One Size Fits All? Informational Accessibility and Inclusivity in Online Platforms

(Authors’ names blinded for peer review)

Size inclusion has become a major issue in the fashion industry over the last decade. Over 67% of American women wear a size 14 or above, and top retailers have started offering a wide range of sizes. While inclusive sizing is becoming increasingly common among retailers, this change is not accompanied by increased information available for plus-sized consumers when making purchase decisions. In this study, we partner with a US-based apparel rental firm and leverage novel, large-scale review generation and click-level consumption data to study the conditions that lead to increased informational asymmetry for plus-sized users. First, we document a significant under-representation in reviews and photos from plus-sized users, despite uniform inventory distribution and rental activities across all users. Second, we utilize a Difference-in-Differences design to demonstrate that photo reviews from plus-sized users significantly increase purchases from the plus-sized population, evidencing that the under-representation of plus-sized users is particularly detrimental to sales among plus-sized users. Third, we deploy a policy study and a rental-level hierarchical model to elucidate the dynamics behind this under-representation and find that privacy acts as a key deterrent to plus-sized users’ active contribution of reviews and photos. Our study underscores the importance of privacy considerations in alleviating informational asymmetry for underrepresented populations on review platforms, especially since this asymmetry stems from social and cultural stigma.

Key words: Information Asymmetry, Diversity, Privacy, Size Inclusion, Photo Reviews

1. Introduction

In the last decade, popular media, ad campaigns, and activism have played a crucial role in bringing size inclusion and the lack thereof to the forefront of global consciousness. The fashion industry has long been criticized for lacking inclusion and discrimination along body-size lines (Lewis 2019). Interestingly, according to NPD, while the sale of plus-sized women’s apparel was over 21 billion dollars in 2016 and contributed to 6% of the overall apparel market, plus-sized brands represented only 2.3% of the total number of brands carried by the top multi-brand retailers. This is not due to lack of demand — according to a report by the firm Plunkett 67% of American women wear a size 14 or greater and often have limited fashion choices despite the explosion in online e-commerce platforms 1. To address the lack of diversity in body size, an increasing number of brands are now expanding their product lines to be more inclusive 2.

The increase in offerings from online retailers is not complemented by an increase in information for plus-sized consumers available online. On one hand, most of the photos of models provided by the retailer typically reflect small-sized users, perpetuating an industry standard that doesn’t reflect the diversity of its customer base. According to Maguire et al. (2023), of the 219 fashion shows in 2023 around the world, only 0.6% were from plus-sized models. On the other hand, user-generated content, a crucial resource for many consumers, is similarly lacking in representation. Despite the large purchasing power wielded by plus-sized consumers, they find themselves navigating a digital landscape marked by informational scarcity. The lack of plus-sized user-generated reviews serves to exacerbate information asymmetry, making it exceedingly challenging for plus-sized consumers to make informed purchasing decisions. This disconnect is particularly problematic given the importance of online reviews and user-generated content in shaping consumer choices. Therefore, our study seeks to probe these disparities, exploring the subsequent impact of the lack of representative information on consumer behavior and the reasons behind it.

Information asymmetry on e-commerce platforms can significantly decrease customer satisfaction and increase returns, and create other detrimental outcomes for platforms. Online reviews play a crucial role in alleviating this information asymmetry and help consumers make better decisions (Chatterjee 2001, Chen and Xie 2005, Chevalier and Mayzlin 2006, Forman et al. 2008, Moe and Schweidel 2012, Gao et al. 2015, Hu et al. 2006, Archak et al. 2011, Zervas et al. 2021, Hu et al. 2009b). However, studies in IS literature show that review platforms suffer from significant bias in online reviews because of acquisition bias (a consumer who buys a product is more likely to review the product) and underreporting bias (only consumers with extreme opinions are more likely to leave a review) leading to a “J-shaped” review curve (Hu et al. 2006, 2017, 2009a, Gao et al. 2015, Zervas et al. 2021). This literature has entirely focused on the experiential aspect of consumption and the decision to write reviews, but not on the user-level aspects that might prevent them from writing reviews.

Writing reviews is a significant act of altruism – one where the consumers strive to inform other consumers about product quality by expending considerable energy and time (Hennig-Thurau et al. 2004, Zhang and Zhu 2011, Qiao et al. 2020). However, when consumers write reviews, they cede some level of privacy by expounding on their experience, both positive and negative. A significant imbalance in the reviews can exist when privacy costs are high, an aspect unstudied in the current literature. In particular, privacy costs might be significantly high among consumers of certain body types due to societal stigma and lived experiences of anti-fat bias (Lin and Reid 2009, Bissell and Hays 2010, Teachman et al. 2003, Wang et al. 2004). This leads to a situation where plus-sized consumers
face more informational uncertainty when purchasing apparel because other plus-sized users face a higher privacy cost in writing reviews, exacerbating the cycle of informational asymmetry.

In this study, we first empirically document the nature of imbalance along the size lines and the resulting information asymmetry in user-generated content. Next, we show how reviews, particularly reviews with photos, from similar-sized users affect purchase decisions. Then, we demonstrate that reviews from similar-sized users are particularly important for plus-sized consumers who often encounter models extremely different from their own body types. Particularly, the review photos from plus-sized users increase the demand for a product. Finally, we tease out the mechanisms that might influence this imbalance in reviews.

To do so, we leverage large-scale, novel, proprietary consumer-click-level data from an apparel rental platform to empirically answer these questions. This platform operates on a subscription model, and users of the platform can rent clothes for a flat-fee similar to streaming platforms like Netflix. The platform requires the customers to provide star ratings for a product after the rental, but the decision to write reviews or add photos is completely optional, similar to other e-commerce platforms.

Since consumers of this platform are subscribers and thus, are repeat customers, we are uniquely positioned to observe the content generation, pre-consumption and post-consumption processes. Further, the platform collects information about the users’ size and preferences when they sign-up. Observational data obtained from e-commerce platforms usually have an issue of selection bias, where researchers cannot observe the consumers who don’t post reviews. However, unlike other papers in this literature, we can precisely identify consumers who rent a product and choose not to review the product. This data allows us to delve deeper to discover mechanisms of why consumers might write reviews and the conditions that can lead to a significant imbalance in reviews along size lines. We develop a multi-stage logit model to uncover the potential factors that can affect users’ decisions to post reviews and photos in reviews. In our model, we build a hierarchical decision structure to capture the decision-making process of a user in posting reviews and photos. Specifically, we highlight a privacy cost, which is identified by the decision of a user whether they disclose identity-related information when they post photo.

Our preliminary findings reveal that there is a significant under-representation in the reviews from plus-sized users. Interestingly, when plus-sized users leave reviews, they are less likely to leave reviews with photos (henceforth referred to as photo-reviews). However, our click-stream analysis shows that photo reviews from same-sized users play a significant role in increasing conversions from other same-sized users. Interestingly, this effect is highest among plus-sized users. This underscores the critical value and influence that plus-sized users’ photo reviews can exert on consumer behavior. Moreover,
utilizing a Difference-in-Differences design, we find that a review photo posted by a plus-sized user can increase the demand for a product by 6%.

Results from our hierarchical model suggest that same-size reviews tend to discourage users from posting their own reviews, as they reduce the altruistic motivation of a user. Conversely, the presence of photos in reviews, particularly those from users of the same size, appears to encourage others to share reviews and photos. Crucially, the model identifies that plus-sized users face the highest privacy costs, which deters their participation in online communities. This contributes to the issue of underrepresentation of plus size group in these spaces.

The implications of our study are far-reaching. We are the first in the literature to demonstrate how consumers who routinely face social stigma can be less motivated to contribute to the review ecosystem. We find that consumers who face social prejudice have increased privacy costs when deciding to write reviews. We find reviews from similar-sized users are particularly important in the context of apparel, especially for plus-sized users. The increase in privacy cost for plus-sized users to write reviews can in turn lead to significant negative externality for other plus-sized consumers on the platform — they have much lesser information to go by when making purchase decisions, especially since models provided by the platform are vastly different from the focal user.

Most platforms aim to increase user-generated content by trying to appeal to the altruism of the users (Burtch et al. 2018b, Goes et al. 2016, Gallus 2017, Huang et al. 2019, Khern-am nuai et al. 2018, Cabral and Li 2015). However, altruism is only part of the story. Privacy can play a significant role in contributing to the review ecosystem. By understanding the barriers inhibiting users with high-privacy cost from contributing to photo-inclusive reviews, platforms can design features to ameliorate privacy concerns. Platforms can also aim to increase information that is not user generated. If a subset of users makes sub-optimal choices due to reduced information, platforms should be explicitly inclusive in product descriptions. This can be accomplished by increasing the diversity of models. In domains with high privacy costs, increasing the diversity of models is not just an act of virtue signaling. This also empowers consumers with crucial information that can influence purchasing behavior especially when such information is rare in UGC due to privacy concerns.

