

# The Faces of Success: Beauty and Ugliness Premiums in e-Commerce Platforms

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## Abstract

Given the positive bias toward attractive people in society, online sellers are justifiably apprehensive about perceptions of their profile pictures. Although the existing literature emphasizes the “beauty premium” and the “ugliness penalty,” the current studies of seller profile pictures on customer-to-customer e-commerce platforms find a U-shaped relationship between facial attractiveness and product sales (i.e., both beauty and ugliness premiums and, thus, a “plainness penalty”). By analyzing two large data sets, the authors find that both attractive and unattractive people sell significantly more than plain-looking people. Two online experiments reveal that attractive sellers enjoy greater source credibility due to perceived sociability and competence, whereas unattractive sellers are considered more believable on the basis of their perceived competence. While a beauty premium is apparent for appearance-relevant products, an ugliness premium is more pronounced for expertise-relevant products and for female consumers evaluating male sellers. These findings highlight the influence of facial appearance as a key vehicle for impression formation in online platforms and its complex effects in e-commerce and marketing.

## Keywords

attractiveness, beauty premium, e-commerce, social selling, ugliness premium

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The role of attractiveness in social judgments and the beauty premium have been well documented in various social settings such as dating, hiring, selling, and advertising, especially when the task or product is related to appearance (Argo, Dahl, and Morales 2008; Eagly et al. 1991; Langlois et al. 2000). A few studies have found opposite results when a product is not relevant to appearance, but they have not provided coherent explanations for these findings (Kamins 1990; Trampe et al. 2010). Moreover, most researchers have compared attractive models or endorsers with those who are less attractive, largely ignoring people who are unattractive altogether. Recent studies indicate a potential ugliness premium: unattractive people are perceived as more intelligent and earn significantly more than their attractive counterparts (e.g., Gheorghiu, Callan, and Skylark 2017; Kanazawa and Still 2018), which suggests that the effect of attractiveness is nonlinear. Thus, researchers have yet to identify the precise underlying mechanisms and contexts for the beauty premium or that for the ugliness premium, if it exists.

Unlike conventional marketing that relies on celebrities or salespeople promoting a specific product, customer-to-customer (C2C) e-commerce involves large numbers of ordinary people as sellers pitching a variety of products, making seller credibility a critical issue (Luca 2017). While online

sellers exhibit a wide range of attractiveness, their profile pictures, as an integral part of seller identity, serve as a key vehicle for impression formation and evoke feelings that affect buyer decisions (Forman, Ghose, and Wiesenfeld 2008). Most people, however, are not endowed with perfect facial symmetry and proportions. In light of the increasing popularity of social selling, how one's attractiveness or lack thereof affects the sales of various products is of much concern among online sellers and of great interest to marketing researchers and practitioners.

Drawing from the literature on impression formation, the match-up hypothesis, and evolutionary psychology, we argue that both attractive and unattractive online sellers command more attention and source credibility than plain-looking sellers, resulting in a U-shaped effect of attractiveness on sales. In

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contrast to previous studies, we go beyond consumer attitudes toward advertisements and products and focus on trait inferences to explore the underlying mechanisms of beauty and ugliness premiums and their effect on source credibility and purchase intention. We find that while attractive faces fare better in sociability than both plain-looking and unattractive people, they are not considered more competent than unattractive people, who are perceived as more competent than plain people, resulting in a plainness penalty. These relations are moderated by product relevance (appearance vs. expertise) and a cross-gender effect for women looking at male sellers.

The remainder of this article is organized as follows. We first provide a succinct review of the relevant literature and present a conceptual framework for the effect of facial attractiveness on consumers. We extract the geometric features of facial images and adopt a machine learning approach to score large samples of online seller portraits. Next, we investigate beauty and ugliness premiums using a multimethod approach involving large data sets from two e-commerce platforms and two online experiments to assess the potential mediators and moderators. Finally, we discuss the key findings and implications for e-commerce and internet marketing.

## Relevant Literature

### *Impression Formation and Face Perception*

Faces are known to bias decisions (Wheeler and Petty 2001). We form first impressions of others and make judgments about their social traits almost instantaneously on the basis of face perceptions (Samper, Yang, and Daniels 2018; Todorov et al. 2005; Willis and Todorov 2006). The neural mechanism underlying trait impressions of faces involves the amygdala, a subcortical brain region crucial in coding the value of stimuli (e.g., Engell, Haxby, and Todorov 2007). In functional magnetic resonance imaging (fMRI) studies, the amygdala has been observed to be more sensitive to unusual rather than to neutral stimuli, suggesting that our response to both attractive and unattractive faces may be stronger than to plain-looking ones (e.g., Said, Baron, and Todorov 2008).

In addition, the amygdala response to facial attractiveness triggers rapid automatic inferences about people's dispositions, which in turn affects subsequent information processing and decisions (Engell, Haxby, and Todorov 2007). Greater attention to an eye-catching face makes it more likely that people process additional information associated with the face, which may weaken but not change the nature of the relation between inferences from faces and decisions (Todorov et al. 2005; Vuilleumier 2000). Thus, advertisers find it effective to use either attractive or unattractive models to present certain products (Guihaire 2018).

### *Beauty and Ugliness Premiums*

Studies in many fields have concluded that beauty has a premium and ugliness is penalized (Eagly et al. 1991; Langlois

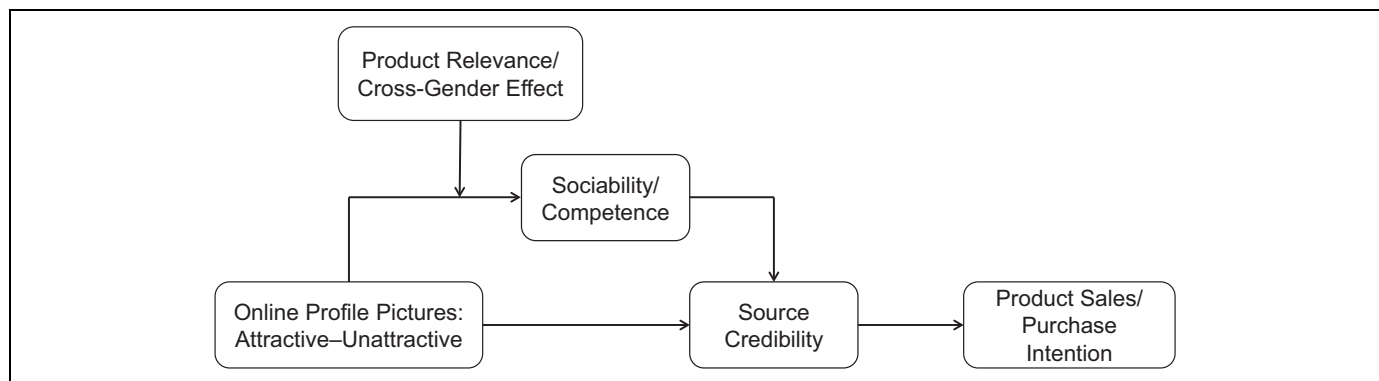
et al. 2000). According to evolutionary psychology (e.g., Magro 1999), an attractive face indicates good health and prospect for survival and reproduction. Beauty is also correlated with perceived intelligence and social skills (Eagly et al. 1991; Hamermesh 2011). Attractive solicitors can obtain twice as much in donations as their unattractive counterparts (Reingen and Kernan 1993), and a good-looking salesperson enhances customer evaluation of a product simply by touching it (Argo, Dahl, and Morales 2008). Although attractiveness is valued in both men and women, men are more responsive to the physical attractiveness of women (Li and Kenrick 2006). Meanwhile, studies have found that attractiveness sometimes fails to work, for instance, when helping children in need or selling an embarrassing product (Fisher and Ma 2014; Wan and Wyer 2015).

Several recent studies show that unattractive faces are associated with certain positive outcomes. Gheorghiu, Callan, and Skylark (2017) find that students rate unattractive professors as better scientists than attractive professors. A study of Nobel laureates reinforces the pervasive stereotype that scientists sacrifice physical appeal for intellectual pursuits (Fidrmuc, Paphawasit, and Tunalı 2017). Kanazawa and Still (2018) indicate that very unattractive executives earn significantly more than their attractive counterparts, although the study does not consider perceptions of competence. These findings support the popular belief that unattractive people exert greater effort to compensate for their disadvantaged appearance; however, these studies fall short of offering plausible explanations for the ugliness premium.

### *Online Profile Pictures*

Online forums and social media have aggravated people's concern with appearance and greatly affected social and consumption behaviors (Grabe, Ward, and Hyde 2008). The advantages of anonymity and lack of immediate social censoring may make such biases more prevalent online (Guan et al. 2015). Online transaction platforms (e.g., Uber, Airbnb) typically require sellers to upload real photos as their profile pictures and to display them in prominent positions. These profile pictures provide impression-bearing information that affects source credibility and behavioral outcomes (Forman, Ghose, and Wiesenfeld 2008; Luca 2017).

Studies of the attractiveness effect have mostly used a small number of pictures in experimental settings rather than assessing real-world situations, leaving the robustness and generalizability of their findings open to question (Langlois et al. 2000). It is not clear from the literature whether social stereotypes based on attractiveness extend to the C2C e-commerce context. Researchers usually adopt a linear model or compare only two levels of attractiveness (i.e., attractive vs. less attractive), neglecting any potential nonlinear effect. Thus, C2C e-commerce platforms involving ordinary people provide an excellent setting to explore the effect of beauty and ugliness premiums and their underlying mechanisms.



**Figure 1.** Conceptual framework.

## Research Framework

To explore the potential nonlinear effect of facial attractiveness on product sales, we focus on the profile pictures of ordinary people in C2C platforms who display a wide range of attractiveness (i.e., attractive, plain-looking, and unattractive). To investigate the mechanism underlying the beauty and ugliness premiums, we conduct online experiments to assess the effect of seller attractiveness on perceptions of sociability and competence, which in turn affect source credibility and purchase intention. With these objectives in mind, we present our conceptual framework in Figure 1 and elaborate the hypotheses in the ensuing sections.

### Mechanism for Beauty and Ugliness Premiums

Faces have a special advantage over other stimuli in terms of visual processing and the attention-orienting mechanism (Vuilleumier 2000). On e-commerce platforms that involve information overload, unusual faces (i.e., both attractive and unattractive) have high arousal values compared with plain-looking faces, and thus their messages are more likely to pass through the attention gate rather than being ignored. Recent studies using fMRI have found that the amygdala, the part of the brain responsible for visual attention and processing, exhibits nonlinear responses to human faces as both attractive and unattractive faces elicit quicker and stronger responses than plain-looking ones (Martín-Loeches et al. 2014; Said, Baron, and Todorov 2008; Winston et al. 2007).

