Can Information Reduce Ethnic Discrimination? Evidence from Airbnb

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Abstract

We use data from Airbnb to identify the mechanisms underlying discrimination against ethnic-minority hosts. Within the same neighbourhood, hosts from minority groups charge 3.2% less for comparable listings. Since ratings provide guests with increasingly rich information about a listing's quality, we can measure the contribution of statistical discrimination, building upon Altonji and Pierret (2001). We find that statistical discrimination can account for the whole ethnic price gap: ethnic gaps would disappear if all unobservables were revealed. Also, three quarters (2.5 points) of the initial ethnic gap can be attributed to inaccurate beliefs by potential guests about hosts' average group quality.

Keywords: ethnic discrimination, statistical discrimination, inaccurate beliefs, rental market, online markets.
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Ethnic discrimination is a pervasive phenomenon and understanding which mechanisms are at work is needed to design effective policies. In their recent reviews, Charles and Guryan (2011) and Lang and Lehmann (2012) stress that empirical attempts to uncover these mechanisms are still inconclusive. This paper takes advantage of the features of Airbnb, a major online marketplace for short-term rentals, to measure to what extent information can influence ethnic price gaps.

Airbnb hosts list their property, set the daily price and provide information about themselves (at least first name and picture) and their properties (precise location, equipment, local amenities, pictures...). Potential guests book properties at given dates at the price set by hosts. In this paper, we study the differential between prices set by hosts who belong to an ethnic minority and those set by majority hosts. We ask whether this ethnic price gap that remains unexplained by differential in observable characteristics is driven by statistical discrimination or other factors.

While taste-based discrimination stems from the existence of racial preferences or an aversion towards cross-racial interaction (Becker, 1957), statistical discrimination is the result of imperfect information and ethnic differences in the mean or the variance of unobservable characteristics (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977). The most direct approach to distinguish statistical discrimination from other mechanisms is to measure how the ethnic gap varies with the amount of information about a service (Farber and Gibbons, 1996; Altonji and Pierret, 2001).

We adapt the Altonji and Pierret (2001) approach to our setting, in which we observe a measure of the quantity and quality of information about a property available to potential guests. In contrast with labour markets, the short-term rental market is well suited for testing statistical discrimination because (i) transactions happen frequently, compared to changes in the quality of the property, (ii) ratings and the number of reviews can be observed, (iii) large-sample and longitudinal data are available. The profiles of new properties contain only self-reported information. After their stay, guests are allowed to leave a quantitative rating and a qualitative assessment of both the property and the host. As the number of reviews grows, more information becomes available to potential guests.

We rely on a simple conceptual framework where the quality of the properties is partially unobservable. Initially, a property has no reviews and potential guests can only infer unobservable quality using hosts' ethnicity, conditional on other observables. As a property accumulates reviews, potential guests aggregate the content of reviews and host's ethnicity to form the best possible guess about the property's unobservable quality. From this model, we derive a first test for the existence of statistical discrimination that relies on the longitudinal nature of the data. In the presence of statistical discrimination, the price gap should decrease with the number of reviews and tend to zero, conditional on observables and on the measure of quality provided by the reviews. If instead the price gap is due to taste-based discrimination or to ethnic differentials in variables that are not observable to the econometrician but observable to potential guests, the price gap should remain stable with the number of reviews.

Guests' beliefs about unobservable quality do not need to be accurate (Bordalo et al., 2016). If potential guests believe that properties belonging to an ethnic minority are on average worse than they actually are, an ethnic price gap will emerge. We categorise this phenomenon as statistical discrimination, as the gap will disappear when more information about quality becomes available. We account for inaccurate beliefs in our conceptual framework, and provide an additional empirical prediction that allows us to measure its contribution to the statistical-discrimination component of the ethnic price gap.

As an illustration, suppose properties held by minority and majority hosts have the same average quality but potential guests believe that minority listings are worth 10% less. When properties have no reviews, minority-held properties will be priced 10% lower. When the number of reviews grows to infinity, the average price will be identical in both groups. Conversely, imagine now that the average quality is indeed 10% lower in the minority group, i.e., beliefs are accurate. In this case, there will be a 10% price gap between the two sets of properties whether there are few or many reviews. However, if we follow two properties of the same quality, one held by a minority host, the other one by a majority host, there will be an initial price gap of 10% that will converge to zero as they accumulate reviews. Formally, we will use the cross-group differential slope of prices with respect to the number of reviews to quantify: (i) the ethnic price gap due to statistical discrimination (when we control for a proxy of the quality of the listing) and (ii) the part of statistical discrimination that is due to inaccurate beliefs (when we don't control for a proxy of the quality of the listing).

Our dataset includes daily prices, characteristics of hosts and properties, as well as associated reviews. We collected data relating to around 670,000 properties, corresponding to apartments to rent in 19 cities in North America and Europe. In total, 21 waves of data, collected between June 2014 and November 2017, form an unbalanced panel of 3,800,000 observations. The ethnic minority groups we consider are hosts with Arabic or Muslim first names and hosts categorised as Black based on their profile pictures.