2. Related Literature

Our study contributes to four streams of literature. First, we contribute to the literature on user-generated content (UGC), particularly around the motivation in contributing to online reviews. Second, we contribute to the literature on anonymity and how anonymity can affect the user’s decisions to contribute to UGC. Third, we contribute to the studies that investigate the consequences of social stigma. Finally, we add to the emerging field of creating inclusive digital platforms and inclusive marketing.
2.1. Role of UGC in Reducing Information Asymmetry

Information asymmetry refers to a situation where one party in a transaction possesses more or superior information compared to the other. It originates from the relationship between a seller and a buyer, as discussed in the context of the used car market by (George et al. 1970), where the seller has more information about the car’s condition. Similarly, in the labor market, as explored by (Spence 1978, Stiglitz 1975), a job seeker might have incentives to misrepresent their skills to an employer, who has limited information on the candidate’s actual capabilities. Information asymmetry can lead to adverse selection, where the party with less information risks selecting inferior products because the quality is misrepresented. Prior studies in this research find a negative impact on market efficiency and equality due to information asymmetry in various contexts, spanning from financial markets (Aboody and Lev 2000, Armstrong et al. 2011, Reuer and Koza 2000, etc.) to health care (Rochaix 1989, Blomqvist and Léger 2005, Khurana et al. 2019, etc.).

In the context of e-commerce platforms, buyers often cannot ascertain the quality of a product firsthand and thus suffer from information asymmetry. E-commerce platforms have adopted several techniques in the last two decades to mitigate information asymmetry. This includes providing elaborate descriptions of the products, photos and an elaborate system of online reviews. UGC in the form of online reviews plays a major role in mitigating information asymmetry, enabling consumers to make more informed decisions based on the experiences of others. There is a rich body of literature that has studied the economic value of online reviews (Chatterjee 2001, Chen and Xie 2005, Chevalier and Mayzlin 2006, Forman et al. 2008, Moe and Schweidel 2012, Gao et al. 2015, Hu et al. 2006, Archak et al. 2011, Zervas et al. 2021, Hu et al. 2009b). UGC not only helps consumers in reducing information asymmetry but also aids firms in improving their product quality using information from the consumers (Ananthakrishnan et al. 2023).

Despite the importance and the ubiquitous presence of online reviews, there is still significant information asymmetry on e-commerce platforms. Studies in the IS literature show that online reviews suffer from acquisition bias (a consumer who buys a product is more likely to review the product) and underreporting bias (only consumers with extreme opinions are more likely to leave a review) leading to a “J-shaped” review curve (Hu et al. 2006, 2017, 2009a, Gao et al. 2015, Zervas et al. 2021).

Information asymmetry poses significant economic challenges both for online retailers and customers alike since most platforms allow customers to return products online https://www.wsj.com/articles/those-new-online-returns-fees-are-driving-away-shoppers-2d3aa5fb. Consumers purchasing apparel online often cite fit and sizing among their top reasons to return the
products (Nestler et al. 2021). Returns have become a major issue for online apparel retailers. The National Retail Foundation estimates that customers returned over 800 Billion US Dollars worth of goods in the US during 2022. Surveys from Invesp, Forrester group and KPMG estimate the return rate to be between 30% and 50% of all online retail.

Therefore, despite significant efforts from online retailers to incorporate UGC on their platforms, the reduction in information symmetry depends on the quantity and quality of reviews. This, in turn, is closely tied to customers’ motivations to review products or services.

2.2. Motivations to contribute on UGC platforms

The motivations of individuals who to contribute to UGC on online platforms have been widely studied in the last decade (for a comprehensive literature review, please refer to ). Users who write reviews share their experiences, both positive and negative, with other customers trying to evaluate the quality of a product before making purchase decisions. Individuals who contribute to UGC devote a significant amount of time and effort in the process. The motivation to contribute to UGC can be intrinsic or extrinsic. Intrinsic incentives are utilities relate to creative expression, gaining attention, audience, or social recognition (Toubia and Stephen 2013, Zhang and Zhu 2011). Extrinsic incentives are factors that are stimulated by platform interventions, including monetary incentives (Burtch et al. 2018b, Khern-am mui et al. 2018, Cabral and Li 2015) and non-monetary incentives (Burtch et al. 2018b, Goes et al. 2016, Gallus 2017, Huang et al. 2019). In the context where users are allowed to post images, users can further gain image-related utility from posting images Toubia and Stephen (2013).

Intrinsic motivation can further be attributed to altruism (Hennig-Thurau et al. 2004, Zhang and Zhu 2011, Qiao et al. 2020). Altruistic incentives require personal resources to craft a review, recall personal experiences and take the time to express thoughts. However, they benefit other potential consumers with essential information about specific products and to caution others about items of subpar quality (Hennig-Thurau et al. 2004, Zhang and Zhu 2011, Qiao et al. 2020).

While altruism motivates users to contribute to online reviews for the benefit of others, self-enhancement (Wien and Olsen 2014) is a compelling internal drive that leads individuals to engage in behaviors aimed at improving their social image and self-worth. Unlike altruism, which focuses more on the collective benefit, self-enhancement is tied to personal decisions users make regarding what they choose to reveal about themselves. This can be prominently observed when users decide to include photos in their reviews. The act of sharing personal photos or images related to their

---

experiences with the product serves as an expressive tool for users to present themselves in a certain light, enhancing their online personas. In this way, users can strategically utilize their reviews to demonstrate their tastes, lifestyles, or expertise, seeking validation and recognition from the online community. This personal image curation and its ensuing rewards underscore the self-enhancement aspect of user motivations in online review participation.

The act of posting personal-related information may expose reviewers to potential privacy risks. Users might feel that their personal experiences, tastes, or even identities could be revealed, analyzed, and used without their consent (Bélanger and Crossler 2011, Lahlou 2008). In particular, sharing images might be considered as an explicit disclosure of personal information, as images can provide a wealth of details about the reviewer, including their appearance, surroundings, lifestyle, and more.

In our study, we consider the dimensions of altruism, self-enhancement, and privacy concerns into account when examining users’ motivation to participate in online review platforms. We consider the distinct differences among these three types of motivations that influence the users’ decision to post reviews and photos. Doing so, we address an important managerial question on what platforms should do to incentivize users, given significant privacy concerns, contribute on review platforms.

2.3. Anonymity

Anonymity is defined as a state of nonidentifiability or “noncoordinatability” of traits. Anonymity hides identifiable characteristics of an individual, ensures privacy and safeguards against unwanted identification (Wallace 1999). Anonymity is achieved when it becomes impossible to associate a known trait with other identifying characteristics. For instance, within an e-commerce context, a user who leaves a product review without disclosing their name retains anonymity, as the only known information is about their experience with the product or service. When names and/or profiles are linked to each review, anonymity is compromised as other consumers of the platform can tie the consumption of a specific product and the experience with a specific user.

Anonymity while contributing to online reviews is particularly salient when the disclosure of consumption could lead to some negative outcome such as stigmatization or discrimination for the person who wrote the review. For example, non-anonymous reviews of healthcare providers could potentially disclose the medical conditions that the reviewers sought care for, including conditions that could lead to social stigma or workplace discrimination. This could lead to self-censoring among reviewers for specific services or products. For example, there could be significant self-censoring among users on non-anonymous review platforms such as Yelp or Google reviews when they review mental health providers or prenatal health care providers since this information could lead to workplace discrimination. Further, non-anonymity on review platforms could lead to unpleasant interactions with the
service providers in the responses. Media reports suggest that some reviewers even get sued over negative reviews by the providers.

Thus, online platforms face privacy-related concerns, which can hinder user engagement, particularly on UGC platforms. Self-censoring due to privacy concerns over social stigma or fear could lead to significant loss of information for other potential customers of the platform. For example, non-anonymity could lead to self-censoring only negative reviews, which could disproportionately bias the reviews towards more positive reviews (Huang et al. 2017). Research indicates that robust privacy policies and assurances can mitigate these concerns, enhancing users’ willingness to share information and make purchases (Goodwin 1991, Hui et al. 2007, Tsai et al. 2011).

However, providing anonymity on platforms also has significant negative consequences, especially in diminishing social presence and credibility.

Thus, there is a significant academic and managerial gap in creating privacy policies on UGC platforms. On one hand, providing anonymity could help users in increasing credibility of UGC. On the other hand, non-anonymity could lead to self-censoring, particularly among users who routinely experience social stigma. This is the subject of our research.

