega^C, 1-\omega^C\}}{2max\{\omega^C, 1-\omega^C\}} & \text{if } \frac{v}{t} \in (min\{\omega^C, 1-\omega^C\}, max\{\omega^C, 1-\omega^C\}]; \\ 1 - \frac{(1-\frac{v}{t})^2}{2\omega^C(1-\omega^C)} & \text{if } \frac{v}{t} \in (max\{\omega^C, 1-\omega^C\}, 1] \end{cases} \tag{10}$$

The demand change attributable to FRI adoption, $\Delta D^{info} = D_1^{info} - D_0^{info}$, is the object of central theoretical interest, as it determines whether and when a seller benefits from deploying the technology. Proposition 2 characterizes the sign of this demand change as a function of the product's vertical value and the structural importance of contextual fit.

Proposition 2 (Demand Effect of FRI Adoption). *Under fully informative reviews, the sign of the demand change following FRI adoption satisfies:*

$$\Delta D^{info} > 0 \iff \frac{v}{t} < min\{\omega^C, \frac{1}{2}\} \tag{11}$$

It means that if the misfit revealed by the new technology is higher weighted than the misfit revealed by the product reviews ($\omega^C > \omega^N$), than the net vertical value v should be lower than the expectation of misfit cost ($\frac{t}{2}$) to increase the demand; otherwise ($\omega^C < \omega^N$), the net value $\hat{v}$ should be lower than the largest potential misfit cost rooted in the contextual fit ($t\omega^C$).

Proposition 2 establishes that FRI adoption increases demand if and only if the product's net vertical value v falls below both $t\omega^C$ — the maximum potential misfit cost attributable to contextual fit — and $\frac{t}{2}$ — the unconditional expected total misfit cost. The binding threshold is whichever is smaller. When ω^C is small ($\omega^C < \frac{1}{2}$), contextual fit constitutes the minority of total misfit, and $t\omega^C$ is the tighter constraint: demand-enhancing FRI adoption requires that the product's net value is smaller than even the worst-case contextual misfit cost, placing it in a regime where contextual fit is genuinely decisive for the marginal consumer. When ω^C is large enough ($\omega^C \geq \frac{1}{2}$), the expected misfit threshold $\frac{t}{2}$ binds instead, and FRI adoption increases demand for any product whose net value falls below the average misfit cost consumers expect to bear. In both cases, the underlying mechanism is the one established in Section 1.2.2: FRI adoption shifts the composition of purchasers toward those with favorable contextual fit, and this recomposition raises aggregate demand precisely when the product's vertical appeal alone is insufficient to sustain broad purchase without the additional resolution of contextual uncertainty.

3.4 The Cold-Start Case

We now consider the polar opposite case, in which no online reviews are available and consumers cannot infer any information prior to the FRI engagement decision. This cold-start setting characterizes products or items with insufficient review history. With no online review information, consumers evaluate the product against their unconditional expectation of v, denoted $\bar{v}$. Lemma 3 establishes that in this environment, FRI engagement depends on the prior of normalized vertical value, $\frac{\bar{v}}{t}$.

Lemma 3: *When no information is available from the online rating system,* $E_{x_i^C}[\Delta EU] > 0$ *almost everywhere iff* $\frac{\bar{v}}{t} \in (\frac{1-\omega^C}{2}, \frac{1+\omega^C}{2})$*, and equals 0 elsewhere.*

Lemma 4 characterizes aggregate demand with and without FRI adoption under cold start.

Lemma 4: *When no information is available from the online rating system,* $E_{x_i^C}[\Delta EU] > 0$ *almost everywhere, and consumers choose to engage the FRI.*

- Without FRI:

$$D_0^{cold} = \begin{cases} 0 & \text{if } 0 < \frac{\bar{v}}{t} \leq \frac{1}{2} \\ 1 & \text{if } \frac{1}{2} < \frac{\bar{v}}{t} < 1 \end{cases} \tag{12}$$

- With FRI:

$$D_1^{cold} = \begin{cases} 0 & \text{if } 0 < \frac{\bar{v}}{t} \leq \frac{1-\omega^C}{2} \\ \frac{2\frac{\bar{v}}{t}-(1-\omega^C)}{2\omega^C} & \text{if } \frac{1-\omega^C}{2} < \frac{\bar{v}}{t} \leq \frac{1+\omega^C}{2} \\ 1 & \text{if } \frac{1+\omega^C}{2} < \frac{\bar{v}}{t} \leq 1 \end{cases} \tag{13}$$

Then the demand change $\Delta D^{cold} = D_1^{cold} - D_0^{cold}$ is characterized by

$$\Delta D^{cold} = \begin{cases} 0 & \text{if } 0 < \frac{\bar{v}}{t} \leq \frac{1-\omega^C}{2} \\ \frac{2\frac{\bar{v}}{t}-(1-\omega^C)}{2\omega^C} > 0 & \text{if } \frac{1-\omega^C}{2} < \frac{\bar{v}}{t} \leq \frac{1}{2} \\ \frac{2\frac{\bar{v}}{t}-(1-\omega^C)}{2\omega^C} - 1 < 0 & \text{if } \frac{1}{2} < \frac{\bar{v}}{t} \leq \frac{1+\omega^C}{2} \\ 0 & \text{if } \frac{1+\omega^C}{2} < \frac{\bar{v}}{t} < 1 \end{cases} \tag{14}$$

We assume that $\frac{\omega^N}{2} < \frac{\bar{v}}{t} < 1 - \frac{\omega^N}{2}$. This condition ensures that consumers have a moderate expectation on the vertical value of the product that when using AR, some but nor all consumers will change their purchase decisions. Without FRI, a cold-start consumer purchases only if $\frac{\bar{v}}{t} > \frac{1}{2}$, which means the expected vertical value exceeds the expected total misfit cost. FRI adoption expands the set of purchasing consumers by resolving contextual uncertainty for those would not purchase on the basis of prior expectations alone but will purchase once favorable contextual fit is revealed. Thus, we have Proposition 3.

Proposition 3 (Demand Effect of FRI Adoption). *When no information is available from the online rating system, the sign of the demand change following FRI adoption satisfies:*

$$\Delta D^{cold} > 0 \iff \frac{1-\omega^C}{2} < \frac{\bar{v}}{t} < \frac{1}{2} \tag{15}$$

3.5 The Informativeness Level

The two cases analyzed in previous sections represent polar extremes of a continuum defined by how much product information consumers can extract from the online review system. In practice, the informativeness of reviews depends on their volume and communication quality: a product with abundant, detailed reviews approaches the fully informative case, while a product with sparse reviews approximates the cold-start case.

We parameterize this continuum through a informativeness level $\alpha \in [0, 1]$, defined as the probability that the available review system is sufficiently informative for a consumer to learn the exact values of v and x_i^N. With probability $1 - \alpha$, the consumer remains uninformed prior to the FRI engagement decision. The fully informative and cold-start cases thus correspond to $\alpha = 1$ and $\alpha = 0$, respectively. The general demand and click-through expressions are convex combinations of the two polar cases, weighted by α and $(1-\alpha)$ and shifted toward the informative case as review volume accumulates over time.

Under this informativeness-dependent framework, the aggregate FRI click-through rate, and the demand with and without FRI adoption, are given by:

$$L = \alpha \times L^{info} + (1 - \alpha) \times L^{cold} \tag{16}$$

$$D_0 = \alpha D_0^{info} + (1 - \alpha) D_0^{cold} \tag{17}$$

$$D_1 = \alpha D_1^{info} + (1 - \alpha) D_1^{cold} \tag{18}$$

Take derivatives, we found that $\frac{\partial L}{\partial \alpha} = L^{info} - 1 < 0$ almost everywhere. We also found that $\frac{\partial D_0}{\partial \alpha} = D_0^{info} - D_0^{cold}$ and $\frac{\partial D_1}{\partial \alpha} = D_1^{info} - D_1^{cold}$. Since all demand functions are non-decreasing on the normalized vertical values, it means that as the review numbers accumulate, if and only if the prior belief about vertical value is low but the actual vertical value is relatively high, demand increases by the transparency level α.

$\frac{\partial D_1}{\partial \alpha} - \frac{\partial D_0}{\partial \alpha} = (D_1^{info} - D_1^{cold}) - (D_0^{info} - D_0^{cold}) = \Delta D^{info} - \Delta D^{cold}$

Proposition 4 (Effect of Review Transparency). (1) The FRI click-through rate L is decreasing in α ($\alpha \uparrow$ leads to $L \downarrow$): more informative reviews reduce consumer motivation to engage the FRI. (2) As the number of reviews accumulate, the product demand change for both FRI-adopted (D_1) and non-adopted (D_0) cases depends on the trend of vertical value inferred from existing information.