Moreover, people instantaneously assign a set of personality-like traits and judgments to faces, particularly along the dimensions of warmth and competence (Fiske, Cuddy, and Glick 2007). Research suggests that good-looking people are regarded as more sociable, likable, intelligent, and persuasive (Hamermesh 2011). Unattractive people may obtain positive judgments derived from inferences of competence (Gheorghiu, Callan, and Skylark 2017). Thus, while the beauty premium will be apparent in online platforms, we also expect that unattractive sellers elicit positive perceptions in certain contexts, which we elaborate in the next section. We propose that compared with plain-looking faces, both attractive and unattractive sellers command greater consumer attention

and desirable trait inferences, which in turn leads to a greater likelihood of a sale.

**H<sub>1</sub>:** Holding other things constant, there is a U-shaped relationship between product sales (or purchase intention) and facial attractiveness of online sellers in that both attractive and unattractive people perform better than plain-looking people.

However, gaining more attention cannot solely justify the advantages of attractive and unattractive faces over plain faces. In line with the implicit personality theory, trait inference is the key mechanism underlying the effect of attractiveness (Eagly et al. 1991). In addition to the primary messages such as product quality and price, source credibility is a key factor that influences consumer decisions (Goldsmith, Lafferty, and Newell 2000). Consumers use nonverbal cues (e.g., face attractiveness) to infer the perceived trustworthiness and expertise of a source (i.e., two determinants of source credibility), which in turn affects their perceptions of the products (Ohanian 1990).

Previous research has suggested that a salesperson's attractiveness does not directly affect sales performance but, rather, influences some aspects of the customer's impression of the salesperson such as sociability or competence (Ahearne, Gruen, and Jarvis 1999; Debevec, Madden, and Kernan 1986). In online platforms, the pictorial and aesthetic features of profile pictures have a profound influence on consumers' assessments of source credibility (Carusi 2008). Meanwhile, attractiveness has been found to be moderately correlated with perceived sociability, less so with competence, and almost not at all with honesty (Eagly et al. 1991; Grabe, Ward, and Hyde 2008). Thus, it is plausible that beauty and ugliness premiums operate under different mechanisms in terms of sociability and competence.

Beauty, as an endowment, has many benefits. Because of beauty's halo effect, attractive faces lead to a higher level of arousal and inferences of sociability and competence (Langlois et al. 2000). Strong empirical evidence suggests that attractive individuals are perceived to possess more socially desirable traits and exhibit greater persuasive power in selling products with which they are associated (Eagly et al. 1991; Ohanian

1990). Thus, because attractive individuals are perceived as more likable and competent, they are considered more credible than plain-looking and unattractive ones.

**H<sub>2</sub>:** Compared with plain-looking faces, attractive faces enhance (a) perceived sociability and (b) competence, which in turn affect (c) source credibility and (d) purchase intention.

For unattractive faces, attention alone may not be sufficient to induce a positive effect. In light of the overwhelming beauty premium for attractive people and the ugliness penalty in sociability, unattractive people have an advantage only over plain-looking people in perceived competence for several reasons. Compensatory adaptation is a widely held perception that unattractive people often work harder to compensate for their disadvantaged appearance, leading to a perception of greater competence than those with plain-looking faces (Kock 2003). There is an ingrained perception that whereas attractive people obtain everything more easily, particularly in settings that require social skills, unattractive people must exert greater effort to compensate for their disadvantaged appearance and often shift to areas that do not demand social skills, such as scientific pursuits (Fidrmuc, Paphawasit, and Tunalı 2017).

Moreover, the “ugly Einstein” effect suggests that the stereotypical expert may be an impartial truth seeker with limited personal appeal (Crane and Patterson 2012; Gheorghiu, Callan, and Sylark 2017). The stereotypical belief that attractiveness and intelligence are negatively associated is also prevalent, particularly for women (Heilman et al. 2004). This argument is used to explain the “dumb blonde” stereotype, in which attractive women rely on their looks to advance rather than intelligence (Ruffle and Shtudiner 2015). Not surprisingly, much anecdotal evidence exists on the perceived creativity and extraordinary characteristics of unattractive people (Guihaire 2018; Kaplan 1978). Our research extends these notions and proposes that the ugliness premium operates through perceived competence, which in turn enhances source credibility and purchase intention.

**H<sub>3</sub>:** Compared with plain-looking faces, unattractive faces enhance (a) perceived competence, which in turn affects (b) source credibility and (c) purchase intention.

### Product Relevance

Studies in labor economics and human resource management suggest that based on perceived fit, people of various degrees of attractiveness may self-select or be selected into occupations and positions that are “suitable” for their appearance (Biddle and Hamermesh 1994; Heilman et al. 2004). Attractive people are perceived as more fitting for positions in which a pleasing appearance and sociability are appreciated, whereas unattractive people are regarded as more competent in professions for which technical or professional expertise matters (Gheorghiu, Callan, and Skylark 2017; Lee et al. 2018). Likewise, the beauty premium has been found to accrue in situations centered

on social interactions (Agthe, Spörrle, and Maner 2011), whereas the ugliness premium plays a role in assessing professional competence (Gheorghiu, Callan, and Skylark 2017; Kanazawa and Still 2018). Therefore, the context of evaluation influences the effect of beauty and ugliness premiums on trait perceptions and outcomes.

Product relevance is well grounded in the existing literature on attractiveness in marketing and serves as a key moderator on how the attractiveness of an endorser or salesperson affects their performance (Trampe et al. 2010). According to the match-up hypothesis, endorsers of various degrees of attractiveness are more effective when their perceived ability and credibility are relevant for presenting and interpreting the products (Kamins 1990). Following this logic, we expect that the advantages of attractive and unattractive faces are greater when they are aligned with a product relevant to the positive traits derived from their appearances. Whereas attractive people are more effective in presenting appearance-relevant products that enhance sociability, unattractive faces bring an advantage over plain-looking faces when they are associated with a product related to technical or professional expertise (e.g., Bower and Landreth 2001; Kang and Herr 2006).

**H<sub>4</sub>:** Product relevance moderates the mediating effect of sociability (competence) between beauty (ugliness) premium and source credibility. (a) The mediating effect of sociability is stronger for attractive people selling appearance-relevant products, whereas (b) the mediating effect of competence is stronger for unattractive people selling expertise-relevant products.

### Gender Differences

Gender greatly influences perceptions based on appearance, and gender bias can be regarded as a subset of attractiveness bias (Agthe, Spörrle, and Maner 2011). Unlike dating or hiring, online shopping does not involve social decisions or represent a competitive environment, so the negative vigilance toward an attractive person of the same sex found in previous studies is unlikely (e.g., Maner et al. 2009). Due to the opposites attract principle, studies have found that people are more subject to the influence of attractiveness in the opposite sex (Kaplan 1978; Li and Kenrick 2006). Thus, we expect that beauty and ugliness premiums are stronger in a cross-gender context than in a same-gender one.

Moreover, attractiveness affects men and women differently. Studies of evolutionary psychology indicate that men place greater importance on female attractiveness, so male consumers are more likely to award a beauty premium to attractive female sellers (Agthe, Spörrle, and Maner 2011). However, although women may value attractiveness in men, they are more likely to prioritize other considerations and place greater emphasis on competence and favor status and intelligence in men because these qualities indicate the ability to acquire resources and provide security (Sprecher, Sullivan, and Hatfield 1994). Thus, the ugliness premium in competence is

likely to be stronger for female consumers looking at male sellers.

**H<sub>5</sub>:** Compared with a same-gender setting, (a) the mediating effect of sociability for attractive female sellers is stronger for male buyers and (b) the mediating effect of competence for unattractive male sellers is stronger for female buyers.

In the following sections, we use field data from two transactional sites to provide empirical evidence for the U-shaped relationship between seller attractiveness and product sales (Study 1). As social traits and source credibility are not directly observable online, we examine the different mechanisms underlying the beauty and ugliness premiums and the moderating effects of product relevance and gender in two online shopping experiments (Study 2).

## Study 1: Profile Pictures in Online Platforms

### Research Settings

Airbnb and 5miles are the research settings for our field studies. These C2C e-commerce platforms provide information on sellers, including their photos, which serve as a means of identity verification and narrow the social distance between buyers and sellers (Luca 2017). Airbnb is a sharing economy platform in which travelers are matched with hosts who have properties for rent. We examine how an Airbnb host's facial attractiveness affects their listing's occupancy rate. 5miles is a mobile app that connects buyers with sellers of different products, and it enables us to assess the effect of a seller's facial attractiveness on the likelihood of a sale.

### Assessing Facial Attractiveness with Machine Learning

Determining the facial attractiveness of profile pictures on Airbnb and 5miles is a challenging task, as these sites have over 1 million hosts and 100,000 sellers, respectively. Because standards of facial attractiveness are universal across cultures, ethnic groups, sexual orientations, and ages, facial attractiveness is a quantifiable trait that can be assessed by both people and computer algorithms (Langlois et al. 2000; Magro 1999). We apply a machine learning method to process a large quantity of profile pictures with a high level of accuracy, making cumbersome human coding of all the portraits unnecessary.

First, we retrieved a random sample of 32,386 profile pictures from Yelp and recruited ten male and ten female raters between 19 and 25 years old. Each image was randomly assigned to five raters (two men and three women or three men and two women), who scored it on a five-point scale from 1 ("very unattractive") to 5 ("very attractive"). The final attractiveness score is the average of the five ratings. We randomly divided the raters into two groups and consistently obtained correlations of .87 to .96 for the average ratings between groups. The insignificant t-statistic confirms that the raters used similar criteria to assess facial attractiveness. A chi-

square test on the distribution of ratings between male and female raters also revealed no significant differences.

Second, we used image processing techniques to retrieve key pictorial features. Substantial evidence from computing and aesthetics research suggests that symmetry and proportional facial features (e.g., distance between the eyes, cheek width, size of nose and forehead) are good predictors of facial attractiveness (Gunes and Piccardi 2006). We used a set of 68 facial landmarks to extract these features and compute various facial ratios and proportions. For example, the aesthetic standard of the golden ratio can be obtained by comparing the distance between the eyes and mouth to the distance between the mouth and chin.

Third, we applied several machine learning methods (linear regression, Bayesian ridge regression, Gaussian regression, support vector machine regression, random forest regression, and convolutional neural networks) to learn the relationship between facial geometrics and the attractiveness scores from the human raters. We used 80% of the portrait data as the training set for model fitting and the remaining 20% for validation and model selection. Random forest regression achieved the best performance in terms of the Pearson correlation, the mean absolute errors, as well as the computational cost. We thus applied random forest regression to predict the facial attractiveness of all the profile pictures in the Airbnb and 5miles data sets as follows:

$$\bar{r}_n(X, D_n) = E_{\Theta} [r_n(X, \Theta_m, D_n)], \quad (1)$$

where  $r_n(X, \Theta_m, D_n)$  refers to the randomized base regression tree.  $\Theta_1, \Theta_2, \dots, \Theta_m$  are identically and independently distributed outputs of the randomized variables.  $E_{\Theta}$  denotes the expectation with respect to the random parameters, conditional on the data set  $D_n$  and  $X$ . The predicted scores are highly correlated with those of the raters ( $r = .71$ ). In addition to the cross-validation using the training data set, we adopt two other procedures<sup>1</sup> to assess the accuracy of machine learning. The validation tests suggest that the algorithm works well for faces from different genders, age, and ethnicity, and that the results from human raters are highly consistent with those from random forest regression.