2.4. Social Stigma

Finally, we contribute to the literature on social stigma and how stigma moderates users’ behavior on UGC platforms. Goffman and Goffman (1963) defines stigma as an attribute that deeply discredits an individual’s social identity. Building on this framework, Dudley (2000) characterizes stigma as the stereotypes or negative perceptions assigned to an individual or group when their traits or behaviors are perceived as different from social norms. Campbell and Deacon (2006) further outlines stigma into physical deformities, deviations in personal traits, and tribal affiliations, highlighting how these deviations from societal norms fuel stigma. Research indicates that stigma can have profound effects on individuals, including reduced access to resources (Clement et al. 2015), social isolation (Livingston and Boyd 2010), psychological distress (Corrigan and Watson 2002), and poor health outcomes (Hatzenbuehler et al. 2013).

The concept of body inequality primarily refers to the societal discrepancies and prejudices that exist about body size and shape. According to the categorization of stigma by Campbell and Deacon (2006), body inequality is classified as “overt or external deformities”. Research has widely demonstrated that cultural and media norms have historically favored slim, “ideal” body shapes, particularly for women, and such standards can lead to negative body image, low self-esteem, and even health

---

4 https://www.cnbc.com/2019/10/10/can-you-get-sued-over-a-negative-yelp-review.html
issues like eating disorders (Grabe et al. 2008, Spitzer et al. 1999). For instance, Grabe et al. (2008) illustrates how media exposure propagates thin-ideal internalization, body dissatisfaction, and disordered eating in women. Moreover, studies suggest that these body ideals can manifest in negative attitudes, stereotypes, and discrimination toward individuals who do not conform to these societal standards, particularly those who are overweight or obese (Pomeranz 2008, Brewis et al. 2011, Carels et al. 2018). Discrimination faced by plus-sized people has been well-studied. For example, O’Brien et al. (2013) demonstrate how anti-fat prejudice and affects the perception of leadership potential, starting salary, and overall employability. Plus-sized people are routinely stereotyped by educators (Neumark-Sztainer et al. 1999, Lynagh et al. 2015), at work and during hiring (O’Brien et al. 2007, Flint et al. 2016, Roehling 1999, Sartore and Cunningham 2007, O’Brien et al. 2013), by healthcare providers (Sabin et al. 2012, Schwartz et al. 2003, Pausé 2014, Lee and Pausé 2016, Teachman and Brownell 2001) and in social settings (Bartels and Nordstrom 2013, Crandall 1995, Carels et al. 2018). This discrimination and stereotyping also extends in the digital space. Stigmatized individuals exhibit reluctance to engage in online communities due to fear of judgment or discrimination (Lin and Reid 2009, Puhl and Heuer 2009). Anecdotal evidence suggests that body-shaming plus-sized celebrities and influencers on social media platforms are routinely subjected to harassment and unpleasant comments about their weight on digital media platforms.  

Privacy concerns associated with UGC platforms are likely to be amplified among plus-sized users to face widespread social stigma in their everyday lives. Therefore, plus-sized users might choose to self-censor their opinions on clothes, lest they receive negative feedback about their appearance instead of the product they are reviewing. This decision could be even more salient in reviews accompanied by photos.

Our study is the first in the literature to study the interplay between privacy, social stigma and the decision to participate on UGC platforms. We document a notable underrepresentation of plus-sized users in reviews and photos, despite the fact that they consume as much as non-plus sized users. This discrepancy underscores the deterrent effect of privacy concerns and societal biases against fuller body types, contributing to a cycle of informational asymmetry. This is especially important since the models on apparel product pages typically tend to be vastly dissimilar in body type to plus-sized users. In other words, plus-sized users face higher uncertainty about fit and sizing since over 99% of the models are not plus-sized, and this uncertainty is exacerbated by the fact that other plus-sized users are less likely to leave photo reviews due to privacy concerns and social stigma. Thus,

we contribute to the emerging literature on the design of inclusive platforms that foster engagement and interactions from all users by promoting a safe and welcoming digital environment (Holland and Tiggemann 2016, Mitkina et al. 2022).

3. Hypotheses Development

Prior literature on UGC has explored several motivations rooted in altruism or self-enhancement (Dichter 1966, Sundaram et al. 1998), often overlooking the pivotal role of privacy concerns. Any disclosure of voluntary information online leads to some level of privacy concern. This has been studied in the context of crowdsourcing platforms on how the incentive to contribute to a campaign changes for consumers with changes to the provision of information control features (Burtch et al. 2015) and how this can have downstream consequences of other users contributing to the campaign (Burtch et al. 2016). This effect is likely to be even more pronounced in the context of online reviews, which disclose the consumption of particular products or services. Wang (2010) provide descriptive evidence of how the presence of users’ names on Yelp might lead to more reviews compared to other platforms where this information is available. However, online review platforms are built on the fundamental altruism of users who are ready to share this information.

Privacy concerns on UGC platforms can be heightened under two circumstances. First, this occurs when the consumption information is sensitive. For example, a non-anonymous review of a physician who specializes in maternal health care might reveal that the user who wrote the review is likely to be pregnant, which is something that the user might not have liked to disclose. Similarly, consuming products that have social or cultural stigma might also heighten privacy concerns, lowering the likelihood of the user leaving a review post-consumption. This can happen if a user is reviewing a particularly violent movie or a salacious book. Second, there is significant heterogeneity among users in writing reviews Lin (2022) notably highlights the heterogeneity in privacy costs across different demographic groups. Writing reviews can heighten privacy concerns, particularly among users who have faced social stigma or public stereotyping in an offline context based on appearance, identity, or religion. Such users would have the highest preference for anonymity when it relates to revealing their offline identity in an online setting. This is even more so in the context of apparel reviews, where photo reviews are almost always photos of the users wearing the apparel.

Designing information controls can be crucial to ensure the delicate balance between addressing privacy concerns but also to provide enough information to users, especially among users who might feel judged on appearance. Interestingly, our partner firm has a unique design where users’ identities were not revealed in the text reviews during the period of our analysis. The only instance where users’ images could be revealed is in the photos (the users could choose to blur their faces with photo
editing tools available on most smartphone photo apps). However, in April of 2023, the platform decided to make all reviews (both text and photos) non-anonymous and other users could click on each reviewer’s name and view the reviewers’ rental history and other reviews.

If privacy concerns played a role in the production of UGC, we would observe a decrease in the number of supply of photo reviews after the change in platform design. Further, this reduction in photo reviews would be higher among users who face social stigma about their appearance. However, deanonymizing reviews would have no change in textual reviews since textual reviews do not reveal appearance-related information. This leads to our third, fourth and fifth hypotheses.

Plus-sized individuals may experience marginalization due to prevailing beauty standards that valorize thinness. Link and Phelan (2001) elaborate on such stigma, emphasizing its role in creating inequalities through processes of labeling, stereotyping, separation, status loss, and discrimination. Applying this to the realm of UGC, plus-sized users may be more hesitant to contribute user-generated photos due to fear of negative evaluation, social rejection, or online harassment (Puhl and King 2013). Fardouly et al. (2015) and Tiggemann and Slater (2013) have explored the impact of social media on body image concerns, suggesting that engagement with image-centric platforms can exacerbate self-objectification, body surveillance, and the internalization of thin ideals. For plus-sized users, the heightened visibility and focus on physical appearance inherent in UGC, especially photographs, may deter their active participation due to the anticipated or experienced body inequality within these platforms.

Integrating the concepts of social stigma and body inequality explains the hypothesized disparity of plus-sized users in UGC contributions. This disparity is not merely a matter of individual choice or preference but is deeply embedded in the structural and societal dynamics that govern digital spaces. Plus-sized individuals may navigate these spaces with an acute awareness of the potential for stigma and discrimination, which in turn influences their willingness to contribute content, especially content that is personally revealing, such as photographs. Based on this, we hypothesis the following,

**Hypothesis 1.** *Plus-sized users contribute less to UGC, especially photo reviews, compared to medium- or small-sized users.*

Information asymmetry can lead to market inefficiencies, where consumers, suffering from making a poor decision, may be hesitant to engage in transactions (George et al. 1970). User-generated content (UGC), especially user-generated photos, can significantly reduce information asymmetry by providing potential buyers with more accurate and relatable product representations. This is particularly relevant for the fashion industry, where fit, size, and appearance can vary widely and are crucial factors in the purchasing decision. User-generated photos offer a form of social proof and
a realistic portrayal of how products look on different body types, thus mitigating the risk perceived by consumers (Chevalier and Mayzlin 2006).