Given the nature of complex and dynamic information environment, we are motivated to estimate the information transparency (i.e., α) and product features (i.e., ω^C, $\frac{v}{t}$) from data and then to simulate D_1 and D_0 under different regimes.

4 EMPIRICAL MODEL

4.1 Estimate Latent Parameters from Observations

The analytical model generates closed-form expressions for FRI click-through rates and product demand as functions of three structural parameters: the importance of contextual fit ω^C, which varies by product category k, the normalized net vertical value $z \equiv \frac{v}{t}$, and the review informativeness level α. None of these quantities is directly observable, but each can be recovered from observable product and market characteristics through the estimation strategy developed below.

Estimating the Normalized Vertical Value. For product j in category k at time t, z_{kjt} denotes the normalized net vertical value. We model z_{kjt} as a logistic function of observable product page characteristics:

$$z_{kjt} = \frac{1}{1 + e^{-(\beta_0 + \boldsymbol{\beta} X_{kjt})}} \tag{19}$$

where X_{kjt} denotes the product characteristics displayed on the product page, including the logged previous product demand, the mean-over-standard-deviation ratio of rating scores, and the category-normalized product price. This specification maps product-level observables into the unit interval $(0, 1)$, consistent with the theoretical constraint $\frac{v}{t} \in [0, 1]$, and ensures that the estimated vertical value responds sensibly to review quality signals and market performance. In the cold-start case, consumers form a prior expectation of the product's vertical value, denoted as $\bar{z}_{jkt}$, before engaging in any information. We assume consumers base this prior on item price information combined with an unbiased expectation of the unobserved online review attributes. To construct $\bar{z}_{jkt}$, we evaluate Equation 19 using the focal product's observed price, but explicitly replace the unobserved, post-search attributes (the rating score signals and logged previous demand) with their respective empirical category means. This direct substitution ensures structural consistency by utilizing the identical β parameters to map both expected and inferred normalized vertical value. Crucially, this specification mathematically ensures a rational, unbiased baseline expectation for an average product in that category at that specific price point.

Smoothing the Piecewise Demand and Click-Through Functions. The theoretical model yields piecewise linear demand and click-through expressions that are not differentiable at their breakpoints, which would complicate gradient-based optimization. We address this by replacing the indicator functions with sigmoid approximations. Specifically, we define:

$$G^{\tau}(x) = \frac{1}{1 + e^{-\gamma(x-\tau)}} \tag{20}$$

When γ is a sharpness parameter set to 100, ensuring that $G^{\tau}(x)$ closely approximates the indicator $\mathbf{1}_{x>\tau}$ while remaining every where differentiable. We further define, for each category k:

$$A_k = min\{\omega_k^C, 1 - \omega_k^C\} \tag{21}$$

$$B_k = max\{\omega_k^C, 1 - \omega_k^C\} \tag{22}$$

These are the break-point thresholds in the piecewise demand and click-through expressions derived in Lemma 2 and Proposition 1. The smoothed click-through rate and demand expressions are then:

$$L_{kjt}^{info} = \frac{1}{1-\omega_k^C} * [z_{kjt} * (1 - G^{A_k}(z_{kjt})) + A_k * (G^{A_k}(z_{kjt}) - G^{B_k}(z_{kjt})) + (1 - z_{kjt}) * G^{B_k}(z_{kjt})] \tag{23}$$

$$L_{kjt}^{cold} = 1 * (G^{\frac{1-\omega^C}{2}}(\bar{z}_{kjt}) - G^{\frac{1+\omega^C}{2}}(\bar{z}_{kjt})) \tag{24}$$

$$\begin{aligned} D_{\mathbb{T}=1,jkt}^{info} = {} & \frac{z_{jkt}^2}{2\omega_k^C(1-\omega_k^C)} * (1 - G^{A_k}(z_{kjt})) + \frac{2z_{jkt} - A_k}{2B_k} * (G^{A_k}(z_{kjt}) - G^{B_k}(z_{kjt})) \\ & + (1 - \frac{(1-z_{jkt})^2}{2\omega_k^C(1-\omega_k^C)}) * G^{B_k}(z_{kjt}) \end{aligned} \tag{25}$$

$$D_{\mathbb{T}=1,jkt}^{cold} = \frac{2\bar{z}_{kt} - (1-\omega_k^C)}{2\omega_k^C} * (G^{\frac{1-\omega_k^C}{2}}(\bar{z}_{kt}) - G^{\frac{1+\omega_k^C}{2}}(\bar{z}_{kt})) + 1 * G^{\frac{1+\omega_k^C}{2}}(\bar{z}_{kt}) \tag{26}$$

$$D_{\mathbb{T}=0,jkt}^{info} = \frac{2z_{kjt} - \omega_k^C}{2(1-\omega_k^C)} * (G^{\frac{\omega_k^C}{2}}(z_{kjt}) - G^{1-\frac{\omega_k^C}{2}}(z_{kjt})) + G^{1-\frac{\omega_k^C}{2}}(z_{kjt}) \tag{27}$$

$$D_{\mathbb{T}=0,jkt}^{cold} = 1 * G^{\frac{1}{2}}(\bar{z}_{kt}) \tag{28}$$

Estimating Review Informativeness. The transparency level α_{kjt} is modeled as a logistic function of the volume of existing reviews available on the product page at time t:

$$\alpha_{kjt} = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 Vol_{kjt})}} \tag{29}$$

where Vol_{kjt} is the logged count of prior reviews.

4.2 Likelihood Function

The full parameter vector is $\theta = \{\omega^C, \beta, \alpha, \sigma_D, \sigma_L\}$, where $\omega^C = \omega_k^C$ denotes the category-specific contextual fit importance, β governs the mapping from product observables to normalized vertical value z_{kjt}, and $\alpha = \{\alpha_0, \alpha_1\}$ govens the mapping from review volume to informativeness α_{kjt}. The model-implied mean demand and click-through rate for product j in category k at time t are the informativeness-weighted combinations of their fully-informative and cold-start counterparts:

$$\mu_{D_{\mathbb{T},kjt}} = \alpha_{kjt} D^{info}_{\mathbb{T},jkt} + (1-\alpha_{kjt}) D^{cold}_{\mathbb{T},kjt}, \mathbb{T} \in \{0,1\} \tag{30}$$

$$\mu_{L_{kjt}} = \alpha_{kjt} L^{info}_{kjt}(z_{kjt}\omega_k^C) + (1-\alpha_{kjt}) L^{cold}_{kjt}(\bar{z}_{kjt}\omega_k^C) \tag{31}$$

We assume that observed demand and click-through rates are drawn from Gaussian distributions centered on these model-implied means, with variances σ_D^2 and σ_L^2 respectively. The negative log-likelihood contributions are

$$\ln f(D_{\mathbb{T},kjt}|\theta, X_j) = -\frac{1}{2}\ln(2\pi\sigma_D^2) - \frac{(D_{\mathbb{T},kjt} - \mu_{D_{\mathbb{T},kjt}})^2}{2\sigma_D^2}, \mathbb{T} \in \{0,1\} \tag{32}$$

$$\ln g(L_{kjt}|\theta, X_{kjt}) = -\frac{1}{2}\ln(2\pi\sigma_L^2) - \frac{(L_{kjt} - \mu_{L_{kjt}})^2}{2\sigma_L^2} \tag{33}$$

The total negative log-likelihood jointly combines demand observations from all products and click-through observations from the subset of products that adopted the FRI:

$$-\ln \mathcal{L}(\theta) = -\sum_{j\in J} \ln f(D_{\mathbb{T},kjt}|\theta, X_j) - \sum_{j \in J^T} \ln g(L_{kjt}|\theta, X_j) \tag{34}$$

where J denotes the full product sample and J^T denotes the subsample of FRI-adopted products for which click-through data are available. Joint estimation over demand and click-through rates exploits the structural link between the two outcome variables through the shared parameters ω_k^C, z_{kjt}, and α_{kjt}, improving identification relative to single-equation approaches.

5 AN EMPIRICAL APPLICATION: AR INTERFACE IN ONLINE RETAILING

5.1 Empirical Context

We assembled a dataset of online retailing platform that launched an FRI feature, an AR-powered "place and view" interface. The platform, similar to Amazon, provide a channel through which brand retailers sell products to individual consumers. As on most online shopping platforms, each product page integrates product information supplied by the retailer and displays online reviews from previous buyers. To better address product fit, especially for home furnishing products, some retailers embed this AR interface in the product information page, allowing consumers to assess the visual match between the product and their own physical space.

Our dataset comprises items from five categories: air conditioner (AC), refrigerator (FG), cabinets (CB), shower heads (SH), and toilets (TL). This context allows us to measure product type differentiation and the category-level heterogeneity of FRI adoption. The data span a 30-week observation period. Of the 636 items in the dataset, 250 never integrated the interface during the observation period; the proportion of adopting items is balanced across the five categories.