### Controls for Potential Confounds

To rule out potential confounding factors, we control for several pictorial features including photographic quality, face proximity, and smiling expressions. Profile pictures vary in resolution, brightness, and quality and range from headshots with high facial prominence (close-up) to full-body shots with low facial prominence (distant). We used the vision libraries available in OpenCV to derive the hue, saturation, and value

<sup>1</sup> Web Appendix 1 presents the procedure and results about inviting MTurkers to code a random sample of profile photos. Web Appendix 2 reports the details from using human coders to score 2,750 host pictures required by SIMEX approach to assess measurement errors.



(HSV) color spectrum for each picture and then aggregated these measures into a single index of photographic quality using principal component analysis. We measured face proximity as the ratio of the area of a face to the whole picture, ranging from 0 to 1. The higher (lower) the facial proximity ratio, the more (less) prominent the face is in the picture. In addition, a smiling face may be equally effective as the attractiveness of the seller because it can evoke a sense of familiarity and increase the positive evaluations of viewers (Scharlemann et al. 2001). We used a random forest regression model to predict the likelihood of smiling for each profile picture in the main sample.<sup>2</sup>

### Study 1a: Sharing Economy Platform (Airbnb)

**Data collection.** We collected all publicly available data for Airbnb listings in Los Angeles through June 15, 2017. We then appended the annual occupancy data from AirDNA (a major supplier of data on worldwide Airbnb listings) covering the same period. We combined the data from these sources and excluded properties without complete information (e.g., the ones less than one year in operation). We downloaded host profile pictures and used image processing techniques to extract the pictorial features. The final sample consists of 17,935 Airbnb properties from 10,979 hosts. Of these listings, 17,749 have a profile picture and 9,953 use a single portrait. We controlled for (1) host characteristics (e.g., identity verification, reputation), (2) listing characteristics (e.g., accommodation type, price, postal code, age of listing, quality of the listing photos), and (3) review characteristics (e.g., number of reviews, property ratings by reviewers, review sentiment). These three groups of variables are critical to rule out potential confounds. For instance, postal codes are frequently used to control for socioeconomic differences such as housing quality across geographic areas, which may affect the outcome variable. This is also true for review volume and sentiments. The dependent variable is the annual occupancy rate, which is a proxy for sales performance. Table 1 provides the variable definitions and summary statistics.

**Model specification.** We used a hierarchical framework to assess the effect of host attractiveness on occupancy rate. Approximately 24% of the hosts own more than one listing, and thus the unit of observation is a listing. We estimated the model in a stepwise fashion. The baseline econometric model is as follows:

$$\text{Occupancy}_{hl} = \beta_0 + \beta_1(\text{pictorial features}) + X_{hl}\beta_2 + Y_h\beta_3 + u_h + e_{hl}, \quad (2)$$

where  $\text{Occupancy}_{hl}$  is a measure of the annual occupancy rate of listing  $l$  owned by host  $h$ . The parameter of interest is  $\beta_1$ , the

effect of pictorial features including facial attractiveness.  $X_{hl}$  represents a set of listing characteristics and review characteristics.  $Y_h$  denotes a set of host characteristics. The random intercept,  $u_h$ , is a host-specific error component that accounts for unobserved heterogeneity across hosts, and  $e_{hl}$  is a listing error component that varies between listing  $l$  and host  $h$ .

**Results.** As Table 2 shows, the coefficients for pictorial features are as expected across all specifications. The presence of a profile picture has a positive effect, resulting in an approximately 4.1% increase in occupancy rate (Spec. 1). Better photographic quality (Spec. 2) and smiling expression (Spec. 3) are positively related to occupancy rate. The results of Spec. 3 show that a one-unit increase in a host's facial attractiveness can increase the occupancy rate by approximately 1.3%, suggesting that the beauty premium is prevalent. We introduced the quadratic term in Spec. 4 and use a three-step procedure to test the U-shaped relationship between facial attractiveness and occupancy rate (Lind and Mehlum 2010). First, the results of Spec. 4 in Table 2 show the joint significance and expected signs of the direct effect ( $b = -.911, p < .01$ ) and the squared term effect ( $b = .150, p < .01$ ). Second, as shown in Figure 2, Panel A, the slope of the lower end is significantly negative ( $-.341, p < .01$ ), and the slope of the higher end is significantly positive ( $.368, p < .01$ ). Third, the turning point ( $3.04, p < .01$ ) is significant and located well within the data range. Thus, these results support  $H_1$ . To account for potential social interactions, we controlled for rental type (room vs. whole unit) by assuming that guests expect to meet their hosts face-to-face when renting a room in the unit. While shared apartment/house has a significant negative effect, the interaction between shared unit and facial attractiveness is found to be insignificant, and thus no concern of social pressure from the expectation of meeting an attractive host is present.

**Correction of measurement errors<sup>3</sup>.** In Specs. 5 and 6, we used the simulation extrapolation method (SIMEX) to account for measurement errors in the machine learning approach. SIMEX is a data-driven approach to correcting measurement errors and requires relatively fewer assumptions and information than alternative methods (Yang et al. 2018). We followed its diagnostic procedure to assess the measurement error using the known attractiveness scores rated by human coders in a random sample of host pictures from 2,750 listings. Compared with the naive model, the parameter estimates of facial attractiveness using the SIMEX corrected model are larger in magnitude, suggesting that the naive model may underestimate the effects. The other variables, however, change little in the presence of measurement error.

<sup>2</sup> We searched for a "smiling human face" and "neutral human face" in a Google image search. After extracting facial geometrics, we used the random forest regression to predict the likelihood of smiling in each of the profile pictures. Web Appendix 1 presents the details.

<sup>3</sup> Web Appendix 2 reports the details for the correction of measurement errors using simulation extrapolation.

**Table 1.** Summary Statistics of Airbnb Data (Study 1a).

Variable	Definition	N	M	SD	Min	Max
<b>Pictorial Characteristics</b>						
Presence of picture	Presence of profile picture	17,935	.990	.101	0	1
Human portrait	Presence of human portrait	17,749	.711	.454	0	1
Photographic quality	Aggregated measure of HSV (hue, saturation, value) and picture resolution	17,749	.303	.154	0	.962
Facial attractiveness	Face attractiveness score determined by the machine learning approach	9,953	3.05	.433	1.91	4.26
Smiling expression	Likelihood of smiling expression determined by the machine learning approach	9,953	.645	.257	0	1
Face proximity (%)	Ratio of the area of a face to the whole picture	9,953	.111	.090	.001	.820
<b>Host Characteristics</b>						
Superhost	Binary indicator of whether the host has a superhost badge representing a good reputation	10,979	.206	.404	0	1
Verified home email	Binary indicator of whether the account is verified by home email	10,979	.972	.166	0	1
Verified work email	Binary indicator of whether the account is verified by work email	10,979	.136	.342	0	1
Verified government-issued ID	Binary indicator of whether the account is verified by government-issued ID	10,979	.445	.497	0	1
Verified phone number	Binary indicator of whether the account is verified by phone number	10,979	.996	.060	0	1
Verified selfie with ID	Binary indicator of whether the account is verified by selfie with ID	10,979	.023	.149	0	1
Linked Facebook account	Binary indicator of whether the account is linked to Facebook account	10,979	.275	.446	0	1
Linked Google account	Binary indicator of whether the account is linked to Google account	10,979	.065	.247	0	1
Linked LinkedIn account	Binary indicator of whether the account is linked to LinkedIn	10,979	.029	.168	0	1
<b>Listing Characteristics</b>						
Response rate	% of new inquiries and reservation requests the host responded to within 24 hours in the past 30 days	17,935	.939	.158	0	1
Average daily rate	The average rate paid for rooms booked	17,935	148.76	164.386	6.670	4,290
Annual occupancy rate	% of total available days in the year with a confirmed booking	17,935	.590	.256	.032	1
Apartment	Binary indicator of whether the listing is an apartment	17,935	.576	.494	0	1
House	Binary indicator of whether the listing is a house	17,935	.291	.454	0	1
Shared apartment/house	Binary indicator of whether the apartment/house is a shared unit	17,935	.350	.477	0	1
# of listing photos	Number of property photos shown	17,935	18.765	13.886	1	255
Quality of main listing photo	Aggregated measure of HSV (hue, saturation, value) and picture resolution	17,935	.506	.261	.049	.950
Listing postal code	A series of dummy variables indicating the listing location, where $X = 1$ ( $X \in$ (all postal codes in Los Angeles)) if the listing is located in the ZIP code tabulation areas $X$ ; 0 otherwise.					
Joined year (age of listing)	The year when the listing joined Airbnb					
<b>Review Characteristics</b>						
Property rating	Average star rating by reviewers	17,935	4.663	.435	1	5
Ln (# of reviews)	Log of the total number of reviews received	17,935	2.424	1.375	0	6.084
Review subjectivity	Average subjectivity of customer review	17,935	.625	.039	.17	.95
Review polarity	Average polarity of customer review	17,935	.411	.065	-.344	1
Review readability	Average readability of customer review	17,935	67.92	7.57	.92	100

Notes: The number of reviews is incremented by one before the log transformation. We assess the review polarity from  $-1$  (negative) to  $1$  (positive), the subjectivity score from  $0$  (objective) to  $1$  (subjective), and readability using Flesch reading ease scale from  $0$  to  $100$ .

### Study 1b: E-Commerce Platform (5miles)

**Data collection.** To validate the findings of Study 1a, we tested the model using data from 5miles. We tracked a random sample of product listings on a daily basis for 60 days (January 31 to March 31, 2019) in three product categories—beauty products (11,842 items), electronics (7,171 items), and bags (7,215 items)—resulting in a sample of 26,228 items from 11,115 sellers. Approximately 46% of the products received at least one offer during the observation period. We used the same method as in Study 1a to extract facial features from seller

profile pictures. We controlled for seller characteristics (e.g., trust level, star rating, gender, identity verifications), and product characteristics (e.g., product category, number of product photos, length of product description, price). We used a topic modeling approach<sup>4</sup> (guided latent Dirichlet allocation) to classify the products on the basis of the degree of relevance to either appearance or expertise. Drawing on the

<sup>4</sup> Web Appendix 2 provides details of the topic modeling approach with guided latent Dirichlet allocation.