In the context of plus-sized products, the availability of user-generated photos from plus-sized users can be particularly impactful. Traditional marketing and product imagery often do not adequately represent the plus-sized demographic, leading to a higher level of information asymmetry and uncertainty for these consumers. By showcasing how products look on bodies similar to theirs, plus-sized users’ photos can significantly enhance trust and reduce the perceived risk, making potential buyers more comfortable and confident in their decision to rent or purchase. The reduction of information asymmetry through user-generated photos can directly influence consumer behavior, leading to increased sales. This is supported by the theory of perceived risk, which suggests that consumers’ willingness to purchase is inversely related to the perceived risk associated with that purchase (Mitchell 1999). By providing clearer, more relatable, and trustworthy information, UGC can lower perceived risk, thereby encouraging transactions. In the case of products targeted at plus-sized demographics, user-generated photos from plus-sized users align closely with the needs and concerns of the target audience, making them more effective in reducing information asymmetry and enhancing sales or rentals.

**Hypothesis 2.** *Photo reviews from plus-sized users increase the rentals of products targeted at plus-sized demographics.*

Anonymity in online platforms can encourage free expression and reduce the fear of judgement or retaliation, as users feel more secure when their real identities are not disclosed (Joinson 2001). Especially when it comes to sharing personal content, such as photo reviews, anonymity shields users from direct personal critique and social stigma. Acquisti and Gross (2006) argue that privacy concerns are also a significant factor influencing online behavior, including the willingness to share personal information. The disclosure of personal identifiers, such as names, can exacerbate these concerns, especially when sharing content that might be subject to scrutiny or judgement, like photographs depicting one’s body. Users may fear negative feedback, which can be more personally targeting when their real identity is known, leading to a reluctance to post such content.

**Hypothesis 3a.** *The disclosure of users’ identities, specifically through revealing their names, discourages users of all size groups from posting photo reviews.*

The negative effects of online identity disclosure are particularly pronounced for plus-sized users. While concerns regarding privacy are common across all size groups, plus-sized individuals face an additional layer of vulnerability due to the heightened social stigma associated with body size, as discussed previously. For plus-sized individuals, revealing personal identifiers such as names and faces
exposes them to potential body shaming and targeted harassment (Puhl and Heuer 2009). Hence, it may significantly reduce their participation in activities like posting photo reviews. Anonymity serves as a crucial protective mechanism against such stigma, offering a shield against direct personal critique and discrimination. Consequently, revealing their identities is likely to influence plus-sized users the most compared to their medium- and small-sized counterparts. Therefore, we propose the following:

**Hypothesis 3b.** The disclosure of users’ identities, specifically through revealing their names, most significantly deters plus-sized users from posting photo reviews.

**Hypothesis 3c.** The disclosure of users’ identities, specifically through revealing their faces, most significantly deters plus-sized users from posting photo reviews.

4. **Data and Variables**

4.1. **Platform and Context**

We have partnered with a US-based clothing rental platform that operates on a subscription model, catering specifically to professional women. This platform offers customers the opportunity to rent apparel for a fixed monthly charge. Our partner firm allows customers to choose a certain number of items to rent each month, depending on their subscription tier. The selected items are shipped to the customer as a complete package, which they can wear for up to one month before exchanging them for a new set. After each rental period, the returned items are cleaned at the processing center and re-listed on the platform. Customers are encouraged to leave reviews for the items they rent, either in the form of text or photo reviews. If customers are unsatisfied with specific pieces in their package, they have the option to return those items, and the company will ship replacements.

However, this process can be costly for both the company and the customers if the wrong rental choices are made. To minimize these instances and ensure customer satisfaction, the platform strives to provide accurate information that facilitates informed decision-making, as shown in Figure 1. One of the most crucial aspects of the platform is the incorporation of text and photo reviews from previous customers. These reviews serve as valuable resources for potential renters, allowing them to gain insights into the fit, quality, and overall experience with specific items. By relying on the collective feedback of the community, customers can make more confident rental choices, reducing the likelihood of dissatisfaction and the need for returns.

4.2. **Data**

Through our partnership, we acquired a proprietary longitudinal dataset that encompasses the platform’s product offerings and their rentals over time, as well as the users on the platform, including their demographic information, rental patterns, and product reviews.
Our data covers a two-year period from January 1, 2021 to December 31, 2022. In total, we collect 11,445 active users of 66,543 pieces of items rental data until December 2022. During this time, there are 343,821 rental records, 103,540 online reviews, and 17,421 review photos. Each rental record in our dataset is detailed, including

- Product information: This includes the style, color, occasion, price, and the date the product became available on the platform. Note that there could be multiple items for each product.
- User information: This includes the user’s age, body size, and the date they joined the platform.
- Rental information: This includes the timestamp of the rental, the rating given by the user, and any associated reviews and/or review photos. Note that there could be only at most one review but multiple review photos associated with a rental.

4.3. Variables and Summary Statistics

In this study, we aim to address two key research questions. First, we explore whether the body size depicted in photos posted by users affects the future demand of a product. This dataset enables us to examine how product demand varies weekly and assess if various factors, including the depicted body size in user photos, have an impact on the demand. For this part of our study, we aggregate the rental data into an item-week panel dataset. Second, we investigate what factors deter the motivation of plus-sized individuals from posting review photos. For this part of our study, we utilize a rental-level

---

6 During this period, the platform did not implement any policy change that is relevant to our research context. In later sections, we performed a study of policy intervention happening in April 2023. For that specific analysis, we used the data from January 2022 to November 2023.

7 We define active users as those who have rental activity in our observation period.
dataset and consider the review/review photo posting behavior as an independent choice for a user after each rental.

4.3.1. Item-week level panel data For the item-week level panel data, we first filter items that are plus-sized to sharpen our focus on the demand patterns of plus-sized consumers. We next aggregate the data at the item-week level and in total, we have 90,291 item-week observations. Furthermore, we define the weekly demand for each item on the platform as the ratio of the number of days the product is rented out to the number of days it is available for rent. For instance, if an item is returned by a customer and is unavailable for a period due to cleaning, its availability that week might be just 5 days instead of 7 days. If the item, after being available for one day, is then rented out, the demand for that week is calculated as 4/5. Conversely, if a customer keeps the product for an entire week, the demand for that week is expressed as 7/7. This approach to measuring demand reflects the interplay between product availability and rental activity, paralleling demand assessment methodologies used in similar rental platforms like Airbnb, as discussed in Zhang et al. (2022).

The main variable of interest is from AfterPlusPhoto_{it}, defined as whether there is a plus-sized photo associated with the product for item i at period t. This panel data allows us to effectively control for item-level, time-invariant characteristics such as categories, styles, and colors. For time-variant characteristics at the item level, we consider influences from three sources:

- Customer Attention: We also track the total number of clicks TotalClick received for an item in each period to capture the difference in the customer attention for each product in each period.
- Review and rating accumulation: We also track the cumulative impact of user reviews and ratings. We calculate AccReview for the cumulative number of reviews, and AvgRating for the cumulative average ratings.
- Seasonality effect: For instance, a dress designed for summer is likely to see increased demand in that season. To account for this, we incorporate a product-quarter level fixed effect, controlling for different seasonal trends for each product.

Table 1 summarizes the definitions and summary statistics of all item-week observations.

4.3.2. Review posting data We next look into the review posting data. We consider three consumer choices post each rental: no review, posting a review without a photo, posting a review with a photo. Therefore, we construct two binary variables related to each rental Review_r and Photo_r for each rental. The main effect of interest is how the size of each individual affect the review/photo posting behavior.

To have an idea of the differences in review and photo posting behavior among users of different size groups and provide evidence that there exists a significant imbalance in online reviews along
Table 1  Summary Statistics of Item-Week Panel Data

<table>
<thead>
<tr>
<th>Variable Definition</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome Variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Demand</td>
<td>0.48</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>The ratio of the number of days the product is rented out to the number of days it is available for rent for item $i$ at period $t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Independent Variable:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AfterPlusPhoto</td>
<td>0.05</td>
<td>0.22</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1 if there is a plus-sized photo associated with the product for item $i$ at period $t$, 0 otherwise</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TotalClick</td>
<td>9.43</td>
<td>11.84</td>
<td>1</td>
<td>228</td>
</tr>
<tr>
<td>Total number clicks received by item $i$ at period $t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AccReview</td>
<td>9.29</td>
<td>10.75</td>
<td>1</td>
<td>140</td>
</tr>
<tr>
<td>Cumulative number of reviews received by the product associated with item $i$ at period $t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RatingAvg</td>
<td>3.74</td>
<td>0.80</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Cumulative average rating by the product associated with item $i$ at period $t$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

size lines in online review behavior, we first categorize all users into three groups based on their sizes: small-sized group (size below 6), medium-sized group (size from 6 to 12), and plus-sized group (size above 12). The distribution of rentals, reviews, and review photos across different size groups is displayed in Figure 2a, 2b, and 2c, respectively. We observe that the rental distribution is comparable to the review distribution based on the comparison between Figure 2a and 2b. This indicates that a similar percentage of rentals from each group lead to reviews. However, in Figure 2c, there is a notable decrease in the amount of photo reviews for the plus-sized group in comparison to the other two groups. This finding provides initial evidence that plus-sized users are underrepresented in online photo reviews.