For each item-week observation, we obtain the interface integration status, sales volume, AR click-through statistics, and product price. To characterize online ratings, we collect the reviews of each item and compute the valence (the average rating score), the variance, and the cumulative volume as of each observed week. In total, the data contain 16,472 item-weekly observations — 8,262 with the AR interface active and 8,210 without.

5.2 Parameter Estimates: Three-Layer Measurements

Applying the MLE procedure described in the previous section, we estimate the parameters θ that measures cross-category differences in contextual fit importance and recovers the perceived vertical value and the informativeness of online reviews. Table 2 reports the maximum likelihood estimates of θ. These structural estimates yield three layers of measurement: the informativeness of the review system at the time of observation, the item's vertical position within its category, and the category-level heterogeneity in product type.

Review informativeness. As developed in the theoretical model, α governs the probability that the review system is informative about the product's vertical value and non-contextual fit. The two parameters α_0 and α_{counts} map review volume to the latent informativeness α. The intercept $\alpha_0 = -6.07$ implies near-zero informativeness for cold-start products, consistent with the theoretical model. The estimated coefficient $\alpha_{counts} = 1.93$ (s.e. = 0.12) confirms that informativeness rises steeply with review volume. As shown in Figure 3, α_{kjt} reaches high levels rapidly by about 80 reviews; and it approaches the effective fully informative case ($\alpha_{kjt} > 0.96$) once accumulation

Table 2: Estimation Results

Variables	Estimates	S. E.
$\beta_{signal2noise}$	0.4770 ***	0.0061
β_{prev_counts}	0.3595 ***	0.0030
β_{price}	-0.2654 ***	0.0048
β_0	-4.1837 ***	0.0169
α_{counts}	1.9267***	0.1158
α_0	-6.0673 ***	0.4128
ω^C_{AC}	0.1326 ***	0.0107
ω^C_{FG}	0.2126 ***	0.0072
ω^C_{CB}	0.4770 ***	0.0138
ω^C_{SH}	0.2204 ***	0.0079
ω^C_{TL}	0.2995 ***	0.0069
$\log(\sigma_D)$	-4.1655 ***	0.0055
$\log(\sigma_L)$	-4.2407 ***	0.0079

passes approximately 120 reviews. This implies that a relatively modest review base is sufficient for consumers to resolve most non-contextual uncertainty. In contrast, only items with fewer than 10 reviews remain in the low-informativeness regime ($\alpha_{kjt} < 0.2$), where consumers limitedly rely on the information conveyed in existing reviews.

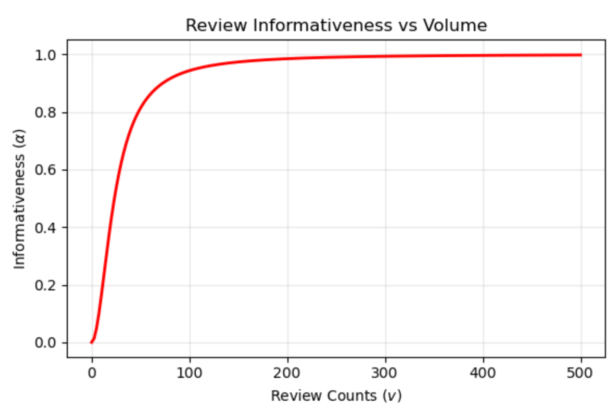

Figure 3: Informativeness along with the review counts

Perceived item values. Given the accumulated review information, consumers form a perception of item value on which they base their purchase decisions. In our framework, the normalized vertical value z_{kjt} is determined by the estimated β coefficients and the observed product features. As shown in Figure 4, z_{kjt} is increasing in the mean-deviation ratio, **the prior demand**, and decreasing in price. This derived latent, with two properties follow, offers an item-level, time-varying measure of the consumer's perceived vertical position within a category. First, because the information environment, including the review volume, the balance of positive and negative ratings, and rating variance, evolves over time, the value inferred from rating characteristics evolves alongside it. Second, because z_{kjt} captures $\frac{v}{t}$ and t is assumed category-intrinsic, a higher z_{kjt} indicates a higher perceived quality-adjusted net value ($v = q - p$). Comparing two items in the same category, the item with higher ratings and lower rating variance is inferred to have the higher quality (relative to the misfit cost), whereas a higher price compresses the net value for a given perceived quality.

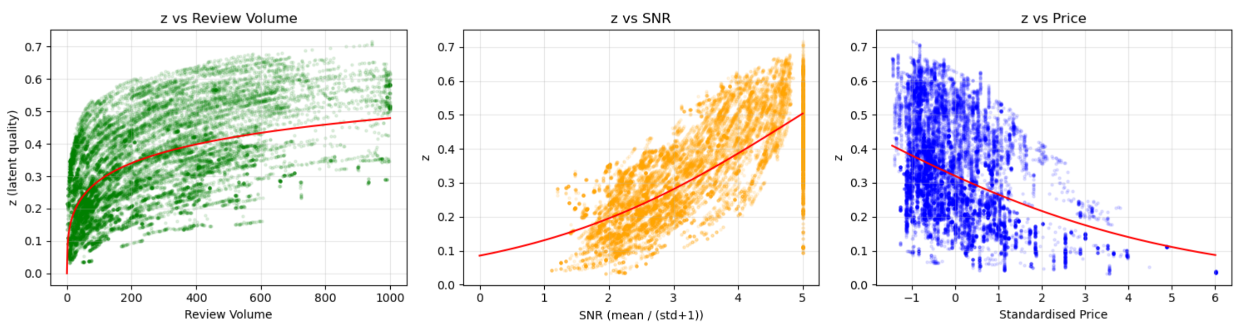

Figure 4: z estimates along with the review features

Category-level product type. The estimates also represent product at the categorical level. Notice that we assumed two category-intrinsic variables: the misfit cost t and the importance weight ω^C. Thus we discuss the product type measure from two dimensions.

First, the normalized value $z \equiv v/t$ admits a different reading at the category level. If t is fixed, z_{kjt} orders items by their perceived vertical value, as the item-level layer above. Across categories, t is intrinsic and varies, so the comparison of z distributions carries information about the categorical misfit cost itself. Because the five categories are sold on the same platform in mature, competitive markets, and because our specification maps category-normalized observables into z with common coefficients, the distributions of product vertical value $v = q - p$ should be broadly comparable across categories. Under this premise, the z distribution of category k is the common v distribution scaled by $1/t_k$, and the relative position of the distributions reflects the

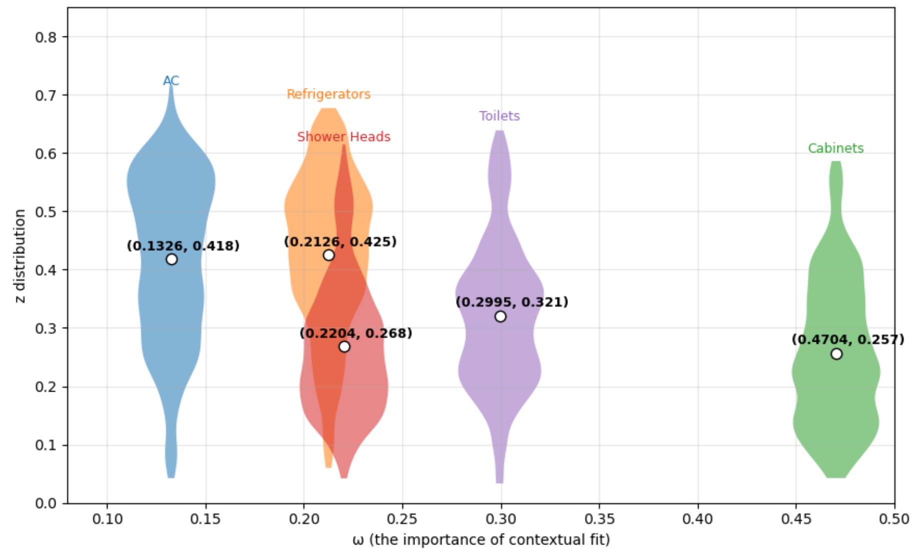

Figure 5: Categorical Product Type Measure

relative magnitude of the category-intrinsic misfit cost.