**Table 2.** Estimation Results for Occupancy Rate (Study 1a).

	Spec. 1	Spec. 2	Spec. 3	Spec. 4	Spec. 5 (SIMEX)	Spec. 6 (SIMEX)
<b>Pictorial Characteristics</b>						
Presence of picture	.041** (.020)	—	—	—	—	—
Photographic quality	—	.059*** (.014)	.062*** (.018)	.059*** (.018)	.052*** (.016)	.044** (.017)
Human portrait	—	.025*** (.005)	—	—	—	—
Smiling expression	—	—	.024** (.011)	.044*** (.011)	.024*** (.009)	.064*** (.009)
Face proximity	—	—	.221*** (.032)	.228*** (.032)	.193*** (.028)	.211*** (.029)
Facial attractiveness	—	—	.013** (.007)	-.911*** (.082)	.014** (.006)	-1.899*** (.150)
Facial attractiveness <sup>2</sup>	—	—	—	.150*** (.013)	—	.310*** (.024)
<b>Listing Characteristics</b>						
Response rate	.151*** (.014)	.149*** (.015)	.162*** (.020)	.161*** (.020)	.169*** (.018)	.167*** (.015)
Average daily rate	-2.26e-04*** (2.25e-05)	-2.24e-04*** (2.26e-05)	-2.59e-04*** (3.90e-05)	-2.62e-04*** (3.73e-05)	-2.85e-04*** (3.62e-05)	-2.81e-04*** (3.38e-05)
Apartment	.024*** (.006)	.024*** (.006)	.014* (.008)	.012* (.008)	.019*** (.007)	.019*** (.007)
House	.022*** (.007)	.022*** (.007)	.020** (.009)	.019** (.009)	.015* (.008)	.014* (.008)
# of listing photos	1.61e-04 (1.56e-04)	1.86e-04 (1.56e-04)	1.95e-04 (2.26e-04)	1.90e-04 (2.24e-04)	-1.71e-04 (2.20e-04)	-1.23e-04 (2.20e-04)
Quality of main listing photo	-.003 (.006)	-.002 (.006)	.003 (.008)	.003 (.008)	-.005 (.008)	-.002 (.009)
Shared apartment/house	-.068*** (.005)	-.068*** (.005)	-.072*** (.007)	-.072*** (.007)	-.076*** (.006)	-.076*** (.006)
Postal code fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Joined year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
<b>Host Characteristics</b>						
Superhost	.019*** (.005)	.018*** (.005)	.018*** (.007)	.017** (.007)	.012** (.005)	.011* (.006)
Host identity variables	Yes	Yes	Yes	Yes	Yes	Yes
<b>Review Characteristics</b>						
Property rating	.015*** (.005)	.015*** (.005)	.014* (.007)	.014** (.007)	.022*** (.007)	.025*** (.007)
ln (# of reviews)	.063*** (.002)	.063*** (.002)	.058*** (.002)	.057*** (.002)	.063*** (.002)	.062*** (.002)
Avg. review polarity	-.060* (.031)	-.062** (.031)	-.031 (.041)	-.034 (.040)	-.020 (.047)	-.027 (.043)
Avg. review subjectivity	.081 (.054)	.076 (.054)	.115 (.071)	.128* (.071)	.170** (.072)	.192*** (.071)
Avg. review readability	1.14e-03*** (2.27e-04)	1.17e-03*** (2.29e-04)	1.26e-03*** (3.11e-04)	1.25e-03*** (3.08e-04)	1.56e-03*** (3.31e-04)	1.55e-03*** (3.64e-04)
# of observations	17,935	17,749	9,953	9,953	9,953	9,953

Notes: Host identity/verification information is also included in estimation but not reported for brevity. Heteroskedasticity consistent robust standard errors are reported in parentheses. \* $p < .10$ ; \*\* $p < .05$ ; \*\*\* $p < .01$ .

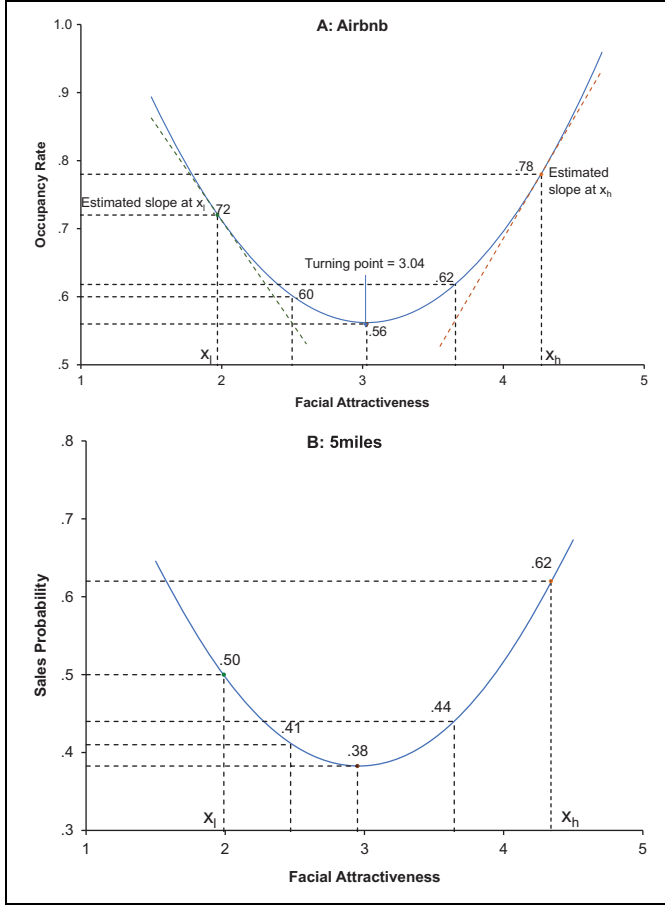
topic dominance in product descriptions, we classify 5,977 listings as expertise-relevant, 8,841 listings as appearance-relevant, and the other listings for which neither appearance nor expertise topics are dominant serve as the baseline group. Table 3 provides the variable definitions and summary statistics.

**Model specification.** We specify the utility that affects the sale of product  $j$  as follows:

$$U_{ijt} = \beta_0 + \beta_1 PD_{ij} + X_{jt} \beta_2 + S_i \beta_3 + e_{ijt}, \quad (3)$$

where  $PD_{ij}$  is the picture decision of seller  $i$  who lists product  $j$ ,  $X_{jt}$  represents a vector of product characteristics, and  $S_i$





**Figure 2.** Relationship between facial attractiveness and sales performance.

Notes: This curve is drawn at the average level for all other variables.

represents seller characteristics. To accommodate unobserved seller heterogeneity, we split the error term ( $e_{ijt} = \mu_i + \epsilon_{ijt}$ ) into  $\mu_i \sim N(0, \sigma^2)$ , which is specific to seller  $i$ , and  $\epsilon_{ijt}$ , which is unique for each listing.

Most sellers have only one item to sell, and this item may be requested by multiple buyers at different times. While a sale is made to one of the offers, we cannot observe which offer received a sale. Thus, the time to receipt of the first offer is one of the most important outcomes that can be attributed to facial appearance, among other factors. Given this dynamic process, we model the time-to-offer using a discrete-time proportional hazard model:

$$h(d_{ijt}, PD_{ij}, X_{jt}, S_i) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(d_{ijt} \leq T < d_{ijt} + \Delta t | T > d_{ijt})}{\Delta t}$$

$$= h_0(d_{ijt}) \exp\{\beta_0 + \beta_1 PD_{ij} + X_{jt} \beta_2 + S_i \beta_3 + \mu_i\}, \quad (4)$$

where  $h(d_{ijt}, PD_{ij}, X_{jt}, S_i)$  is the hazard rate for product listing  $j$  receiving an offer in time period  $t$  given that it has not received an offer before time  $t$ , and  $T$  is a stochastic representation of the time duration.  $h_0(d_{ijt})$  is the baseline hazard rate capturing the likelihood of receiving an offer. The hazard rate depends on both the independent variables and the length of time a listing is

at risk. We estimated the model using a binary choice model with time fixed effects, as it is equivalent to a piecewise exponential hazard model when the data are observed at discrete time points. We thus adopted the probit specification and Equation 4 as a discrete time duration model.

$$\Pr(y_1 = 1 | PD_{ij}, X_{jt}, S_i) = \Phi[\beta_0 + \beta_1 PD_{ij} + X_{jt} \beta_2 + S_i \beta_3 + \mu_i + k_{t-t_0}], \quad (5)$$

where  $y_1 = 1$  if  $U_{ijt} > 0$ , and  $k_{t-t_0}$  represents a set of temporal dummy variables.

**Results.** The Kaplan–Meier survival curves in Figure 3 show that at any point in time, sellers with profile pictures of themselves are more likely to receive offers from buyers sooner (i.e., the lowest survival rate) than those with nonhuman pictures or without profile pictures. The survival curves for the three groups show that plain-looking sellers are associated with a higher survival rate, suggesting that their listings (compared with either attractive or unattractive sellers) have a longer sales cycle. Again, the results of Spec. 1 and Spec. 2 in Table 4 suggest that the mere presence of a profile picture ( $b = .255$ ,  $p < .01$ ) and a human portrait ( $b = .118$ ,  $p < .01$ ) are positively related to sales performance. After controlling for smiling expressions in Spec. 3, the coefficient of facial attractiveness remains significantly positive ( $b = .086$ ,  $p < .01$ ). We include the quadratic term of facial attractiveness in Spec. 4, and the result is consistent with that of Study 1a, in that both attractive and unattractive sellers are more likely to receive offers sooner than plain-looking sellers (slope:  $b = -1.001$ , quadratic term:  $b = .177$ ;  $p < .01$ ). Thus,  $H_1$  is again supported. In Spec. 5, we introduce the interaction between facial attractiveness and product relevance. Compared with less attractive sellers, attractive sellers perform better for appearance-relevant products ( $b = .082$ ,  $p < .10$ ) but worse for expertise-relevant products ( $b = -.138$ ,  $p < .05$ ). These results provide support for  $H_4$ .

### Robustness Checks<sup>5</sup>

We tested the robustness of results in a number of ways. We obtained the variance inflation factors for all the covariates in Study 1a (see Table W2-6 in Web Appendix 2). They are all below the conventional threshold of 4, indicating that multicollinearity does not appear to be a concern. We then explore the potential problem arising from outliers. For example, we excluded observations within the top 5% of the average daily rate (Spec. 2). We also excluded listings in the top 5% of the distribution of occupancy (Spec. 3). The reestimated results remain robust in terms of sign, magnitude, and statistical significance.

<sup>5</sup> Web Appendix 2 reports the detailed results of robustness checks including multicollinearity, outliers, alternative DVs, and alternative U-shaped specifications for Study 1a and 1b. It also provides details for the propensity score matching method to address potential selection bias.