In our study, we also explore various other factors that could affect user behavior regarding review and review photo postings. This includes the user’s experience of a particular rental, captured by UserRating, and the influence of existing feedback, as indicated by the quantity of accumulated reviews (TotalFeedback) and photos (TotalPhoto) until the rental happens. Additionally, we consider the existing average ratings (AvgRating) of items, which might impact user perception. Item-specific
attributes such as the price (Price) and duration on the platform (ItemAge) are also taken into account, as they could influence user interactions with the item. The tenure of the user on the platform (UserTenure) and their age (UserAge) are further variables included in our analysis. To specifically understand the impact of body size in the context of reviews and photos, we also construct variables SameSizeReview and SameSizePhoto, which calculate the percentage of reviews and review photos respectively, coming from users who share the same body size as the user of the rental. This allows us to differentiate the effects of reviews and photos between same-size and different-size users. Table 2 summarizes the definitions and summary statistics of variables for the review posting data.

Table 2 Summary Statistics of Review Posting Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Outcome Variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Review</td>
<td>1 if a review is posted after a rental, 0 otherwise</td>
<td>0.37</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Photo</td>
<td>1 if one or more photos are posted after a rental, 0 otherwise</td>
<td>0.03</td>
<td>0.18</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Face</td>
<td>1 if one or more photos are posted with the face after a rental, 0 otherwise</td>
<td>0.03</td>
<td>0.17</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Independent Variables:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SmallSize</td>
<td>1 if the user associated with the rental is small-sized, 0 otherwise</td>
<td>0.35</td>
<td>0.48</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>LargeSize</td>
<td>1 if the user associated with the rental is plus-sized, 0 otherwise</td>
<td>0.21</td>
<td>0.41</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>UserAge</td>
<td>The age of the user associated with the rental</td>
<td>42.24</td>
<td>7.74</td>
<td>11.38</td>
<td>123.20</td>
</tr>
<tr>
<td>Price</td>
<td>The price paid by the platform for the item associated with the rental</td>
<td>70.80</td>
<td>44.11</td>
<td>0</td>
<td>525</td>
</tr>
<tr>
<td>UserRating</td>
<td>The user’s rating of the rented item</td>
<td>4.02</td>
<td>1.09</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>UserTenure</td>
<td>The tenure of the user since the date that the user joined the platform</td>
<td>1.66</td>
<td>1.48</td>
<td>0.00</td>
<td>6.04</td>
</tr>
<tr>
<td>UserTotalFeedback</td>
<td>The total number of reviews from the user prior to this rental</td>
<td>206.86</td>
<td>244.77</td>
<td>0</td>
<td>1306</td>
</tr>
<tr>
<td>AvgRating</td>
<td>The average rating of the item prior to this rental</td>
<td>3.95</td>
<td>0.46</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>TotalFeedback</td>
<td>The total number of reviews received by the item prior to this rental</td>
<td>17.58</td>
<td>20.19</td>
<td>0</td>
<td>259</td>
</tr>
<tr>
<td>TotalPhoto</td>
<td>The total number of photos received by the item prior to this rental</td>
<td>1.64</td>
<td>2.29</td>
<td>0</td>
<td>24</td>
</tr>
<tr>
<td>PhotoAesthetic</td>
<td>The aesthetic score of the photo posted by the user, if any</td>
<td>0.14</td>
<td>0.77</td>
<td>0</td>
<td>6.06</td>
</tr>
<tr>
<td>ItemAge</td>
<td>The number of years since the first day that the item is available on the platform</td>
<td>1.69</td>
<td>1.19</td>
<td>0</td>
<td>6.04</td>
</tr>
</tbody>
</table>

Note: The statistics for RetailPrice are reported after rescaling due to the nondisclosure agreement.

5. Empirical Evidence

In this section, we seek to verify hypotheses 1 and 2. First, we establish that there is a marked difference in the way plus-sized women contribute to UGC which can in turn exacerbate the informational asymmetry. Second, we demonstrate why this informational asymmetry is important. Our rich data
allows us to observe purchase decisions before and after a photo review is provided. We provide evidence of how photo reviews from similar-sized users are more likely to influence subsequent purchase decisions, and how this effect is particularly salient among plus-sized users.

5.1. Photo Review Posting Behavior Across Different User-Sizes

To gain insights into different review and photo review posting behavior across user size groups, we formulate the following regression model to provide model-free evidence:

\[
Y_r = \beta_0 + \beta_1 \text{Plus}_u + \theta \text{Control}_r + \delta_t + \lambda_i + \epsilon_r, \quad (1)
\]

In Equation 1, \( r \) represents a rental from user \( u \) for item \( i \) at time \( t \). We consider two binary dependent variables (\( Y_r \)): whether the user \( u \) posts a review and whether the user posts a review photo for rental \( r \). \( \text{Plus}_u \) is a binary variable indicating if the user \( u \) is from the plus-sized group. In addition to each user’s size, we also include the user’s age (\( \text{Age}_r \)) and the duration of their membership on the platform (\( \text{UserTenure}_r \)) as control variables. We further include \( \log(\text{AccReviews})_r \) to account for the number of reviews of an item \( i \) at rental time \( t \), and \( \text{RatingAvg}_r \) to control for the accumulated rating of item \( i \) at time \( t \). The variable \( \text{ItemAge}_r \) represents the time interval from when item \( i \) first became available on the platform until time \( t \). Week-level fixed effects \( \gamma_t \) are included to manage common calendar shocks, while \( \lambda_i \) accounts for item-specific characteristics.

Table 3 demonstrates the variations in online review behavior among different size user groups. Our results show that plus-sized users show a marked decrease in the likelihood of posting reviews or photo reviews after renting, indicated by coefficients of -3% and -1% respectively, compared to their small or medium-sized counterparts. These results highlight a notable imbalance in review and photo review contribution behaviors across different size groups, emphasizing a particular under-representation of plus-sized users in both reviews and photos. It is also important to note that in the duration of this analysis, the reviews were anonymous and the only way the users can reveal their identity is via photos, as demonstrated in Figure 3.

This finding suggests that the likelihood of contributing to UGC is correlated with the users’ size, controlling for user and product-related characteristics. Further, the users’ size also affects the likelihood of leaving photo reviews on the platform. This confirms our hypothesis H1 and furthers the argument that users facing significant social stigma in everyday life might be less likely to participate in online forums, especially in situations that decrease their anonymity. Thus, there is a significant impact of users’ size on their decision to participate in the supply side of UGC leading to informational asymmetry. Next, we analyze if this informational asymmetry can have any ramifications on the demand.
Table 3  Review and Review Photo conversion

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Review</td>
<td>Photo</td>
</tr>
<tr>
<td>Large</td>
<td>-0.03***</td>
<td>-0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>UserAge</td>
<td>0.00***</td>
<td>-0.00***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>UserTenure</td>
<td>-0.03***</td>
<td>-0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Experience</td>
<td>-0.03***</td>
<td>0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>ItemAge</td>
<td>0.17***</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Log(AccReview)</td>
<td>-0.14***</td>
<td>-0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>AvgRating</td>
<td>-0.02*</td>
<td>-0.01*</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.45***</td>
<td>0.08*</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Year-Month FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Item × Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>163400</td>
<td>163400</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.421</td>
<td>0.418</td>
</tr>
</tbody>
</table>

Standard errors clustered at the item level are in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

The unit of analysis is rental (r) level.

Figure 3  An Example of a Review

This was super cute and flattering! The fit was generous overall - the one place it was a bit tight was in the arms. A shame because that made it a little bit less comfortable to wear in the summer. Great work dress!

Size rented: 2  •  Fit: Runs large
Usually wears: 2-4  •  Height: 5’7”  •  Bust: 36B

5.2. Impact of Plus-sized Review Photos on Demand Among Plus-sized Users

In this section, we study how plus-sized users affect the demand for a product. The product page on the platform is not static — each item accrues reviews over time as users consume them over time. In other words, the information available to each customer visiting a product page varies based on the information present in reviews at a particular time $t$. Thus, a customer visiting an item with
no reviews only has the baseline information provided by the platform (description and the model) while the customer visiting an item with textual and or photo reviews has more information. The variation in the level of information available to each customer provides us with the identification, which we exploit in our analysis.