We take categorical average of the derived z_{jkt} and denote it as Z_k. Figure 5 displays these distributions on the y-axis. The z mass of air conditioners ($Z_{AC} = 0.418$) and refrigerators ($Z_{FG} = 0.425$) sits high, indicating a low misfit cost: the average vertical value translates into a high normalized net value because deviations from the ideal product are inexpensive. The mass of cabinets ($Z_{CB} = 0.257$), shower heads ($Z_{SH} = 0.268$), and toilets ($Z_{TL} = 0.321$) is compressed toward lower values, indicating a higher misfit cost t_K in these categories. Consistent with the scaling interpretation, both the location and the dispersion of z contract in the high-t categories. Equivalently, the category mean Z_k is exactly the inverse of the *degree of experience* (t/v) defined by Chen et al. (2021): by this measure, cabinets, shower heads, and toilets lie closer to the experience-good end of the search–experience spectrum than air conditioners and refrigerators.

Second, we add a new dimension to this product type measurement. We introduce ω_k^C, the *contextual fit importance*, which measures the share of horizontal utility whose misfit remains unresolved by product reviews even at maximum informativeness ($\alpha = 1$) and can be revealed only through the new fit-revealing tool.

In this empirical application, the estimated ω_k^C parameters exhibit meaningful cross-category variation that aligns closely with theoretical expectations. Figure 5 show the variation of ω_k^C on the x-axis. Cabinets ($\omega^C = 0.470$, s.e. = 0.014) carry the highest contextual fit weights, reflecting the strong spatial and installation constraints this product category impose. Other categories, such as toilets ($\omega^C = 0.300$, s.e. = 0.007), shower heads ($\omega^C = 0.220$, s.e. = 0.008), and refrigerates ($\omega^C = 0.213$, s.e. =0.007) carry lower ω^C estimates than cabinets. Particularly, air conditioners ($\omega^C = 0.132$, s.e. =0.011) carries lowest ω^C estimates, indicating that functional performance attributes, captured in reviews, dominate over contextual fit considerations.

The two dimensions in Figure 5 are therefore complementary characterizations of product type: the vertical placement of a category's z distribution reflects how costly misfit is overall relative to vertical value, while ω_k^C reflects what share of that misfit is contextual, determining to what extend the fit revelation through FRI operates. The configuration is informative about where FRI adoption should matter: cabinets combine the highest contextual share with relatively down-scaled net values, whereas air conditioners exhibit the reverse pattern. We will contrast the categories on the quantified heterogeneous effects in the counterfactual analysis below.

5.3 Product Demand Change

To quantify the economic value of the feature adoption, we conducted a counterfactual simulation using the estimated structural parameters. For each product category, we estimate the average treatment effect (ATE) as follow:

$$ATE_k = E[\hat{D}^1_{jkt} - \hat{D}^0_{jkt}] \tag{35}$$

Overall, we find that ATE is approximately 3.94% relative lift from the control group. In the following subsections, we investigate the heterogeneous ATE and show how FRI adoption interacts with the three-layer product characteristics to reshape demand.

5.3.1 Heterogeneity by Informativeness Level

We first examine how the treatment effect varies with the informativeness level, α. For each observation, we compute the individual treatment effect $\hat{D}^1_{jkt} - \hat{D}^0_{jkt}$ from Equation (35) at the observation's estimated state $(z_{jkt}, \bar{z}_{kt}, \alpha_{jkt}, \omega_k)$, flipping only the adoption indicator. We then sort observations into quantile bins of the estimated α_{jkt} and report the within-bin mean ATE together with the within-bin range. Because the binning is performed on individual effects rather than on covariate averages, the resulting profile is a consistent estimate of $E[\hat{D}^1 - \hat{D}^0 \mid \alpha]$ and is not distorted by the nonlinearity of the demand function. Separately, we sort observations into bins of the observed review count, the primary observable driver of α, and report the within-bin ATE.

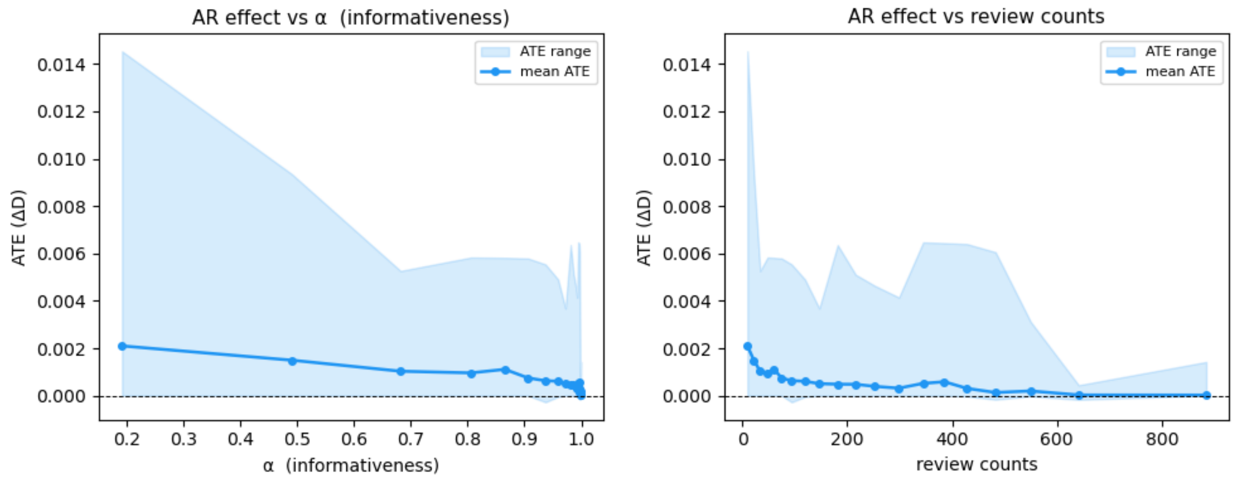

Figure 6: ATE over varying informativeness level

Figure 6 shows a clear monotone decline. The mean ATE is largest for products in the least informative environments and falls when α approaches one. The review-count figure (right panel) tells the same story in observable units: the effect is concentrated among products with few accumulated reviews, declines steeply over the first one hundred reviews, and is essentially exhausted beyond roughly six hundred reviews.

5.3.2 Heterogeneity by Product Vertical Values

We next trace the treatment effect over the two perceived-value states, z (the item-week-specific perceived net value) and $\bar{z}$ (the item cold-start signal). Because the two states operate through different channels of the demand function—z enters only the informed component, whose weight is α, while $\bar{z}$ enters only the cold-start component, whose weight is $(1-\alpha)$—pooling all observations would confound the two gradients. We therefore apply channel-matched conditioning: the z profile is estimated on the high-informativeness subsample ($\alpha > 0.8$; N=13,679), where the informed channel dominates, and the $\bar{z}$ profile on the low-informativeness subsample ($\alpha < 0.2$; N=485), where demand is effectively cold-start driven. Within each subsample we again form quantile bins of the conditioning state and report the mean and range of the individual treatment effects.

The two panels of Figure 7 are consistent with Propositions 2 and 3. In the left panel, the

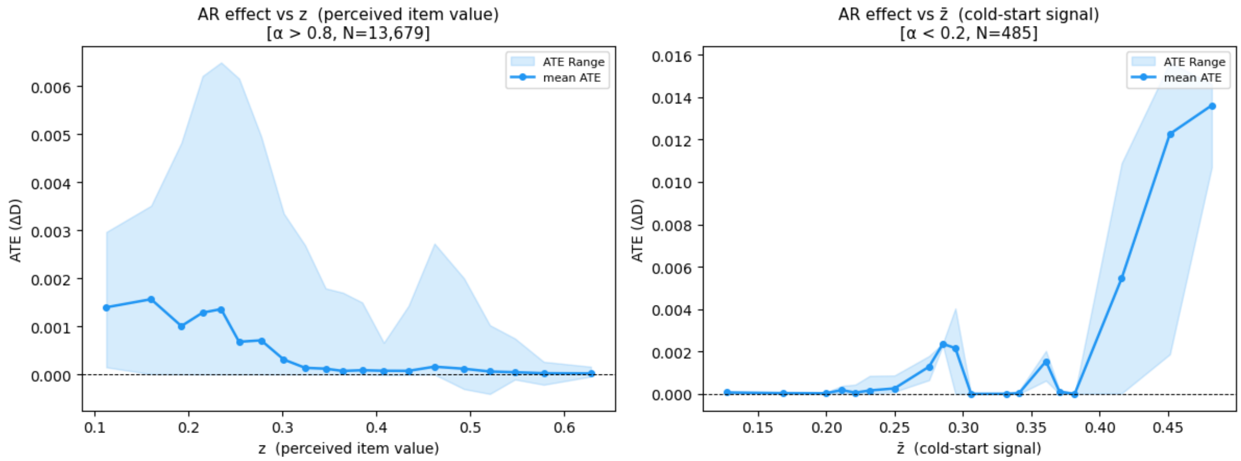

Figure 7: ATE over varying perceived product values

ATE is positive and sizable only for products with low perceived value, $z \lesssim 0.3$, and converges to zero as z increases. This is consistent with the informed-channel prediction of Proposition 2: for high-vertical-value products in each category (z above the fit threshold), consumers purchase even with the contextual fit uncertainty, so FRI adds little; for low-vertical-value products, fit revelation converts consumers who would otherwise not buy.