**Table 3.** Summary Statistics of 5miles Data (Study 1b).

Variable Definition		N	M	SD	Min	Max
<b>Pictorial Characteristics</b>						
Presence of picture	Presence of profile picture	26,228	.853	.354	0	1
Human portrait	Presence of human portrait	22,371	.453	.498	0	1
Photographic quality	Aggregated measure of HSV and picture resolution	22,371	.295	.162	0	.982
Facial attractiveness	Face attractiveness score determined by the machine learning approach	8,184	3.08	.425	1.99	4.35
Smiling expression	Likelihood of smiling expression determined by the machine learning approach	8,184	.543	.254	.020	1
Face proximity (%)	Ratio of the area of a face to the whole picture	8,184	.188	.142	.001	.949
<b>Seller Characteristics</b>						
Female	Binary indicator of the seller gender: female = 1, otherwise = 0	11,115	.523	.498	0	1
Trust level of seller	Seller's trust level determined by the platform	11,115	2.48	2.19	0	11
Seller star rating	Average star rating by reviewers	11,115	.707	.431	0	1
Log (# of seller followers)	Log number of followers the seller has	11,115	2.81	1.30	0	7.89
Verified email	Binary indicator of whether the account is verified by email	11,115	.736	.441	0	1
Verified phone number	Binary indicator of whether the account is verified by phone number	11,115	.953	.211	0	1
Linked Facebook account	Binary indicator of whether the account is linked to Facebook account	11,115	.395	.489	0	1
<b>Product Characteristics</b>						
# of product photos	Number of product photos shown	26,228	2.99	2.23	0	12
Log length of listing description	Log of the total number of words in the product description	26,228	2.46	1.15	.69	7.06
Price of the product	Listing price	26,228	107.36	236.06	1	7,000
Offer made by buyers	Binary indicator of whether an offer is received	26,228	.460	.498	0	1

Notes: The number of seller followers and length of listing descriptions are incremented by one before the log-transformation.

For Study 1a, the use of linear regression may be inappropriate if the dependent variable is not normally distributed. The residuals of the model fit are approximately normal, suggesting that the possible violation of nonnormality is not likely. We also took the log-transformation of the occupancy rate and rerun the model in Spec. 4 and the results remain consistent. In addition, the use of a percentage as a dependent variable (i.e., occupancy rate) in ordinary least squares regression may cause predictions that are nonsensical (below 0 or above 1). We thus rerun the model using beta regression, which is appropriate for a response variable that is restricted to the interval (0, 1), and find that the parameter estimates remain robust. To explore the alternative specifications of the U-shaped relationship. We used the inverse form rather than the quadratic form to specify the relationship between facial attractiveness and sales. The results of the parameter estimates are robust, as both the direct and inverse terms are significant. In addition, including the cubic term of facial attractiveness does not improve model fit, thus further supporting the U-shaped relationship. For Study 1b, in addition to the duration to receiving an offer, we used the seller's offer (i.e., a sale dummy) as an alternative dependent variable and find the parameter estimates to be consistent with the duration survival model (Figure 2, Panel B).

Finally, sellers' uploading portraits with varying degrees of attractiveness may affect the accuracy of the parameter estimates. We examined the distribution of attractiveness scores for both data sets and find them to be normally distributed. For Airbnb data, we found an insignificant correlation between hosts' facial attractiveness and property ratings ( $r = .0016$ ).

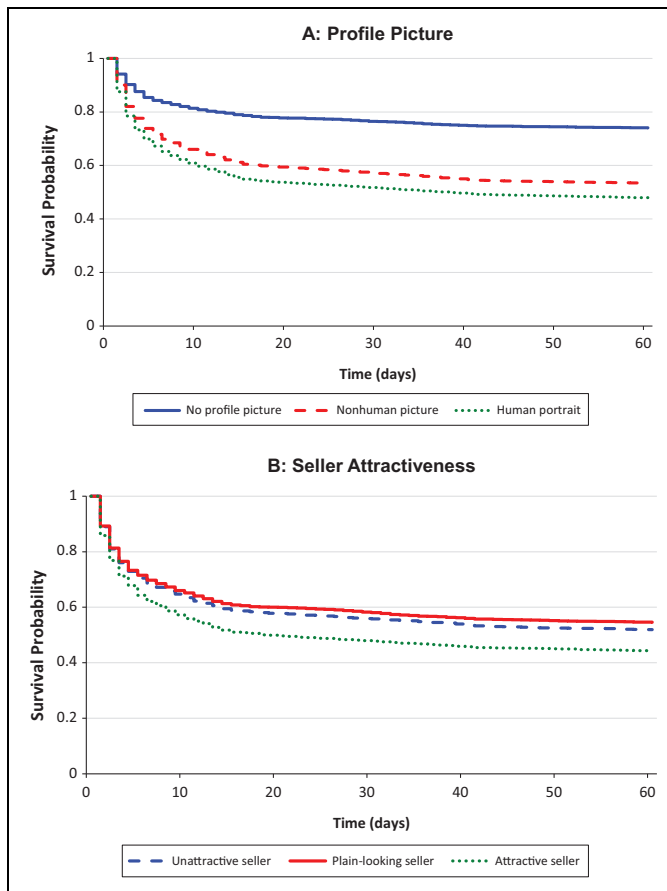
We also adopted the propensity score matching approach to examine the sample with and without profile pictures and find them to be comparable in terms of products, seller, and review characteristics.

## Study 2: Online Experiments

To investigate the mechanism underlying the beauty and ugliness premium, we first conduct online experiments to examine the mediating roles of perceived sociability and competence in the relationship between seller attractiveness and source credibility and purchase intention.

### Study 2a: Main Effects and Mechanisms

**Stimuli.** We selected seller photos from Chicago Face Database, which provides high-resolution, standardized photographs of male and female faces. Extensive norming data are available for each individual photo including physical attributes as well as subjective ratings by independent judges (e.g., attractiveness, trustworthy, feminine/masculine). The manipulation of attractiveness, while successful, may influence the perception of seller trustworthiness. Following previous research (e.g., Kamins 1990; Till and Busler 2000), we avoided this problem by choosing sellers who vary in attractiveness yet are of equivalent trustworthiness. To control for facial expressions and gender, we chose three male and three female photos with attractive, plain-looking, and unattractive faces, all with neutral expressions. Except for the photos, the scenario for the shopping task was identical across conditions.



**Figure 3.** Kaplan–Meier survival curves (Study 1b).

**Procedure and measures.** We randomly assigned 350 participants (187 men;  $M_{\text{age}} = 36.76$  years,  $SD = 12.83$ ) recruited from consumer panelists on Amazon’s Mechanical Turk (MTurk) to one of the three (attractive, plain-looking, unattractive) between-subject conditions. They were first instructed to read the materials describing a hypothetical shopping task for a digital camera and then asked to investigate the seller and their product carefully. They had to click the “next” button to go to the questions. Then they were asked to first indicate their purchase intention on a scale from 1 (“I definitely would not buy”) to 5 (“I definitely would buy”). Next, they assessed the seller’s credibility on a four-item scale (“To what extent do you think the source is credible/reliable/trustworthy/an expert?” Chaiken and Maheswaran 1994). The responses were averaged to form a composite score of source credibility ( $\alpha = .91$ ). The participants then rated the perceived sociability (“The seller is easy to like/a fun person to be around/like a good friend/a very nice person”;  $\alpha = .92$ ; MacInnis and Park 1991) and competence (“The seller is competent/intelligent/capable/skillful”;  $\alpha = .91$ ; Wang et al. 2017) of the seller. All these measures use a five-point scale from 1 (“strongly disagree”) to 5 (“strongly agree”). To rule out potential confounds, we also measured face familiarity (1 = “does not look familiar at all,” and 5 = “looks very

familiar”) and perceived trustworthiness (“The seller is someone I feel I can trust/never tries to mislead me/is always honest in his/her dealing with others”;  $\alpha = .89$ ; Sirdeshmukh, Singh, and Sabol 2002).

**Manipulation check.** The participants rated the attractive sellers ( $M_{\text{attractive}} = 3.55$ ) as significantly more attractive than the plain-looking ( $M_{\text{plain}} = 3.03$ ;  $p < .01$ ) and unattractive ( $M_{\text{unattractive}} = 2.57$ ;  $p < .01$ ) sellers. All pairwise comparisons between conditions are significant at the .01 level, and there is no significant difference in attractiveness between male and female sellers within the same condition. The differences in perceived trustworthiness turn out to be insignificant among the three groups ( $M_{\text{attractive}} = 3.37$ ,  $M_{\text{plain}} = 3.43$ ,  $M_{\text{unattractive}} = 3.54$ ;  $F(2, 347) = .84$ ,  $p = .43$ ).

**Visual attention.** To examine whether unattractive and attractive faces on the first page receive more attention from participants, we recorded the browsing time between when a seller picture is completely loaded and when the “next” button is clicked. We find that the participants take more time (in seconds) to browse the pages of either attractive or unattractive faces than those of plain-looking faces ( $M_{\text{attractive}} = 34.29$ ,  $M_{\text{plain}} = 26.75$ ,  $M_{\text{unattractive}} = 33.03$ ;  $F(2, 347) = 3.22$ ,  $p < .05$ ). Given that everything except for the picture is identical across the groups, this finding confirms the U-shaped relationship between attractiveness and attention.

**Purchase intention and source credibility.** Consistent with the findings from field studies, seller attractiveness has a U-shaped relationship with purchase intention ( $F(2, 347) = 4.18$ ,  $p < .05$ ), in support of  $H_1$ . Changing from unattractive to plain-looking decreases purchase intention ( $M_{\text{unattractive}} = 3.86$  vs.  $M_{\text{plain}} = 3.65$ ;  $F(1, 229) = 3.44$ ,  $p < .10$ ). Beyond that point, however, additional attractiveness increases the purchase intention ( $M_{\text{plain}} = 3.65$  vs.  $M_{\text{attractive}} = 3.95$ ;  $F(1, 238) = 9.44$ ,  $p < .01$ ). There is no difference in purchase intention between unattractive and attractive conditions ( $F < 1$ ). As for source credibility, we observe a significant difference among the three conditions ( $F(2, 347) = 5.97$ ,  $p < .01$ ). Both attractive sellers ( $M_{\text{attractive}} = 4.07$  vs.  $M_{\text{plain}} = 3.74$ ;  $F(1, 238) = 12.87$ ,  $p < .01$ ) and unattractive sellers ( $M_{\text{unattractive}} = 3.91$  vs.  $M_{\text{plain}} = 3.74$ ;  $F(1, 227) = 2.87$ ,  $p < .10$ ) are perceived as more credible than plain-looking sellers. There is no significant difference in perceived credibility between unattractive and attractive faces ( $p > .10$ ). Source credibility is highly correlated with purchase intention ( $r = .80$ ).