Further, unlike other observational studies in the online review literature (e.g., Chevalier and Mayzlin 2006, Zervas et al. 2021) which mostly rely only on reviews written on a platform, we have a unique opportunity to observe the demand for any item $i$ in week $t$ at a subscriber level as the item gets more reviews. This presents us with a way to identify how reviews impact demand. In this analysis, each item refers to each unique product that is available for rental on a platform. Each item $i$ is available in multiple sizes. If a plus-sized user rents an item $i$ in her size, she can choose to write a textual review and/or leave a photo review after her rental. The timing of a photo review from a plus-sized user for an item is exogenous to the demand for the product at that time. This identification assumption is further strengthened by the fact users can review the item at any point during their use or immediately after sending it back. There is a large variance in the timing of a photo review as shown in Fig 4. This variance in turn affects the information available to each customer of each item when they visit the product page. For example, user A at time $t_1$ might not have seen a photo review, while user B at time $t_2$ sees a photo review and thus has more information. We exploit this informational shock to determine how the demand for the item $i$ changed before and after a photo review from a plus-sized user.

This presents us with Difference-in-Differences (DiD) framework. We consider an item to be treated as soon as it receives the first plus-sized photo review. This implies that each item gets treated at a different point in time, which provides us with a staggered variation. In the staggered adoption framework, each untreated item (the items that have not yet received any photos from plus-sized users) serves as a control for the treated category until it gets treated.

We write down the model as below

$$y_{it} = \beta_0 + \beta_1 \text{AfterPlusPhoto}_{it} + \gamma \text{Control}_{it} + \delta_q \times \lambda_i + \mu_t + \varepsilon_{it}$$  \hspace{1cm} (2)$$

Here the outcome variable is $y_{it}$, which is the demand (measured by rentals) from plus-sized users for item $i$ in week $t$. We denote the treatment as $\text{AfterPlusPhoto}_{it}$. Since the information to plus-sized users increase substantially after the item receives the first plus-sized photo, $\text{AfterPlusSized}_{it}$ remains 1 from the week $t$ when it received the first plus-sized photo (Proserpio and Zervas 2017, Chevalier et al. 2018, Ananthakrishnan et al. 2023).

$^8$ Given that items without a plus-sized inventory can only have demand $= 0$, we exclude these items from our analysis.
\( \beta_1 \) is the coefficient of interest and provides us with the average treatment effect (ATE), which is the average difference of the differences between the average outcomes of the treated and the control products in each period. We add item-level fixed effects for item-level time invariant characters like such as brand, style which can influence the demand and time-fixed effects to account for the common calendar shock that could influence demand for all products, following prior literature (Autor 2003, Angrist and Pischke 2009, Greenwood and Wattal 2017, Burtch et al. 2018a). In addition to adding the two-way fixed effects, we include item-quarter interaction fixed effects to control for seasonal effects that affect the demand for specific products. For example, red and party dresses are more likely to be in demand during the holiday season, while flowy or linen dresses are in higher demand during the summer. This changes in seasonal demand tied to each product is captured by the item-quarter fixed effects (Zervas et al. 2017).

Our unique dataset also allows us to add a series of control variables. We add the total number of reviews each product has received at time \( t \), the cumulative average rating at time \( t \), and the number of clicks received by this item at \( t \) (to control for interest in item) as shown in §4.3.1. We estimate this model using a matched-sample procedure (Xu et al. 2017, Chan and Wang 2018). There is a large long tail of items (over 75%) that are never rented on the platform, and we remove these items from our analysis.

Table 4 shows the estimation results of our DiD design. Specifically, Column (1) presents the results without the control variable and Column (2) presents the results with the control variables included.
The coefficient of AfterPlusPhoto is positive and significant, indicating that a review photo from a plus-sized user positively influences product demand. On average, a photo from a plus-sized user is associated with a 10% increase in demand.

For the DiD analysis to be valid, we verify the parallel trend assumption. We do so by replacing the AfterPlusPhoto with the months since treatment for five periods before and after the treatment. Figure 5 shows the event study estimates using the TWFE estimator. Reassuringly, there are no significant differences between the control and treated groups in the pre-period thus verifying the parallel trends assumption. We also show that there is a significant increase in demand among plus-sized users in the periods after the reception of the first plus-sized photo.

Table 4 Impact of Photos from Plus-sized Users on Demand

<table>
<thead>
<tr>
<th></th>
<th>(1) demand</th>
<th>(2) demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>AfterPlusPhoto</td>
<td>0.12***</td>
<td>0.10***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>TotalClick</td>
<td>-0.01***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>Log(AccReview)</td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td>RatingAvg</td>
<td>-0.06*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>DaysOpen</td>
<td>0.03***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.47***</td>
<td>0.67***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Item FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Week FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Item*Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>148969</td>
<td>90291</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.550</td>
<td>0.563</td>
</tr>
</tbody>
</table>

Standard errors clustered at the item level are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01
The unit of analysis is item (i) - week (t) level.

Recent studies have raised some concerns about negative weights in the staggered DiD estimation using TWFE estimators (De Chaisemartin and d’Haultfoeuille 2020, Sun and Abraham 2021, Goodman-Bacon 2021). To address this issue, we present the main results using the estimator proposed by Callaway and Sant’Anna (2021) (henceforth referred to as CS). We find consistent results. We show the event study estimates from the CS estimator in Figure 6.

Together, our analysis shows the importance of photo reviews from plus-sized users for other plus-sized users, thus confirming hypothesis H2. Our findings suggest the presence of significant
information asymmetry among plus-sized users, and how removing this asymmetry could benefit other plus-sized users. This leads to our next question — what are the main drivers of this information asymmetry? What can platforms do to alleviate this informational asymmetry? We address this in the next section.

6. Mechanisms

In this section, we aim to uncover the mechanisms contributing to the imbalance in review photos among various uses of different size groups. In the theoretical section, we explored several reasons that might drive the intent to contribute to UGC. In this section, we will provide evidence of the potential mechanisms contributing to the imbalance in review photos among users of different sizes and verify the hypotheses derived in from the theoretical section.
6.1. The Role of Privacy

Our partner platform initially only displayed the reviews and anonymized the reviewers’ names. In April 2023, our partner platform implemented a major change to its review page by displaying the names of reviewers. Further, other subscribers to the platform could click on the reviewers’ profile and view their rental history on the platform. This significant change in informational control could lead to two potential outcomes. On one hand, deanonymizing reviewers’ names could boost the production of reviews, as reviewers might be incentivized to enhance their status on the platform. On the other hand, deanonymizing reviewers’ names could heighten privacy concerns, particularly for photo reviews, where other subscribers could view the photos and also the profiles of the reviews posting photo reviews. This privacy concern might be even more salient among plus-sized users. Therefore, this policy change presents an ideal backdrop for our investigation into how privacy concerns influence users’ willingness to post reviews and photos as described in hypotheses H3-H5.

To do so, we estimate following model:

\[ Y_{r} = \beta_0 + \beta_1 \text{AfterPolicy}_{r} + \beta_2 \text{AfterPolicy}_{r} \times \text{Plus}_u + \delta_i \times \lambda_i + \mu_t + \gamma_u + \epsilon_{it}, \]  

(3)

In Equation 3, \( Y_r \) is the dependent variable. This refers to \( \text{Review}_r \) or \( \text{Photo}_r \), indicating whether a review or photo review is posted following a rental. \( \text{AfterPolicy}_r \) is a binary variable that indicates if the rental \( r \) occurred after the deanonymization policy change. The coefficient of the interaction term between \( \text{AfterPolicy}_r \) and \( \text{Plus}_u \) captures the potential differential effects of the policy change among users of different sizes. We include the user-level fixed effect to account for time-invariant user-level characteristics that might influence their decision to write reviews. Similar to the analysis in §5.1, we also include the \( \text{Experience}_r \) as control as well as the Year-Month FE and Item-Quarter fixed effects.

We run this model using all the rental data from Jan 2022 to Nov 2023\(^9\). The results are provided in Table 5. Column (1) of Table 5 indicates that deanonymizing reviews do not have a significant effect on textual review posting behavior, verifying hypothesis H3. The policy change did not impose additional privacy costs on plus-sized users in the context of review postings. However, the scenario differs for photo postings. Post-policy, there is a noticeable decline in photo postings specifically among plus-sized users, thus confirming hypotheses H3 and H4. Together, these results suggest that there is a significant heterogeneity in privacy concerns. Further, privacy concerns can significantly reduce the generation of UGC among plus-sized users. This differential impact underscores the importance of considering varying privacy costs in designing informational controls that can balance privacy concerns and yet, provide incentives for users to contribute to UGC platforms.