In the right panel, the ATE is indistinguishable from zero for a low $\bar{z}$, turns positive in an intermediate range, and rises steeply to an order of magnitude above the informed-channel effect as $\bar{z}$ approaches 0.5. This matches the cold-start prediction of Proposition 3, which restricts the gains to the window $\frac{1-\omega_k}{2} < \bar{z} < 1/2$: absent any fit information, cold-start demand is negligible whenever the item net value expectation falls below the purchase threshold of $\bar{z} = 1/2$, whereas FRI allows undecided consumers with promising-but-unproven expectations to resolve their fit and purchase. The category-specific boundaries $\frac{1-\omega_k}{2}$ also explain the staggered pattern of the increase, as categories with larger ω_k enter their eligibility window at lower values of $\bar{z}$.

Taken together, the two figures show that the aggregate lift masks sharply targeted incidence: FRI creates demand almost exclusively for products that are informationally poor (low α, few reviews), perceived as low quality relative to fit importance (z below the category threshold), or situated in categories whose prior beliefs hover just below the purchase margin ($\bar{z}$ just below $1/2$).

5.3.3 Heterogeneity by Product Category

As we discussed in the category-level product type measure, the five categories fall into two groups by their z distributions: air conditioners and refrigerators have nearly indistinguishable value distributions ($Z_{AC} = 0.418$, $Z_{FG} = 0.425$) toward the search-good end of the spectrum, while shower heads, toilets, and cabinets have compressed distributions (Z_k between 0.257 and 0.321) toward the experience-good end. We thus compare how the ω measure affects ATEs *within-group*, when z distributions are similar.

In both groups, the treatment effect increases in ω_k^C. Among search goods, air conditioners and refrigerators share an identical control mean (0.023), yet the relative lift rises from 0.44% ($\omega^C = 0.133$) to 2.70% ($\omega^C = 0.213$). Among experience goods, the lift rises monotonically from 1.93% for shower heads ($\omega^C = 0.220$) to 3.20% for toilets ($\omega^C = 0.300$) to 40.87% for cabinets ($\omega^C = 0.477$). The mechanism follows from Proposition 2 and 3: a higher ω_k^C widens the demand-increasing region in either information cases, so a larger share of the category's items falls where revealing contextual fit converts marginal consumers into purchasers. With five categories, these comparisons are descriptive patterns consistent with the theory rather than a formal test. Nevertheless, the ordering of category-level effects supports the model's central comparative static: holding perceived value fixed, the returns to FRI adoption increase in the contextual fit importance.

Table 3: ATE of Different Product Category

	Z	**estimated ω**	**Control Mean**	**ATE by item**	**Relative Lift**
Overall	-	-	1.570	0.062	3.94%
AC	0.418	0.133	2.320	0.010	0.44%
Refrigerator	0.425	0.213	2.325	0.063	2.70%
Shower Heads	0.268	0.220	1.114	0.022	1.93%
Toilets	0.321	0.300	1.366	0.044	3.20%
Cabinets	0.257	0.477	0.529	0.216	40.87%

Note: The numerical values of control mean and ATE are percentage points of market share.

6 CONCLUSION AND DISCUSSION

This study investigates how the adoption of fit-revealing interfaces (FRI) as an alternative information source synergistically works with online review systems to influence product sales. We first develop predictions through an analytical model, then provide empirical support using item-weekly-level data from a leading online shopping platform. Although lacking consumer-level impacts and actions, this study provides valuable insights for online retailers and business operators seeking effective strategies for FRI adoption. It makes a contribution to both theory and practice in the domain of information provision within online shopping.

We focus on understanding the mechanism by which the introduction of a new information tool — one that resolves contextual fit uncertainty unaddressed by existing descriptive information — influences product demand and its interplay with established information sources. Taking a perspective of information integration, our analytical model predicts how consumers respond to the availability of FRI alongside online reviews. Notably, by endogenizing consumers' decisions to engage with FRI, we add depth and realism to the investigation. Our findings reveal that FRI engagement reflects not just consumer interest in the technology but also the residual uncertainty that remains after processing existing information — a function of the product's inferred vertical value, the volume of available reviews, and the relative importance of contextual fit in the product category. This result explains the persistently low engagement rates observed in practice as a rational outcome of sequential information acquisition rather than a shortcoming of the technology, filling a critical gap in the existing literature.

From a managerial perspective, our findings offer actionable insights for retailers formulating FRI adoption strategies. We characterize the conditions under which consumers are most likely to engage with FRI, aiding businesses in identifying where these tools deliver the greatest value. Our analysis highlights that the factors contributing to low engagement rates are systematic and predictable — products with very high or very low inferred quality generate little incremental demand from FRI, while products in the intermediate range benefit most. Furthermore, we explore the capacity of FRI to assist in the discovery and evaluation of cold-start products, providing retailers with insights into how FRI can compensate for limited review histories. We also examine how FRI can enhance consumer confidence and shift the relative weight of online reviews in purchase decisions for products where contextual fit is salient. These findings have direct relevance for retailers seeking to leverage FRI as a tool for product differentiation and customer engagement in the competitive online marketplace.

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Appendix A Proofs of Theoretical Results

This appendix provides proofs for all lemmas and propositions in Section 3. Throughout, we use the notation established in the main text: $\omega^C + \omega^N = 1$ with $\omega^C, \omega^N > 0$, consumers are uniformly distributed over $(x_i^N, x_i^C) \in [0,1]^2$, and the normalized net vertical value is $\frac{v}{t} \in (0,1)$. The utility of consumer i is

$$U_i = \frac{v}{t} - \omega^C x_i^C - (1-\omega^C)x_i^N.$$

Appendix A.1 The Fully Informative Case

Lemma 1. *With fully informative online reviews, consumer i has an incentive to engage the FRI if and only if $x_i^N \in [0,1] \cap (\frac{v}{t\omega^N} - \frac{\omega^C}{\omega^N}, \frac{v}{t\omega^N})$.*

Proof. If a consumer observes online reviews and becomes fully informed on $\frac{v}{t}$ and x^N, her expected utility of not using AR interface is

$$E[U|x_i^N, \frac{v}{t}] = \frac{v}{t} - (\frac{\omega^C}{2} + \omega^N x_i^N)$$

with using AR interface, the expected utility is

$$E_{x_i^C}\left[E\left[U|x_i^C, x_i^N, \frac{v}{t}\right]\mathbf{1}_{E\left[U|x_i^C, x_i^N, \frac{v}{t}\right]\geq 0}\right]$$

For the consumer located at (x_i^N, x_i^C), she knows the exact value of x_i^N and $\frac{v}{t}$, and make decisions based on the inferred information.

- For $x_i^N \geq \frac{v}{t\omega^N}$, $E[U|x_i^N, \frac{v}{t}]$ and $E[U|x_i^N, x_i^C, \frac{v}{t}]$ are both negative, consumers don't purchase regardless, so $\Delta EU = 0$ for any $x_i^C \in (0,1)$.
- For $\frac{v}{t\omega^N} - \frac{\omega^C}{2\omega^N} < x_i^N < \frac{v}{t\omega^N}$, consumers don't purchase without using AR, but probably purchase if using AR to uncover x_i^C.

$$\begin{aligned}
E_{x_i^C}\left[E\left[U|x_i^C, x_i^N, v\right]\mathbf{1}_{E\left[U|x_i^C, x_i^N, v\right]\geq 0}\right] &= \int_0^{\frac{1}{\omega}(v-x_i^N)} (v - \omega x_i^C - x_i^N) f(x_i^C) dx_i^C \\
&= \int_0^{\frac{1}{\omega}(v-x_i^N)} (v - x_i^N) f(x_i^C) dx_i^C - \int_0^{\frac{1}{\omega}(v-x_i^C)} \omega x_i^C f(x_i^C) dx_i^C \\
&= \frac{1}{\omega}(v - x_i^N)^2 - \frac{\omega}{2} \times \frac{1}{\omega^2}(v - x_i^N)^2 \\
&= \frac{1}{2\omega}(v - x_i^N)^2 > 0
\end{aligned} \tag{36}$$

- For $v-\omega < x_i^N < v-\frac{\omega}{2}$, consumers purchase without using the AR interface, but probably not purchase if using AR to uncover the contextual experience.

$$\begin{aligned}\Delta EU &= \frac{1}{2\omega}(v-x_i^N)^2 - (v-(\frac{\omega}{2}+x_i^N)) \\ &= \frac{1}{2\omega}[(v-x_i^N)^2 - 2(v-x_i^N)\omega + \omega^2] \\ &= \frac{1}{2\omega}(v-x_i^N-\omega)^2 > 0\end{aligned} \tag{37}$$

- For $x_i^N \leq v-\omega$, consumers make a purchase regardless, so $\Delta EU = 0$ for any $x_i^C \in (0,1)$.