**Perceived sociability and competence.** There is a significant difference in perceived sociability ( $F(2, 347) = 9.04$ ,  $p < .01$ ) and competence ( $F(2, 347) = 3.81$ ,  $p < .05$ ) among the three conditions. Attractive sellers are perceived as more sociable than plain-looking ones ( $M_{\text{attractive}} = 3.63$  vs.  $M_{\text{plain}} = 3.34$ ;  $F(1, 238) = 7.08$ ,  $p < .01$ ) and unattractive ones ( $M_{\text{attractive}} = 3.63$  vs.  $M_{\text{unattractive}} = 3.15$ ;  $F(1, 227) = 18.03$ ,  $p < .01$ ). The results reveal no significant difference in sociability between plain-looking and unattractive sellers ( $p = .105$ ). Perceived

**Table 4.** Estimation Results from Duration Model (Study 1b).

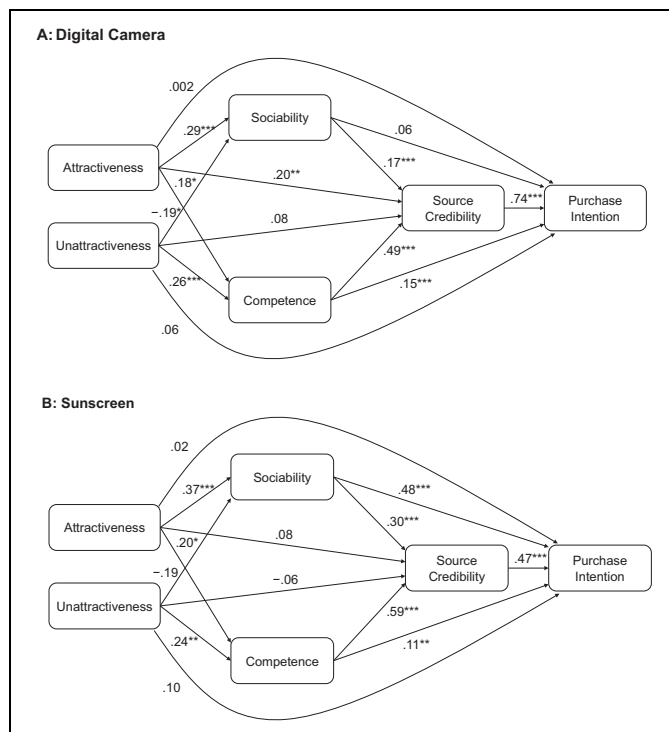
	Spec. 1		Spec. 2		Spec. 3		Spec. 4		Spec. 5	
	Estimate	Hazard Ratio	Estimate	Hazard Ratio	Estimate	Hazard Ratio	Estimate	Hazard Ratio	Estimate	Hazard Ratio
<b>Pictorial Characteristics</b>										
Presence of picture	.255*** (.018)	1.29	—	—	—	—	—	—	—	—
Photographic quality	—	—	.254*** (.036)	1.29	.218*** (.063)	1.24	.212*** (.063)	1.24	.215*** (.063)	1.24
Human portrait	—	—	.118*** (.012)	1.13	—	—	—	—	—	—
Smiling expression	—	—	—	—	.120*** (.037)	1.13	.148*** (.037)	1.16	.122*** (.037)	1.13
Face proximity (%)	—	—	—	—	.177*** (.067)	1.19	.181*** (.066)	1.20	.173*** (.067)	1.19
Facial attractiveness	—	—	—	—	.086*** (.020)	1.09	−1.001*** (.252)	.37	.072*** (.022)	1.08
Facial attractiveness <sup>2</sup>	—	—	—	—	—	—	.177*** (.041)	1.19	—	—
Facial attractiveness × ER	—	—	—	—	—	—	—	—	−.138** (.061)	.87
Facial attractiveness × AR	—	—	—	—	—	—	—	—	.082* (.044)	1.09
<b>Seller Characteristics</b>										
Female	−.002 (.011)	1.00	−.016 (.012)	.98	−.044** (.019)	.96	−.042** (.019)	.96	−.043** (.019)	.96
Trust level of seller	.071*** (.005)	1.07	.063*** (.005)	1.07	.065*** (.008)	1.07	.063*** (.008)	1.07	.064*** (.008)	1.07
Seller star rating	.023*** (.001)	1.02	.023*** (.001)	1.02	.023*** (.001)	1.02	.023*** (.001)	1.02	.023*** (.001)	1.02
ln (# of seller followers)	.011 (.007)	1.01	.021*** (.007)	1.02	.021* (.012)	1.02	.022* (.012)	1.02	.022* (.012)	1.02
Seller identity variables	(Included in estimation)									
<b>Product Characteristics</b>										
Price of the product	−.015*** (.000)	.99	−.014*** (.000)	.99	−.014*** (.000)	.99	−.014*** (.000)	.99	−.014*** (.000)	.99
# of product photos	.016*** (.003)	1.02	.017*** (.003)	1.02	.023*** (.005)	1.02	.023*** (.005)	1.02	.023*** (.005)	1.02
Log length of listing description	.013** (.005)	1.01	.015*** (.005)	1.02	.023** (.009)	1.02	.022** (.009)	1.02	.022** (.009)	1.02
Product categories	(Included in estimation)									
# of observations	26,228		22,371		8,184		8,184		8,184	
Log likelihood at convergence	−40,756.18		−36,820.86		−13,531.48		−13,522.19		−13,523.17	

\* $p < .10$ .\*\* $p < .05$ .\*\*\* $p < .01$ .

Notes: Seller verification information and product categories are included in estimation but not reported for brevity. Heteroskedasticity consistent robust standard errors are reported in parentheses.

competence was significantly higher for unattractive and attractive faces than for plain-looking faces ( $M_{\text{unattractive}} = 3.94$  vs.  $M_{\text{plain}} = 3.69$ ;  $F(1, 229) = 6.73$ ,  $p < .05$ ;  $M_{\text{attractive}} = 3.87$  vs.  $M_{\text{plain}} = 3.69$ ;  $F(1, 238) = 3.88$ ,  $p < .10$ ). There is no difference between the unattractive and attractive conditions ( $F < 1$ ). Perceived sociability/competence were positively correlated with source credibility ( $r = .46/.58$ ,  $p < .01$ ) and purchase intention ( $r = .45/.57$ ,  $p < .01$ ).

**Mediation.** We took a bias-corrected bootstrapping approach with 5,000 samples to simultaneously test sociability and competence as mediators, generating a 95% confidence interval around the following paths: (1) from attractive faces to sociability to source credibility to purchase intention and (2) from unattractive faces to competence to source credibility to purchase intention. The path coefficients from serial multiple mediated models are presented in Figure 4, Panel A. It is worth



**Figure 4.** Mediation path diagram (Study 2a).

\* $p < .10$ .

\*\* $p < .05$ .

\*\*\* $p < .01$ .

noting that the direct effect of attractive faces on sociability is much greater than that on competence ( $b = .29$  vs.  $b = .18$ ). The indirect effect of attractive faces on purchase intention via sociability/competence and source credibility is significant and positive ( $b = .037/.065$ ,  $SE = .017/.034$ , 95% bootstrap confidence interval [BCI] =  $[-.003, .071]$ ,  $p = .06$ ). The indirect effect of unattractive faces on purchase intention through competence and source credibility is also significant ( $b = .092$ ,  $SE = .036$ , 95% BCI =  $[-.022, .164]$ ). These results support  $H_2$  and  $H_3$ . We conducted a test of the alternative causal chain by reordering the mediators and testing the following pathways: (1) from attractive faces to source credibility to sociability to purchase intention and (2) from unattractive faces to source credibility to competence to purchase intention. However, the confidence intervals for these alternative mediation model contain zero (sociability:  $b = .010$ ,  $SE = .007$ , 95% BCI =  $[-.004, .025]$ ; competence:  $b = .014$ ,  $SE = .010$ , 95% BCI =  $[-.006, .034]$ ). Thus, we concluded that the causal chain occurs only in the predicted directions.

**A replication study.** We recruited 479 participants from MTurk and randomly assigned them to one of four between-subject conditions (no picture, attractive, plain-looking, and unattractive). Except for the shopping task for a sunscreen, everything else is identical to the original study. The presence of a picture is found to have a positive effect on source credibility ( $M_{\text{picture}} = 3.84$  vs.  $M_{\text{no picture}} = 3.63$ ;  $F(1, 477) = 5.35$ ,  $p < .05$ ) and

purchase intention ( $M_{\text{picture}} = 3.84$  vs.  $M_{\text{no picture}} = 3.60$ ;  $F(1, 477) = 5.05$ ,  $p < .05$ ). The results from mediation analysis on the sunscreen setting (shown in Figure 4, Panel B) are largely consistent with those on the digital camera setting. In particular, the indirect effect of attractive faces on purchase intention via sociability/competence and source credibility is significant and positive ( $b = .051/.054$ ,  $SE = .022/.031$ , 95% BCI =  $[-.010, .093]$ ,  $p = .076$ ). The indirect effect of unattractive faces on purchase intention via competence and source credibility is also significant ( $b = .066$ ,  $SE = .035$ ,  $p = .056$ ). Thus, we found consistent beauty and ugliness premiums and the mediating mechanisms via sociability and competence for both digital camera and sunscreen.

**Other potential mediators.** Following the recommendations of Zhao, Lynch, and Chen (2010), we examined potential mediators simultaneously alongside sociability and competence. We performed serial mediation analyses on visual attention and test whether it is a potential mediator driving the results. Although attractive and unattractive faces attract greater attention ( $b_{\text{attractive}} = 7.54$ ,  $SE = 3.17$ ,  $p < .05$ ;  $b_{\text{unattractive}} = 6.28$ ,  $SE = 3.19$ ,  $p < .05$ ), visual attention does not significantly affect source credibility ( $b = .001$ ,  $SE = .001$ ,  $p > .10$ ), which influences purchase intention. The 95% BCI  $[-.015, .03]$  of its indirect effect also includes zero. These results confirm our conjecture that attention is only the starting point for perceptions but not sufficient to induce a positive effect on the outcomes. The potential mediating effects of trustworthiness and face familiarity are also found to be insignificant.<sup>6</sup> While source credibility is an inference of expertise and trust based on the perception of all available cues (with attractiveness being just one of them), visual-based trustworthiness is the trustworthiness judgment based on an online profile photo (Ert, Fleischer, and Magen 2016). Thus, it is independent of a purchase context. In contrast, source credibility is more context-specific, especially relevant for evaluating products for purchase. That explains why visual-based trustworthiness does not play a significant mediating role between facial attractiveness and source credibility.