\(^9\) For all other analyses, we used data from Jan 2021 to Dec 2022.
Table 5  Impact of Privacy Policy Shock on Review and Photo Posting Behavior

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Review</td>
<td>Photo</td>
</tr>
<tr>
<td>After</td>
<td>0.001</td>
<td>-0.013***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>After × Large</td>
<td>-0.007</td>
<td>-0.008***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Experience</td>
<td>-0.039***</td>
<td>0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.562***</td>
<td>0.012***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Year-Month FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Item × Quarter FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>User FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>240520</td>
<td>240520</td>
</tr>
<tr>
<td>R²</td>
<td>0.748</td>
<td>0.755</td>
</tr>
</tbody>
</table>

Standard errors clustered are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01
The unit of analysis is at rental level.

6.2.  The Mechanisms of Review and Photo Posting

Finally, we delve into exploring the mechanisms that guide users of different sizes in posting reviews and photos. Following Toubia and Stephen (2013), we first consider two types of utility that guide the decision of review and review photo posting of each user: intrinsic utility, which influences the decision to post a review, and image-related utility, which comes into play when adding a photo to the review. Furthermore, to understand the varying privacy concerns across user groups with different body sizes, we examine the reluctance associated with sharing identity-revealing information, particularly through face-revealing photos in reviews.

6.2.1.  Model Setup

We assume that each customer follows a 3-stage decision making process when deciding posting a review, review photo with and without identity-related information.

Stage 1: Review Posting Decision

After each rental, users assess their experience and existing reviews. The utility of posting a review is determined by:

\[ u_{\text{review},ijtr} = \beta_0 + \beta_1 X_{ijtr} + \varepsilon_{ijtr} \]

\[ \text{Review}_{ijtr} = 1, \text{ if } u_{\text{review},ijtr} > 0 \]

Where \( X_{ijtr} \) represents factors affecting the intrinsic utility of posting a review. Specifically, we consider characteristics of existing reviews of this product, (including the total number of existing feedback,

\[ 10 \text{ For examples of both face-revealing and non-face-revealing review photos, please see Online Appendix A.} \]
total number of existing photos, percentage of same-size feedback, percentage of same-size photo), the characteristics of this product (average rating, price of the product, the length since the product is on this platform), the experience of this rental (user $i$’s rating of this product), and the characteristics of this user (user $i$’s tenure on the platform, age, size).

**Stage 2: Photo Posting Decision**

If a review is posted, the user then decides whether to add a photo. The utility of posting a photo is expressed as:

$$u_{\text{photo},ijtr} = \beta_0^2 + \beta_2^2 X_{ijtr} + \gamma^2 W_{ijtr} + \varepsilon_{ijtr}^2$$

$$Photo_{ijtr} = 1, \text{ if } u_{\text{photo},ijtr} > 0 \text{ and } Review_{ijtr} = 1$$

We integrate both the fundamental characteristics, denoted as $X_{ijtr}$, and the unique photo-related features, represented by $W_{ijtr}$. Specifically, we consider the aesthetic score of the photo.

**Stage 3: Identity Disclosure Decision**

Following the decision to post a photo, the user contemplates revealing identity-related information. The utility for sharing a photo with a face, incorporating privacy costs, is calculated by:

$$u_{\text{face},ijtr} = \beta_3^3 + \text{SmallSize}_i + \text{MediumSize}_i + \text{PlusSize}_i + \gamma^3 W_{ijtr} + \varepsilon_{ijtr}^3$$

$$Face_{ijtr} = 1, \text{ if } u_{\text{face},ijtr} > 0 \text{ and } Photo_{ijtr} = 1$$

For identification purposes, we normalize $\text{MediumSize}_i$ to zero. We also include the quality of the photo to capture the correlation between the photo’s quality and the decision to disclose identity-related information.

**6.2.2. Model Estimation** We specify the distribution of $\varepsilon_{ijtr}^1$, $\varepsilon_{ijtr}^2$, and $\varepsilon_{ijtr}^3$ as i.i.d. (independently and identically distributed) logistic distribution, the model is essentially a multi-stage logit model. Given the utility specifications provided and assuming that $\varepsilon_{ijtr}^1$, $\varepsilon_{ijtr}^2$, and $\varepsilon_{ijtr}^3$ are i.i.d. following a logistic distribution, the likelihood function of the described multi-stage logit model can be derived.

For Stage 1 (posting a review):

$$P(Review_{ijtr} = 1) = \frac{e^{u_{\text{review},ijtr}}}{1 + e^{u_{\text{review},ijtr}}}$$

$$P(Review_{ijtr} = 0) = 1 - P(Review_{ijtr} = 1)$$

For Stage 2 (posting a photo, given a review):

$$P(Photo_{ijtr} = 1|Review_{ijtr} = 1) = \frac{e^{u_{\text{photo},ijtr}}}{1 + e^{u_{\text{photo},ijtr}}}$$

$$P(Photo_{ijtr} = 0|Review_{ijtr} = 1) = 1 - P(Photo_{ijtr} = 1|Review_{ijtr} = 1)$$
For Stage 3 (showing a face in the photo, given a photo):

\[
P(\text{Face}_{ijtr} = 1|\text{Photo}_{ijtr} = 1) = \frac{e^{u_{\text{face},ijtr}}}{1 + e^{u_{\text{face},ijtr}}}
\]

\[
P(\text{Face}_{ijtr} = 0|\text{Photo}_{ijtr} = 1) = 1 - P(\text{Face}_{ijtr} = 1|\text{Photo}_{ijtr} = 1)
\]

Given the independence across observations, the likelihood for each individual can be expressed as the product of the probabilities across the three stages. Thus, the likelihood function \( L \) for a given observation can be expressed as:

\[
L = P(\text{Review}_{ijtr}) \times P(\text{Photo}_{ijtr}|\text{Review}_{ijtr}) \times P(\text{Face}_{ijtr}|\text{Photo}_{ijtr})
\]

For a dataset, the likelihood is the product of \( L \) across all observations. This function captures the probabilities of the decisions at each stage based on the utilities. We further apply the maximum likelihood to estimate the model parameters.

6.2.3. Model Result Table 6 shows the result of parameter estimates. At the stage of review, users exhibit lower likelihoods as the volume of existing feedback, especially feedback of similar size, increases. This suggests a diminishing altruistic incentive when there is an abundance of reviews. In contrast, the presence of more photos, particularly of similar size, encourages users to share their reviews. Additionally, higher product prices and lower user ratings positively affect review posting. Furthermore, older users demonstrate a higher probability of review posting compared to their younger counterparts. Additionally, we find that medium-sized users are the most motivated to post reviews, while small and plus-sized users exhibit a lower level of incentive in review posting. Furthermore, older users tend to post reviews more frequently than younger users, contributing to a nuanced understanding of user behavior.

At the stage of photo decision, we find that a similar dynamic unfolds regarding existing reviews and photos. Users are less inclined to share photos when a product accumulates more reviews but more likely to do so with a growing number of existing photos. Notably, users with higher ratings exhibit a greater likelihood of posting photos. Moreover, the likelihood of posting a photo increases with a higher aesthetic score of the photo. Mirroring the findings in review posting, medium-sized users are the most motivated to post photos, followed by small-sized users. Interestingly, younger users exhibit a stronger inclination to share photos than their elder counterparts.