$\square$

Proposition 1. *The FRI click-through rate under fully informative reviews is*

$$L\Big(\frac{v}{t},\omega^C\Big) = \begin{cases} \dfrac{1}{1-\omega^C}\cdot\dfrac{v}{t} & \text{if } \dfrac{v}{t} \in \big(0,\ \min\{\omega^C, 1-\omega^C\}\big]\,, \\ \dfrac{\min\{\omega^C,1-\omega^C\}}{1-\omega^C} & \text{if } \dfrac{v}{t} \in \big(\min\{\omega^C,1-\omega^C\},\ \max\{\omega^C,1-\omega^C\}\big]\,, \\ \dfrac{1-v/t}{1-\omega^C} & \text{if } \dfrac{v}{t} \in \big(\max\{\omega^C,1-\omega^C\},\ 1\big)\,. \end{cases}$$

Proof. By Lemma 1, the set of consumers who engage FRI is $\{x_i^N \in [0,1] \cap (a,b)\}$, where

$$a = \frac{v/t-\omega^C}{1-\omega^C}, \qquad b = \frac{v/t}{1-\omega^C}.$$

Since $x_i^N \sim U[0,1]$, the click-through rate L equals the length of the interval $[0,1]\cap(a,b)$. Note that $b-a = \omega^C/(1-\omega^C)$ for all parameter values. We compute L by checking where a and b fall relative to the boundaries 0 and 1.

Region 1: $v/t \leq \min\{\omega^C, 1-\omega^C\}$.

Then $a \leq 0$ (since $v/t \leq \omega^C$) and $b \leq 1$ (since $v/t \leq 1-\omega^C$). The interval $(a,b)\cap[0,1] = (0,b)$, so

$$L = b - 0 = \frac{v/t}{1-\omega^C}.$$

Region 2: $\min\{\omega^C,1-\omega^C\} < v/t \leq \max\{\omega^C,1-\omega^C\}$.

Sub-case $\omega^C < 1/2$: Then $\omega^C < v/t \leq 1-\omega^C$, giving $a > 0$ and $b \leq 1$. So $L = b-a = \omega^C/(1-\omega^C)$.

Sub-case $\omega^C > 1/2$: Then $1-\omega^C < v/t \leq \omega^C$, giving $a \leq 0$ and $b > 1$. Both endpoints are clipped: $L = 1-0 = 1 = (1-\omega^C)/(1-\omega^C)$.

In both sub-cases, $L = \min\{\omega^C,1-\omega^C\}/(1-\omega^C)$.

Region 3: $v/t > \max\{\omega^C,1-\omega^C\}$.

Then $a > 0$ and $b > 1$. The interval is clipped at the right: $(a,b)\cap[0,1] = (a,1)$, so

$$L = 1-a = 1-\frac{v/t-\omega^C}{1-\omega^C} = \frac{1-v/t}{1-\omega^C}.$$

$\square$

Lemma 2 (Demand under Fully Informative Reviews). (1) Without FRI adoption,

$$D_0^{info} = \begin{cases} 0 & \text{if } \frac{v}{t} \in (0, \frac{\omega^C}{2}]; \\ \frac{1}{1-\omega^C}(\frac{v}{t} - \frac{\omega^C}{2}) & \text{if } \frac{v}{t} \in (\frac{\omega^C}{2}, 1 - \frac{\omega^C}{2}]; \\ 1 & \text{if } \frac{v}{t} \in (1 - \frac{\omega^C}{2}, 1) \end{cases} \tag{38}$$

(2) With FRI adoption,

$$D_1^{info} = \begin{cases} \frac{1}{2\omega^C(1-\omega^C)}(\frac{v}{t})^2 & \text{if } \frac{v}{t} \in (0, min\{\omega^C, 1-\omega^C\}]; \\ \frac{2\frac{v}{t} - min\{\omega^C, 1-\omega^C\}}{2max\{\omega^C, 1-\omega^C\}} & \text{if } \frac{v}{t} \in (min\{\omega^C, 1-\omega^C\}, max\{\omega^C, 1-\omega^C\}]; \\ 1 - \frac{(1-\frac{v}{t})^2}{2\omega^C(1-\omega^C)} & \text{if } \frac{v}{t} \in (max\{\omega^C, 1-\omega^C\}, 1] \end{cases} \tag{39}$$

Proof. **Part (1): Demand without FRI (D_0^{info}).** With reviews only, consumer i purchases iff $E[U_i \mid x_i^N, v/t] \geq 0$, i.e.,

$$\frac{v}{t} - \frac{\omega^C}{2} - (1-\omega^C)x_i^N \geq 0 \quad \Longleftrightarrow \quad x_i^N \leq \frac{v/t - \omega^C/2}{1-\omega^C}.$$

Since $x_i^N \sim U[0,1]$, aggregate demand is $D_0^{info} = \min\{ \max\{\frac{v/t-\omega^C/2}{1-\omega^C}, 0\}, 1\}$, yielding:

$$D_0^{info} = \begin{cases} 0 & \text{if } v/t \leq \omega^C/2, \\ \dfrac{v/t - \omega^C/2}{1-\omega^C} & \text{if } \omega^C/2 < v/t \leq 1 - \omega^C/2, \\ 1 & \text{if } v/t > 1 - \omega^C/2. \end{cases}$$

Part (2): Demand with FRI (D_1^{info}).

With FRI, a fully informed consumer at (x_i^N, x_i^C) purchases iff $U_i = v/t - \omega^C x_i^C - (1-\omega^C)x_i^N \geq 0$. Geometrically, the set of purchasers is the region of the unit square $[0,1]^2$ below the zero-utility line

$$x_i^C = \bar{x}^C(x_i^N) \equiv \frac{v/t - (1-\omega^C)x_i^N}{\omega^C}.$$

Aggregate demand equals the area of $\{(x_i^N, x_i^C) \in [0,1]^2 : U_i \geq 0\}$. The zero-utility line intersects the axes at $x_i^N = \frac{v/t}{1-\omega^C}$ (horizontal axis, where $x_i^C = 0$) and $x_i^C = \frac{v/t}{\omega^C}/$ (vertical axis, where $x_i^N = 0$). How these intercepts fall relative to the unit square determines the geometry. We derive the demand separately for $\omega^C < 1/2$ and $\omega^C \geq 1/2$, then unify the expressions.

Case I: $\omega^C < 1/2$ **(equivalently** $\omega^C < 1-\omega^C$**).**

The vertical intercept satisfies $\frac{v/t}{\omega^C} > \frac{v/t}{1-\omega^C}$ since $\omega^C < 1-\omega^C$, so the zero-utility line is steeper in x_i^N than in x_i^C. The breakpoints in v/t are ω^C and $1-\omega^C$ (where the horizontal intercept equals 1).

(I.a) $0 < \frac{v}{t} \leq \omega^C$*:* The horizontal intercept $\frac{v/t}{1-\omega^C} \leq \frac{\omega^C}{1-\omega^C} < 1$, and the vertical intercept $(v/t)/\omega^C \leq 1$. The purchase region is a right triangle with legs $v/t/(1-\omega^C)$ along the x^N-axis and $(v/t)/\omega^C$ along the x^C-axis:

$$D_1^{info} = \frac{1}{2} \cdot \frac{v/t}{1-\omega^C} \cdot \frac{v/t}{\omega^C} = \frac{(v/t)^2}{2\omega^C(1-\omega^C)}.$$

(I.b) $\omega^C < v/t \le 1-\omega^C$*:* Now the vertical intercept $(v/t)/\omega^C > 1$, so the zero-utility line exits through the top edge ($x_i^C = 1$) at $x_i^N = (v/t-\omega^C)/(1-\omega^C) \equiv a$. Meanwhile the horizontal intercept $v/t/(1-\omega^C) \le 1$. The purchase region consists of a rectangle $[0,a]\times[0,1]$ (area $= a$) plus a right triangle with base $v/t/(1-\omega^C) - a = \omega^C/(1-\omega^C)$ and height 1 (area $= \omega^C/[2(1-\omega^C)]$):

$$D_1^{info} = a + \frac{\omega^C}{2(1-\omega^C)} = \frac{v/t-\omega^C}{1-\omega^C} + \frac{\omega^C}{2(1-\omega^C)} = \frac{2v/t-\omega^C}{2(1-\omega^C)}.$$

(I.c) $1-\omega^C < v/t < 1$*:* Both intercepts exceed 1: $v/t/(1-\omega^C) > 1$ and $(v/t)/\omega^C > 1$. The zero-utility line exits through the right edge ($x_i^N = 1$) at $x_i^C = (v/t-(1-\omega^C))/\omega^C \equiv c < 1$, and through the top edge at $x_i^N = a > 0$. The non-purchase region is a right triangle in the upper-right corner with legs $1-a = (1-v/t)/(1-\omega^C)$ and $1-c = (1-v/t)/\omega^C$:

$$D_1^{info} = 1 - \frac{1}{2}\cdot\frac{1-v/t}{1-\omega^C}\cdot\frac{1-v/t}{\omega^C} = 1 - \frac{(1-v/t)^2}{2\omega^C(1-\omega^C)}.$$

Case II: $\omega^C \ge 1/2$ **(equivalently** $\omega^C \ge 1-\omega^C$**).**

The zero-utility line is now shallower in x_i^N, with vertical intercept $(v/t)/\omega^C \le v/t/(1-\omega^C)$. The breakpoints in v/t are $1-\omega^C$ and ω^C.