## Study 2b: Product Relevance and Cross-Gender Effects

**Participants and design.** We recruited 556 participants (306 men;  $M_{\text{age}} = 37.15$ ,  $SD = 10.57$ ) from MTurk and randomly assigned them to a 3 (unattractive, plain-looking, and attractive faces)  $\times$  2 (product relevance: appearance vs. expertise)  $\times$  2 (seller gender: male vs. female) between-subjects conditions. The experiment simulates online shopping for a cookbook. To rule out potential confounds from the difference between products in terms of features, prices, and so on, we followed the practice of using one product positioned to be different in its relevance, as it is possible that a product may be relevant to

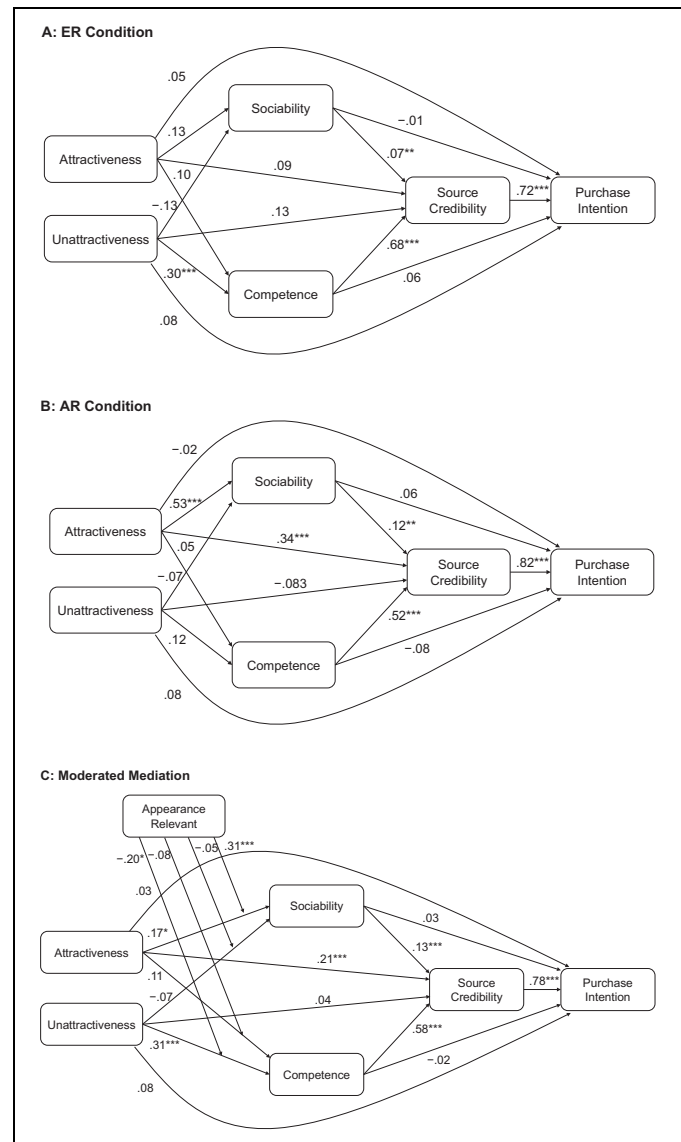
<sup>6</sup> Web Appendix 3 reports the mediation analysis and results for other potential mediators such as trustworthiness and face familiarity.

appearance or expertise to varying degrees (Bower and Landreth 2001; Trampe et al. 2010). Thus, unlike some studies that only used product type as a measure of product relevance (e.g., Trampe et al. 2010), we manipulated product relevance by inserting a positioning message: “This cookbook contains many beauty secrets in its recipes that will give you a healthy and radiant appearance” in the appearance-relevant (AR) condition and “this cookbook can help you spend less time preparing nutritious meals and provide better cooking through science” in the expertise-relevant (ER) condition. Participants went through the same procedure as described in Study 2a. We also asked questions regarding the manipulation check of product relevance: “This book would improve the appearance of an unsatisfactory physical feature” and “this product would improve the efficiency of cooking through scientific methods.” Participants responded using a five-point scale (1 = “does not describe at all,” 5 = “describes completely”). At the end of the study, we collected the genders of the participants to examine the cross-gender effect.

**Manipulation check.** Participants viewed attractive sellers as significantly more attractive than plain-looking and unattractive sellers ( $M_{\text{attractive}} = 3.36$  vs.  $M_{\text{plain}} = 2.71$  vs.  $M_{\text{unattractive}} = 2.24$ ;  $F(2, 553) = 58.2, p < .01$ ). Those in the AR condition believed that the cookbook could help improve appearance more than those in the ER condition ( $M_{\text{AR}} = 2.65$  vs.  $M_{\text{ER}} = 2.15$ ;  $F(1, 554) = 24.34, p < .01$ ). In addition, participants in the ER condition believed that the cookbook could improve the efficiency of cooking more than those in the AR condition ( $M_{\text{AR}} = 3.09$  vs.  $M_{\text{ER}} = 3.75$ ;  $F(1, 554) = 49.10, p < .01$ ).

**Purchase intention and source credibility.** Consistent with previous studies, seller attractiveness has a U-shaped relationship with purchase intention ( $F(2, 553) = 5.12, p < .01$ ) and source credibility ( $F(2, 553) = 6.77, p < .01$ ). Moving from unattractive to plain-looking sellers decreases purchase intention ( $M_{\text{unattractive}} = 3.91$  vs.  $M_{\text{plain}} = 3.72$ ;  $F(1, 366) = 4.42, p < .05$ ) and source credibility ( $M_{\text{unattractive}} = 3.84$  vs.  $M_{\text{plain}} = 3.69$ ;  $F(1, 366) = 3.02, p < .10$ ). Beyond that, however, additional attractiveness increases purchase intention ( $M_{\text{plain}} = 3.72$  vs.  $M_{\text{attractive}} = 3.98$ ;  $F(1, 371) = 9.81, p < .01$ ) and source credibility ( $M_{\text{plain}} = 3.69$  vs.  $M_{\text{attractive}} = 3.99$ ;  $F(1, 371) = 13.71, p < .01$ ). Source credibility is highly correlated with purchase intention ( $r = .74$ ).

**Moderated mediation for product relevance.** First, we performed separate mediation analyses for the AR and ER conditions (Figures 5, Panels A and B), simultaneously testing perceived sociability and competence as mediators. For the AR condition, the indirect effect of attractive sellers on purchase intention via sociability and source credibility is significant and positive ( $b = .053, SE = .028, p = .052$ ) whereas the path via competence is not significant ( $b = .02, SE = .055, p = .72$ ). For the ER condition, the effect of unattractive faces on purchase intention via competence and source credibility is significant and



**Figure 5.** Moderated mediation path diagram (Study 2b).

\* $p < .10$ .

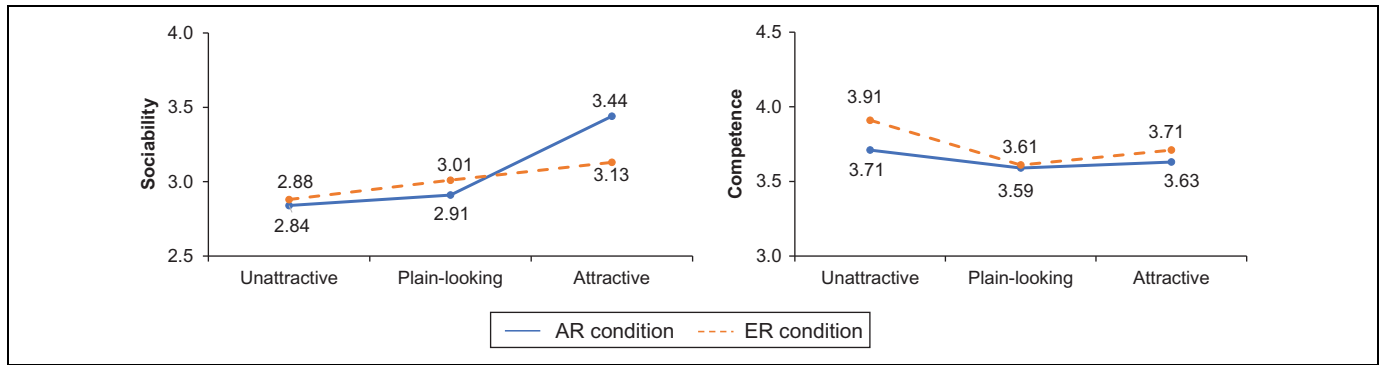
\*\* $p < .05$ .

\*\*\* $p < .01$ .

positive ( $b = .147, SE = .057, 95\% \text{ BCI} = [.034, .261]$ ).  $H_{4a}$  and  $H_{4b}$  are largely supported.

Second, a moderated mediation analysis yields similar results (Figure 5, Panel C). In particular, the AR product moderates the sensitivity to sociability ( $b = .31, SE = .12, p < .01$ ), and sociability is positively related to source credibility ( $b = .13, SE = .04, p < .01$ ). The conditional indirect effects show that perceived sociability matters more in the AR condition ( $b = .049, SE = .021, 95\% \text{ BCI} = [.008, .089]$ ) than in the ER condition ( $b = .017, SE = .012, 95\% \text{ BCI} = [-.007, .041]$ ). We also found that the ER product moderates the sensitivity to competence ( $b = -.20, SE = .12, p < .10$ ) and that competence is positively related to source credibility ( $b = .58, SE = .04, p < .01$ ). The conditional indirect effects show that perceived





**Figure 6.** The interaction between attractiveness and product relevance (Study 2b).

competence matters more in the ER condition ( $b = .140$ ,  $SE = .045$ , 95%  $BCI = [.052, .228]$ ) than in the AR condition ( $b = .054$ ,  $SE = .048$ , 95%  $BCI = [-.043, .228]$ ).

Finally, by examining their relative values across AR versus ER conditions, we further assessed how perceived sociability and competence together influence source credibility, which in turn affects purchase intention (Figure 6). For both conditions, attractiveness increases perceived sociability. When a seller is attractive, perceived sociability is significantly higher in the AR condition than in the ER condition ( $M_{AR} = 3.44$  vs.  $M_{ER} = 3.13$ ;  $F(1, 186) = 6.42$ ,  $p < .05$ ). When a seller is unattractive, perceived competence is significantly lower in the AR condition than in the ER condition ( $M_{AR} = 3.71$  vs.  $M_{ER} = 3.91$ ;  $F(1, 181) = 3.11$ ,  $p < .10$ ). These results confirm that product relevance affects the attractiveness–purchase relationship by influencing perceived sociability and competence, respectively.

**Cross-gender effect.** We created two dummy variables to test the moderating effect of cross-gender: MBFS takes a value of 1 if a male buyer faces a female seller, FBMS takes a value of 1 if a female buyer faces a male seller, and both take 0 for pairs of the same gender. To test  $H_{5a}$ , we conducted a moderated mediation analysis (from seller attractiveness to sociability to source credibility to purchase intention, with MBFS as the moderator) with 5,000 bootstrapped samples. For attractive sellers, there is no evidence of moderated mediation for the MBFS group from sociability to source credibility to purchase intention ( $b = .16$ ,  $SE = .11$ ,  $p = .139$ ). The conditional indirect effect also suggests that perceived sociability does not matter more in the MBFS condition than in the other conditions ( $p > .10$ ). Thus,  $H_{5a}$  regarding a stronger beauty premium in the MBFS setting is not supported. For unattractive faces, a similar moderated mediation analysis (from seller attractiveness to competence to source credibility to purchase intention with FBMS as the moderator) suggests that unattractive men moderate the sensitivity of female buyers to perceived competence ( $b = .30$ ,  $SE = .11$ ,  $p < .01$ ), and perceived competence is positively related to source credibility ( $b = .59$ ,  $SE = .04$ ,  $p < .01$ ), which in turn affects purchase intention ( $b = .78$ ,  $SE = .04$ ,  $p < .01$ ). A bootstrapping test with 5,000 resamples indicates a significant

indirect effect (95%  $BCI = [.089, .307]$ ). Thus,  $H_{5b}$  regarding a stronger ugliness premium in the FBMS setting is supported.