In the decision-making stage of whether to post a photo with a face, we can discern the impact of privacy concerns when posting identity-related information. Our findings reveal that plus-sized users incur the highest privacy costs, which discourage them from sharing photos containing faces. Similarly, small-sized users also contend with relatively elevated privacy costs. In summary, it becomes evident that plus-sized users exhibit a natural inclination to participate less in both review and photo-sharing activities, with privacy considerations acting as an additional deterrent.
Table 6  Parameter Estimates of Hierarchical Model of Review and Photo Decision Making Process

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Stage 1</td>
<td>Stage 2</td>
<td>Stage 3</td>
</tr>
<tr>
<td>TotalFeedback</td>
<td>-0.078***</td>
<td>-0.415***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.035)</td>
<td></td>
</tr>
<tr>
<td>TotalPhoto</td>
<td>0.089***</td>
<td>0.395***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>SameSizeFeedback</td>
<td>-0.013**</td>
<td>-0.248***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.052)</td>
<td></td>
</tr>
<tr>
<td>SameSizePhoto</td>
<td>0.041***</td>
<td>0.376***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>AvgRating</td>
<td>-0.002</td>
<td>-0.004</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>0.011**</td>
<td>-0.023</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.032)</td>
<td></td>
</tr>
<tr>
<td>ItemAge</td>
<td>0.001</td>
<td>0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.043)</td>
<td></td>
</tr>
<tr>
<td>Experience</td>
<td>-0.133***</td>
<td>0.667***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>UserTenure</td>
<td>-0.158***</td>
<td>-0.091***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>UserAge</td>
<td>0.135***</td>
<td>-0.279***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.017)</td>
<td></td>
</tr>
<tr>
<td>SmallSize</td>
<td>-0.125***</td>
<td>-0.312***</td>
<td>-0.235***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.028)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>LargeSize</td>
<td>-0.193***</td>
<td>-0.773***</td>
<td>-0.626***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.029)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>PhotoAesthetic</td>
<td>4.205***</td>
<td>0.188***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.604***</td>
<td>-4.922***</td>
<td>1.550***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.034)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Observations</td>
<td>251,720</td>
<td>92,166</td>
<td>8,125</td>
</tr>
</tbody>
</table>

Standard errors are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01

7. Robustness Check
7.1. Full Sample without Matching
In our main model, we used a matched sample to address the issue of the unbalance in the treatment assignment. Here we re-run our main model using the full-sample without the propensity score matching. Figure 7 shows the result and it is consistent with our main result.

7.2. Alternative Measure of Demand
In our main model, we use the ratio of number of days that an item is rented to the number of days that the item is available as the measure of the product demand. In this robustness check, we adopt an alternative demand metric: the rental conversion rate derived from click-level data.
Figure 7  Robustness Check: The Impact of Photos from Plus-sized Users on Demand using Full Sample

We specify our model as follows:

\[ \text{RentalIndicator}_c = \beta_0 + \beta_1 \text{SamesizePhotos}_c + \beta_2 \text{SamesizePhotos}_c \times \text{Plus}_u + \beta_3 \log(\text{AccReviews})_c + \beta_4 \text{RatingAvg}_c + \delta_q \times \lambda_i + \gamma_t + \mu_u + \epsilon_c , \]  \hspace{1cm} (4)

where \( c \) stands for a click from user \( u \) on item \( i \) at time \( t \). We use all the clicks from Jan 2021 to Dec 2023. Our outcome variable RentalIndicator\(_c\) indicates whether user \( u \) decides to rent item \( i \) after clicking on it, it equals 1 if the conversion happens, 0 otherwise. The variable of interest, SamesizeAccPhotos\(_c\), represents the proportion of accumulated review photos for item \( i \), contributed by users of the same size as the focal user \( u \) across all review photos of item \( i \), at the time of click \( c \). To examine the varying impact of same-size photos on different size groups, we include one the interaction term of SamesizeAccPhotos\(_c\) and Plus\(_u\), which equals to 1 if the user is plus-sized. Subsequently, we incorporate several control variables similar to our main model. We include Log(AccReviews)\(_c\) to capture the number of reviews of item \( i \) at click time \( t \). We also include RatingAvg\(_c\) to capture this rating of item \( i \) at click time \( t \). We include the item-quarter interaction fixed effect and the running week fixed effect as in our DID design. Moreover, we include the user-level fixed effect to control any characteristics corresponding to the user. Our results are presented in Table 7. Column (1) shows the result without the interaction term while Column (2) shows the result with the interaction term. The coefficient of the interaction term, that is \( \beta_2 \) in (4), captures how the number of same-size photos impacts rental from the baseline group, specifically plus-sized users. On average, an additional review photo from the plus-sized group is associated with a 1% increase in the possibility of rental conversion. These findings indicate that review photos from same-size users have a positive impact on the rental conversion of a click and this effect is greater for plus-sized users. This further confirms our main finding: photos from plus-sized users significantly increase future demand from plus-sized users.
8. Conclusion and Discussion

Our analysis uncovers significant disparities along size lines on e-commerce platforms. Plus-sized users face substantial informational uncertainty due to their under-representation in reviews and review photos. Despite the increasing purchases, we find that plus-sized users are less likely to leave text or photo reviews, which can in turn contribute to even less information for subsequent plus-sized users. This information asymmetry is particularly detrimental to sales among plus-sized users, as demonstrated through our DID model and click-level analysis, which show that photo reviews from plus-sized users significantly increase purchases from the plus-sized population.

By deploying a policy change on the platform, we empirically uncover the mechanisms behind such underrepresentation. In April 2023, the platform began displaying users’ names, introducing potential privacy concerns. For plus-sized users, the social stigma associated with identity revelation could exacerbate these privacy concerns. A comparison of user behavior before and after the policy launch indicates that all users reduced their photo postings, with plus-sized users being the most affected.

Beyond privacy concerns, we also identify other factors contributing to this underrepresentation by constructing a hierarchical choice model. We find that review photos from similar-sized users significantly influence the review and photo posting behavior. Specifically, a user has more incentive to post a photo or a review when there are more similar-sized photos posted already. We also find
that the privacy cost is higher among plus-sized users, which also contributes to their reticence in
sharing face-inclusive reviews.

Our research contributes to the existing literature by highlighting the role of privacy in the review-
ing behavior of consumers who routinely face social stigma. This is not unique to clothes. Anecdotal
evidence suggest that plus-sized users have significant uncertainty when visiting restaurants or enter-
tainment places. In fact, this has led to the creation of exclusive apps where plus sized consumers can
inform other plus-sized consumers about relevant issues\textsuperscript{11}. Reports in media also points to lack of
information in reviews for consumers with disabilities who might have questions about accessibility.

Therefore, it is incumbent on platforms to fill in the missing informational void by customers. For example, platforms could provide anonymity features for customers to write reviews, make it
easier to provide photos by auto blurring faces or solicit crucial information from vendors when
such information is not brought up in reviews. Review platforms like Yelp and Google Maps address
this by providing information about accessibility, suitability for families with children etc. Plus-
sized customers play a significant role in the apparel market. Given the over-representation in the
population and the under-representation on platforms, platforms should increase the informational
value by providing models of different sizes than conforming to the pervasive zero-sized model because
a zero-sized model provides very less information about the fit of the product for most users of the
platform. Platforms can provide filtering and sorting options to discover reviews from users closest
to their size. An inclusive and representative environment in their promotional materials and user-
generated content is not just for branding. Customers empowered with information are less likely to
have a poor experience and less likely to return a product with a poor fit.

While our research offers valuable insights into the challenges faced by plus-sized consumers on
e-commerce platforms, several limitations should be noted. First, our study focuses specifically on
e-commerce platforms, which means that the findings may not be directly applicable to other types
of platforms where user-generated content also plays a significant role. Secondly, the demographics of
our user sample, possibly limited in gender, age, geography, and socioeconomic status, could introduce
biases that may affect the generalizability of our findings. Lastly, the intervention suggestions we put
forth, such as anonymity features and auto-blurring faces in review photos, are grounded in theory
but have yet to be empirically tested for effectiveness. These limitations provide avenues for future
research to delve deeper into these and related areas.

\textsuperscript{11} \url{https://www.nytimes.com/2019/03/12/dining/larger-customers-restaurants.html}
References


Campbell C, Deacon H (2006) Unravelling the contexts of stigma: from internalisation to resistance to change.


Pomeranz JL (2008) A historical analysis of public health, the law, and stigmatized social groups: the need for both obesity and weight bias legislation. *Obesity* 16(S2):S93–S103.


Online Appendix to “One Size Fits All? Informational Accessibility and Inclusivity in Online Platforms”

Appendix A: Face Revealing in Photo reviews

Figure A1  Review photo examples with or without face revealing

(a) A review photo example with face revealing

(b) A review photo example without face revealing

Note. The displayed photo and name have been modified to protect privacy.
Appendix B: Policy Change

Figure B2  Policy Shock - Display Reviewer’s Name and Profile Photo

(a) Review Example Before Policy Change

This was super cute and flattering! The fit was generous overall - the one place it was a bit tight was in the arms. A shame because that made it a little bit less comfortable to wear in the summer. Great work dress!

Size rented: 2 • Fit: Runs large
Usually wears: 2-4 • Height: 5'7” • Bust: 36B

(b) Review Example After Policy Change

This was super cute and flattering! The fit was generous overall - the one place it was a bit tight was in the arms. A shame because that made it a little bit less comfortable to wear in the summer. Great work dress!

Amy
Height: 5’7” • Bust: 36B
Typical Sizes 2 - 4
Rented Size: 2
Fit: Runs large

Note. The displayed photo and name have been modified to protect privacy.