(II.a) $0 < v/t \le 1-\omega^C$*:* Both intercepts satisfy $v/t/(1-\omega^C) \le 1$ and $(v/t)/\omega^C \le 1$. As in Case I.a, the purchase region is a right triangle:

$$D_1^{info} = \frac{(v/t)^2}{2\omega^C(1-\omega^C)}.$$

(II.b) $1-\omega^C < v/t \le \omega^C$*:* The horizontal intercept $v/t/(1-\omega^C) > 1$, so the zero-utility line exits through the right edge at $x_i^C = c = (v/t-(1-\omega^C))/\omega^C \le 1$. Meanwhile, the vertical intercept $(v/t)/\omega^C \le 1$, so the line enters from the left edge. For all $x_i^N \in [0,1]$, we have $0 < \bar{x}^C(x_i^N) < 1$, and demand is the integral:

$$D_1^{info} = \int_0^1 \frac{v/t-(1-\omega^C)x_i^N}{\omega^C}\,dx_i^N = \frac{1}{\omega^C}\left[\frac{v}{t} - \frac{1-\omega^C}{2}\right] = \frac{2v/t-(1-\omega^C)}{2\omega^C}.$$

(II.c) $\omega^C < v/t < 1$*:* Both intercepts exceed 1. Identical geometry to Case I.c:

$$D_1^{info} = 1 - \frac{(1-v/t)^2}{2\omega^C(1-\omega^C)}.$$

Unified expression. Comparing the two cases, the three regions have the same functional forms but different breakpoints:

Region	$\omega^C < 1/2$	$\omega^C \ge 1/2$
Triangle (low v/t)	$v/t \le \omega^C$	$v/t \le 1-\omega^C$
Trapezoid (mid v/t)	$\omega^C < v/t \le 1-\omega^C$	$1-\omega^C < v/t \le \omega^C$
Complement triangle (high v/t)	$v/t > 1-\omega^C$	$v/t > \omega^C$

In every row, the lower breakpoint is $\min\{\omega^C, 1-\omega^C\}$ and the upper is $\max\{\omega^C, 1-\omega^C\}$. Moreover, the trapezoid expression from Case I.b, $\frac{2v/t-\omega^C}{2(1-\omega^C)}$, and from Case II.b, $\frac{2v/t-(1-\omega^C)}{2\omega^C}$, both equal $\frac{2v/t-\min\{\omega^C,1-\omega^C\}}{2\max\{\omega^C,1-\omega^C\}}$. Therefore, the unified demand with FRI is

$$D_1^{info} = \begin{cases} \dfrac{(v/t)^2}{2\omega^C(1-\omega^C)} & \text{if } v/t \in \big(0,\ \min\{\omega^C, 1-\omega^C\}\big], \\ \dfrac{2v/t - \min\{\omega^C, 1-\omega^C\}}{2\max\{\omega^C, 1-\omega^C\}} & \text{if } v/t \in \big(\min\{\omega^C, 1-\omega^C\},\ \max\{\omega^C, 1-\omega^C\}\big], \\ 1 - \dfrac{(1-v/t)^2}{2\omega^C(1-\omega^C)} & \text{if } v/t \in \big(\max\{\omega^C, 1-\omega^C\},\ 1\big]. \end{cases}$$

This matches Equation (10) in the main text. □

Proposition 2 (Demand Effect of FRI Adoption). *Under fully informative reviews, the sign of the demand change following FRI adoption satisfies:*

$$\Delta D^{info} > 0 \iff \frac{v}{t} < min\{\omega^C, \frac{1}{2}\} \tag{40}$$

Proof. Based on Lemma 2, $\Delta D^{info} = D_1^{info} - D_0^{info}$ depends on the value of v and ω. To be specific,

- if $\omega \leq 1$,

$$\Delta D = \begin{cases} \frac{v^2}{2\omega} > 0 & \text{if } 0 < v \leq \frac{\omega}{2} \\ \frac{(v-\omega)^2}{2\omega} > 0 & \text{if } \frac{\omega}{2} < v \leq \omega \\ 0 & \text{if } \omega < v \leq 1 \\ -\frac{(1-v)^2}{2\omega} < 0 & \text{if } 1 < v \leq 1 + \frac{\omega}{2} \\ -\frac{(1+\omega-v)^2}{2\omega} < 0 & \text{if } 1 + \frac{\omega}{2} < v < 1 + \omega \end{cases} \tag{41}$$

- if $1 < \omega < 2$, then $\frac{1}{2} < \frac{\omega}{2} < 1$ and $1 < \frac{1}{2} + \frac{\omega}{2} < \omega < 1 + \frac{\omega}{2}$,

$$\Delta D = \begin{cases} \frac{v^2}{2\omega} > 0 & \text{if } 0 < v < \frac{\omega}{2} < 1 \\ \frac{(v-\omega)^2}{2\omega} > 0 & \text{if } \frac{\omega}{2} < v < 1 \\ \frac{1}{2\omega}(\omega-1)(1+\omega-2v) > 0 & \text{if } 1 < v < \frac{1+\omega}{2} \\ \frac{1}{2\omega}(\omega-1)(1+\omega-2v) < 0 & \text{if } \frac{1+\omega}{2} < v < \omega \\ -\frac{(1-v)^2}{2\omega} < 0 & \text{if } \omega < v < 1 + \frac{\omega}{2} \\ -\frac{(1+\omega-v)^2}{2\omega} < 0 & \text{if } < 1 + \frac{\omega}{2} < v < 1 + \omega \end{cases} \tag{42}$$

- if $\omega > 2$, then $1 < \frac{\omega}{2}$ and $\omega > 1 + \frac{\omega}{2}$,

$$\Delta D = \begin{cases} \frac{v^2}{2\omega} > 0 & \text{if } 0 < v < 1 \\ \frac{v}{\omega} - \frac{1}{2\omega} > 0 & \text{if } 1 < v < \frac{\omega}{2} \\ \frac{1}{2\omega}(\omega-1)(1+\omega-2v) > 0 & \text{if } \frac{\omega}{2} < v < \frac{1+\omega}{2} \\ \frac{1}{2\omega}(\omega-1)(1+\omega-2v) < 0 & \text{if } \frac{1+\omega}{2} < v < 1 + \frac{\omega}{2} \\ \frac{v}{\omega} - \frac{1}{2\omega} - 1 < 0 & \text{if } 1 + \frac{\omega}{2} < v < \omega \\ -\frac{(1+\omega-v)^2}{2\omega} < 0 & \text{if } \omega < v < 1 + \omega \end{cases} \tag{43}$$

□

Appendix A.2 The Cold-Start Case

Proposition 1.2. *When no information is extracted from the online rating system, consumers expect to have an increase in expected utility $E_{x^C}[\Delta EU] > 0$ almost everywhere, and choose to use the AR interface.*

PROOF: If a consumer observes no information and remains totally uncertain, her expected utility of not using the AR interface is

$$E[U_i] = \overline{v} - \frac{1}{2}(1+\omega)$$

If using the AR interface, her expected utility is $E_{x_i^C}\left[E\left[U_i|x_i^C\right]\mathbf{1}_{E\left[U_i|x_i^C\right]\geq 0}\right]$