## Discussion

### Conclusions

Unlike previous studies of attractiveness that focus on social selections in experimental settings, our field studies examine the effect of facial attractiveness among large numbers of sellers and buyers in an e-commerce context, in which profile pictures serve as a primary vehicle for impression formation and trait inference. Although the literature has documented a beauty premium in a variety of settings and occasionally found an ugliness premium, our analyses of tens of thousands of seller profile pictures from two websites provide converging evidence of a U-shaped relationship between facial attractiveness and sales. As for the underlying mechanisms, our experimental results support previous findings of a beauty premium and of an ugliness penalty when evaluating sellers' sociability. We also find an ugliness premium in perceived competence for unattractive sellers over plain-looking people. Thus, whereas attractive faces signal sociability and competence, unattractive faces elicit an enhanced perception of competence over sellers with plain looks, even slightly more so than the attractive people. Thus, contrary to the notion of the curse of ugliness, our findings indicate that plain-looking faces are caught in the middle without any real advantage, as they are considered less sociable than attractive people and less competent than unattractive people. As such, when consumers make online purchases, sellers' faces serve an important discriminating function to encode sellers' characters, sometimes in unexpected ways.

In addition, the effects of attractiveness and inferred traits are mediated by source credibility and are subject to the influence of important contextual variables—that is, product relevance (to appearance or expertise) and gender. Our results reveal that the mediating role of sociability on the relationship between attractive sellers and source credibility is significantly stronger for products relevant to appearance. In contrast, the mediating effect of competence is more associated with products for which expertise is more important than appearance. Finally, we find a greater ugliness premium for unattractive

male sellers in perceived competence awarded by female consumers. However, male respondents do not reciprocate a greater beauty premium on attractive female sellers, perhaps because online purchases do not involve social selection like dating or hiring. It is not uncommon for attractive women to be viewed negatively for certain products or professions (Heilman et al. 2004; Ruffle and Shtudiner 2015; Samper, Yang, and Daniels 2018) or to draw suspicion for their appearance in online forums (Lo, Hsieh, and Chiu 2013).

### *Implications*

The role of attractiveness in human interactions is complex. Although most studies indicate a prevailing beauty premium, there are many exceptions and counterexamples (e.g., Eagly et al. 1991). Our findings of a U-shaped relationship and the different mechanisms and contexts underlying the beauty and ugliness premiums highlight the complex relations between facial attractiveness and outcomes in C2C e-commerce and, to some extent, reconcile the previous disparate findings. Previous studies of the beauty premium have mainly considered mass media or interpersonal and face-to-face situations. Although social pressure is of lesser concern in C2C e-commerce, attractive individuals retain the beauty premium in sociability and competence, whereas their plain-looking counterparts suffer a penalty. Meanwhile, we find consistent evidence that even unattractive individuals have an edge in perceived competence over plain-looking people. More importantly, we shed light on the different mechanisms and conditions for the beauty and ugliness premiums, that is, social trait inferences, product relevance, and gender interactions. While the marketing and advertising literatures have emphasized the halo effect of beauty, our findings suggest that the effect of attractiveness is more complicated and subject to the influence of these factors, which researchers and practitioners must consider when assessing the effect of seller attractiveness on consumer responses.

Our findings provide meaningful implications for both online sellers and platform operators who want to leverage seller profile pictures to enhance business performance. Posting a photo of oneself instead of an avatar or landscape makes a difference. Having said that, loading a profile picture is not a task to be taken lightly. Similar to the beauty and ugliness premiums in earnings found by studies of labor market (e.g., Biddle and Hamermesh 1994; Kanazawa and Still 2018), our results indicate that one's attractiveness level has a tremendous effect on sales performance in C2C e-commerce platforms. Figure 2, Panel A, suggests that the beauty premium over plainness in the annual occupancy rate on Airbnb is, on average, 6% (62% vs. 56%) and as high as 22% (i.e., 78% vs. 56%) for perfect faces. Thus, everything being equal, good looks sell more. Meanwhile, the ugliness premium over plain-looking hosts is approximately 4%, on average, (60% vs. 56%) and up to 16% (72% vs. 56%) for the most unattractive hosts. Thus, such premiums are much higher for the extreme cases, whether it is extremely attractive or unattractive. Likewise, findings

from the 5miles study show that both attractive and unattractive sellers are more likely to make a sale than their plain-looking counterparts (predicted probability: 44% for attractive, 38% for plain-looking, and 41% for unattractive; Figure 2, Panel B). Our experimental results suggest that while the beauty premium of female sellers does not hold true for male buyers, the ugliness premium only applies to unattractive men seen by female buyers, revealing the inequality in the cross-gender effect of beauty and ugliness premiums.

While the marketing literature is not short of studies emphasizing the effect of attractiveness in sales and customer service encounters (Keh et al., 2013; McColl and Truong 2013), our nuanced findings of the curvilinear relationship between attractiveness and performance and the underlying mechanisms are particularly relevant for today's social selling on e-commerce platforms. First, like candidates in political campaigns who often enhance their images (Mattes et al. 2010), aspiring entrepreneurs in social selling and C2C e-commerce should be mindful of their self-presentation; attractive appearances help create a favorable impression and gain the trust of shoppers. A professional photographer can produce a quality portrait to enhance attractiveness, and sellers can pretest the effect of a portrait on their perceived sociability and competence using services such as photofeelfer.com. As consumers often choose between many sellers pitching similar products online, sellers with different degrees of attractiveness must be cognizant of their source of credibility, that is, sociability and/or expertise, as well as the type of products they are selling. A small perceptual difference based on appearance or credibility can have a nonnegligible effect.

Although e-commerce platform operators have no control over how people take pictures, they should provide guidance and suggestions and encourage sellers to provide attractive portraits of themselves. In addition to a good-quality photograph (i.e., in brightness and pixels), taking a photo from a particular angle may enhance attractiveness to avoid the plainness penalty. While attractive sellers enjoy an advantage, especially for appearance-related products, people without perfect facial symmetry and proportions should not shy away from displaying their true appearance. Emphasizing expertise in technical products can enhance their credibility and performance. Thus, on e-commerce platforms, both attractive and unattractive sellers can increase their performance by enhancing their perceived sociability or competence, especially when they are matched with products associated with the particular strengths derived from appearances. Because a product may be relevant to both appearance and expertise in varying degrees, our treatment of product relevance goes beyond mere product type and is based on product positioning with additional information. For online marketers, this means that given the positioning of a product (as relevant to appearance or expertise), they may select attractive or unattractive sellers as promoters and achieve similar results. Conversely, sellers with attractive or unattractive faces may find themselves better off presenting a product depending on its relevance to appearance or expertise.

With respect to the cross-gender interactions, existing studies in marketing have pointed to the potential positive effect of mismatched gender in service counters (e.g., McColl and Truong 2013) as well as its precarious pitfalls in other cases (Wan and Wyer 2015). Our findings of the inequality in the cross-gender effect of attractiveness and ugliness premiums suggest that attractive female sellers do not have an advantage over their less attractive counterparts in appealing to male buyers, who may not succumb to the female beauty in online purchase given the reduced social pressure. However, female buyers tend to consider unattractive men as more competent than the Average Joes, perhaps perpetuating the stereotype of the tech-savvy nerd. Social sellers and e-marketing managers may heed such complex cross-gender interactions when attempting to leverage the effect of seller appearances in online selling. Altogether, these implications regarding the relevance of product and cross-gender effect of beauty and ugliness premiums are not limited to profile pictures of online sellers and may be pertinent to advertising and marketing aesthetics in general. Thus, researchers should consider a broader range of attractiveness, traits inferred from appearance, and its complex interactions with product relevance and gender.

Recent trends in collaborative consumption increase the already large number of selection decisions facing consumers; this could further contribute to information overload and potentially increase reliance on the physical and facial appearances of sellers. Although poor-quality pictures may dampen consumer confidence, attempts by sellers to make themselves appear more attractive may backfire if they appear otherwise incompetent or suspicious (Lo, Hsieh, and Chiu 2013; Samper, Yang, and Daniels 2018). Although consumers may consider the attractiveness of sellers in their decision making, they should not allow a seller's appearance to cloud their judgment of source credibility and product quality. Due diligence in confirming the veracity of sellers and product information is necessary, as platforms often provide indicators of sellers' reputations, track records, and social media connections.

Methodologically, this study is the first to explore the effect of facial attractiveness using large data sets of real profile pictures in online transaction platforms. This further validates the generalizability of studies based on laboratory methods using a limited number of facial stimuli. The use of online field data and actual sales overcomes the limitations of perceptual measures and strengthens the validity of our findings. The machine learning approach to assessing facial attractiveness proves to be reliable and robust and provides a useful tool for future studies using large data sets for facial recognition and deep learning in online settings.

### Limitations and Directions for Future Research

People make individual choices when uploading a profile picture and selecting the type of products they sell. Future researchers could collect more data from other e-commerce sites to address potential self-selection bias and to validate our findings, particularly the U-shaped relationship between facial

attractiveness and sales and the disadvantages for plain-looking people. This research focuses on facial geometrics to assess attractiveness. Characteristics of attractiveness other than faces could be examined, such as expressions and head tilt, which can affect perceptions of attractiveness. Although they are beyond the scope of this research, extrafacial features such as clothing and body posture, biometric data such as skin tone, color, race, gender, and enhancement by cosmetics and accessories may affect social attributions and provide rich data and broad avenues for future studies. For instance, attractiveness enhanced by cosmetics or perceived expertise from eyeglasses can augment or alter social perceptions.

Greater insight is needed regarding how other dimensions, such as cultural or dispositional variables, may moderate the relationship between seller attractiveness and consumer reactions. Online social interactions, such as messaging and chat, and offline face-to-face meetings between sellers and buyers may influence the effect of seller attractiveness. Software is now commonly used to enhance self-presentation, but excessive manipulation in portraits may be deceptive, raise suspicion, and lead to consumer dissonance and discontent. Thus, how consumers perceive and react to enhanced portraits and facial features warrants investigation. Finally, more tests are necessary to validate the mechanisms through which sociability and competence judgments are derived from facial cues and carried over to decision making. Innovative methods such as neuroscience and fMRI scans may help to reveal how these evaluation processes influence consumer perceptions and purchase decisions.

### Author Contributions

Ling Peng, Geng Cui, and Yuho Chung share equal authorship.

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