- For $\overline{v} \leq \frac{1}{2}$, consumers don't purchase regardless, so $\Delta EU = 0$ for any $\overline{v} \in (0, \frac{1}{2}]$.
- For $\frac{1}{2} < \overline{v} < \omega + \frac{1}{2}$,

$$\begin{aligned} E_{x_i^C}\left[E\left[U_i|x_i^C\right]\mathbf{1}_{E\left[U_i|x_i^C\right]\geq 0}\right] &= E_{x_i^C}\left[(\overline{v} - \frac{1}{2} - \omega x_i^C)\mathbf{1}_{\overline{v}-\frac{1}{2}-\omega x_i^C\geq 0}\right] \\ &= \int_0^{\frac{\overline{v}}{\omega}-\frac{1}{2\omega}} (\overline{v} - \frac{1}{2} - \omega x_i^C) f(x_i^C) dx_i^C \\ &= \int_0^{\frac{\overline{v}}{\omega}-\frac{1}{2\omega}} (\overline{v} - \frac{1}{2}) dx_i^C - \int_0^{\frac{\overline{v}}{\omega}-\frac{1}{2\omega}} (\omega x_i^C) dx_i^C \\ &= (\overline{v} - \frac{1}{2})(\frac{\overline{v}}{\omega} - \frac{1}{2\omega}) - \frac{\omega}{2}(\frac{\overline{v}}{\omega} - \frac{1}{2\omega})^2 \\ &= \frac{1}{\omega}(\overline{v} - \frac{1}{2})^2 - \frac{1}{2\omega}(\overline{v} - \frac{1}{2})^2 \\ &= \frac{1}{2\omega}(\overline{v} - \frac{1}{2})^2 \end{aligned} \tag{44}$$

$$\begin{aligned} \Delta EU &= \frac{1}{2\omega}(\overline{v} - \frac{1}{2})^2 - (\overline{v} - \frac{1}{2}(1+\omega)) \\ &= \frac{1}{2\omega}(\overline{v} - \frac{1}{2} - \omega)^2 > 0 \end{aligned} \tag{45}$$

- For $\overline{v} \geq \omega + \frac{1}{2}$, consumers make a purchase regardless, so $\Delta EU = 0$ for any $\overline{v} \in [\omega + \frac{1}{2}, \omega + 1)$.

Lemma 3. *When no information is available from the online review system, $E_{x_i^C}[\Delta EU] > 0$ almost everywhere, and consumers choose to engage the FRI.*

Proof. Without any information, the consumer's expected utility is

$$E[U_i] = \frac{\overline{v}}{t} - \frac{\omega^C}{2} - \frac{1-\omega^C}{2} = \frac{\overline{v}}{t} - \frac{1}{2},$$

where $\bar{v}/t$ denotes the expected normalized vertical value. With FRI, the consumer learns x_i^C but not v or x_i^N. Her expected utility conditional on x_i^C is

$$E[U_i \mid x_i^C] = \frac{\bar{v}}{t} - \omega^C x_i^C - \frac{1-\omega^C}{2}.$$

She purchases iff $x_i^C \leq c$, where $c \equiv (\bar{v}/t - (1-\omega^C)/2)/\omega^C$.

We consider three cases based on $\bar{v}/t$.

Case 1: $\bar{v}/t \leq (1-\omega^C)/2$.

Then $c \leq 0$, so $E[U_i \mid x_i^C] < 0$ for all $x_i^C \in [0,1]$. Neither with nor without FRI does the consumer purchase. $\Delta EU = 0$.

Case 2: $(1-\omega^C)/2 < \bar{v}/t < 1/2$.

Without FRI: $E[U_i] = \bar{v}/t - 1/2 < 0$, so the consumer does not purchase (utility gain $= 0$).

With FRI: $0 < c < 1$, so she purchases for favorable realizations of x_i^C. The expected utility gain is:

$$E_{x_i^C}[\Delta EU] = \int_0^c \left(\frac{\bar{v}}{t} - \omega^C x_i^C - \frac{1-\omega^C}{2}\right) dx_i^C = \frac{\omega^C c^2}{2} = \frac{\left[\bar{v}/t - (1-\omega^C)/2\right]^2}{2\omega^C} > 0.$$

Case 3: $1/2 \leq \bar{v}/t < (1+\omega^C)/2$.

Without FRI: $E[U_i] = \bar{v}/t - 1/2 \geq 0$, so the consumer purchases.

With FRI: $0 < c < 1$, so the consumer restricts purchase to $x_i^C \leq c$. Let $d \equiv \bar{v}/t - (1-\omega^C)/2 = \omega^C c$. Then:

$$\begin{aligned} E_{x_i^C}[\Delta EU] &= \frac{d^2}{2\omega^C} - \left(d - \frac{\omega^C}{2}\right) = \frac{d^2 - 2d\omega^C + (\omega^C)^2}{2\omega^C} = \frac{(d-\omega^C)^2}{2\omega^C} \\ &= \frac{\left[\bar{v}/t - (1+\omega^C)/2\right]^2}{2\omega^C} > 0. \end{aligned}$$

Case 4: $\bar{v}/t \geq (1+\omega^C)/2$.

Then $c \geq 1$, so the consumer always purchases with or without FRI. $\Delta EU = 0$.

Since $E_{x_i^C}[\Delta EU] > 0$ for all $\bar{v}/t \in ((1-\omega^C)/2,\ (1+\omega^C)/2)$, consumers engage the FRI almost everywhere in the empirically relevant range. □

Lemma 4. *When no information is available from the online review system: (1) Without FRI:*

$$D_0^{cold} = \begin{cases} 0 & \text{if } \bar{v}/t \leq 1/2, \\ 1 & \text{if } \bar{v}/t > 1/2. \end{cases}$$

(2) With FRI:

$$D_1^{cold} = \begin{cases} 0 & \text{if } \bar{v}/t \leq (1-\omega^C)/2, \\ \dfrac{2\bar{v}/t - (1-\omega^C)}{2\omega^C} & \text{if } (1-\omega^C)/2 < \bar{v}/t \leq (1+\omega^C)/2, \\ 1 & \text{if } \bar{v}/t > (1+\omega^C)/2. \end{cases}$$

Proof. **Part (1).** Without FRI, consumer i purchases iff $E[U_i] = \bar{v}/t - 1/2 \geq 0$, i.e., $\bar{v}/t \geq 1/2$. Since this condition is independent of (x_i^N, x_i^C), either all consumers purchase ($D_0 = 1$) or none do ($D_0 = 0$).

Part (2). With FRI, consumers learn x_i^C (but not x_i^N or v). The expected utility conditional on x_i^C is $E[U_i \mid x_i^C] = \bar{v}/t - \omega^C x_i^C - (1-\omega^C)/2$. A consumer purchases iff $x_i^C \leq c$, where $c = (\bar{v}/t - (1-\omega^C)/2)/\omega^C$. Since $x_i^C \sim U[0,1]$:

$$D_1^{cold} = \Pr(x_i^C \leq c) = \min\{\max\{c, 0\}, 1\}.$$

Note $c = 0$ when $\bar{v}/t = (1-\omega^C)/2$ and $c = 1$ when $\bar{v}/t = (1+\omega^C)/2$, yielding the stated piecewise expression. □

Proposition 3. *When no information is available from the online review system, $\Delta D^{cold} > 0$ if and only if*

$$\frac{1-\omega^C}{2} < \frac{\bar{v}}{t} < \frac{1}{2}.$$

Proof. From Lemma 4, $\Delta D^{cold} = D_1^{cold} - D_0^{cold}$. We evaluate across four regions.

(i) $\bar{v}/t \leq (1-\omega^C)/2$*:* $D_1 = 0$, $D_0 = 0$. $\Delta D = 0$.

(ii) $(1-\omega^C)/2 < \bar{v}/t \leq 1/2$*:* $D_1 = (2\bar{v}/t - (1-\omega^C))/(2\omega^C) > 0$, $D_0 = 0$. So $\Delta D > 0$.

(iii) $1/2 < \bar{v}/t \leq (1+\omega^C)/2$*:* $D_1 = (2\bar{v}/t - (1-\omega^C))/(2\omega^C)$, $D_0 = 1$. Then

$$\Delta D = \frac{2\bar{v}/t - (1-\omega^C)}{2\omega^C} - 1 = \frac{2\bar{v}/t - 1 - \omega^C}{2\omega^C} < 0,$$

where the inequality follows from $\bar{v}/t \leq (1+\omega^C)/2$.

(iv) $\bar{v}/t > (1+\omega^C)/2$*:* $D_1 = 1$, $D_0 = 1$. $\Delta D = 0$.

Hence $\Delta D^{cold} > 0$ if and only if $(1-\omega^C)/2 < \bar{v}/t < 1/2$. □

Appendix A.3 The Informativeness Level

Proposition 4 (Effect of Review Informativeness). *(1) The FRI click-through rate L is decreasing in α ($\alpha \uparrow$ leads to $L \downarrow$): more informative reviews reduce consumer motivation to engage the FRI. (2) As the number of reviews accumulate, the product demand change for both FRI-adopted (D_1) and non-adopted (D_0) cases depends on the trend of vertical value inferred from existing information.*