We find that the within-city raw ethnic price gap is around 16%. The set of observable characteristics about the property (including its location) is rich and explains more than 67% of the variance of the price. When the heterogeneity in observable characteristics is accounted for, the ethnic price gap is reduced to a significant 3.2%.[1] This figure may look small, but a price gap of 3.2% represents a gap of 17% of the hosts' surplus, which is substantial.[2] We show that prices increase faster with the number of reviews when the host belongs to an ethnic minority, conditional on the average rating based on reviews received by the listing over the whole observation period. We find that 3.4 percentage points of the price gap (i.e., the whole gap) are accounted for by statistical discrimination. Of these 3.4 percentage points, 2.5 are due to inaccurate beliefs, that is, to the fact that potential guests underestimate the average unobservable quality of minority properties compared to majority ones. The difference, a statistically significant 0.9 percentage point, is due to the true difference in average unobservable quality between the two groups.

Our paper contributes to the growing but largely inconclusive literature on the sources of discrimination. Altonji and Pierret (2001) find little evidence for statis-

[1] Edelman and Luca (2014) are the first to document the existence of significant ethnic price gaps on Airbnb, focusing on the Black-White price gap in New York City.

[2] We use the estimates from Farronato and Fradkin (2018) for the hosts surplus and average price. See Section 1.3 for details.

tical discrimination in wages on the basis of ethnicity on the U.S. labour market. A strand of literature uses the fact that the relevant outcome is perfectly observed ex post. Knowles et al. (2001) show that vehicles of African-Americans are more often searched by the police and that statistical discrimination explains more than the observed gap.[3]

The amount and nature of information available to discriminatory agents can also be manipulated experimentally. On the online rental apartment market, Ewens et al. (2014) find the response to differential quality varies in a way that is consistent with statistical discrimination.[4] Cui et al. (2020), in a paper developed independently from ours, send Airbnb accommodation requests expressed by African-American-sounding-name and white-sounding-name guests in three American cities. They compare requests by guests who have none vs. one review, and find that both positive and negative reviews reduce the ethnic acceptance gap by hosts. Experimental evidence can be complemented by lab games to separate discrimination mechanisms. In the case of the sportscard market, List (2004) finds that the lower offers received by minorities are mainly explained by statistical discrimination.[5]

Other approaches have been used to separate sources of discrimination. Wozniak (2015) shows how a policy (drug-testing legislation) that affects a relevant dimension of the unobservables (drug use) can provide evidence of statistical discrimination against low-skilled African-American men. The heterogeneity in agents' prejudice, whether revealed or assumed, is sometimes used to infer which source of discrimination is more prevalent. Bayer et al. (2017) show that the minority home-buyers pay higher prices in the U.S. housing market regardless of

[3] Using data from a peer-to-peer lending website, Pope and Sydnor (2011) find that African-Americans are likely to be subject to statistical discrimination. Using data from television game shows, Anwar (2012) finds that white contestants believe that Afro-Americans have lower skill levels while Levitt (2004) and Antonovics et al. (2005) find no evidence of discrimination.

[4] Conversely, in their correspondence studies on the U.S. and Canadian labour markets, Bertrand and Mullainathan (2004) and Oreopoulos (2011) find that adding information or enhancing resumes do not benefit minority applicants. Heckman (1998) and Neumark (2018) list some of the challenges associated with the current use of experimental methods for discrimination.

[5] See also Fershtman and Gneezy (2001) and Castillo and Petrie (2010) for papers using lab experiments for this purpose.

the sellers' ethnicity, suggesting statistical discrimination. Zussman (2013) finds that the discrimination towards Arabs on an online market for used cars in Israel is not related to sellers' revealed attitudes towards Arabs. Doleac and Stein (2013) show that online iPod ads featuring dark-skinned hands receive fewer offers, with poorer outcomes in thin markets and those with higher racial isolation and crime.[6]

Following Bordalo et al. (2016), a recent literature has attempted to go beyond the dichotomy between taste-based and statistical discrimination. Customers may have inaccurate beliefs about sellers' quality, which itself could be due to stereotypes. To our knowledge, few papers have tried to isolate this source of differentials from other discriminatory mechanisms. Arnold et al. (2018) and Dobbie et al. (2018) isolate "inaccurate stereotyping" from racial animus in the context of bail decisions and consumer lending, and find that this mechanism explains a large part of the racial bias. In our setting, we classify ethnic gaps coming from inaccurate beliefs as statistical discrimination because new information will reduce these gaps. Bohren et al. (2019) design a randomised experiment on a maths forum to measure the dynamics of discrimination against women, allowing for "belief-based" discrimination.

We also contribute to the growing literature on the role of information provided by online market intermediaries on markets' outcomes.[7] Our paper is related to Autor and Scarborough (2008), who show that, while minorities perform poorly on job tests, introducing job-testing in a large retail firm has no impact on minority hiring.

We contribute to the study of ethnic discrimination on the rental market by the unprecedented scale of our data, covering 19 cities in 8 countries both in Europe and North America. This online marketplace is relevant in itself from an economic

[6]Taking the opposite approach, Charles and Guryan (2008) introduce an indirect test of the Becker prejudice model based on associations between prejudice and wages and find that around one quarter of the unconditional racial wage gap is due to prejudice, while the three other quarters can be due to differences in unobservables or other forms of discrimination.

[7]See e.g. Autor (2001, 2009); Bagues and Labini (2009); Pallais (2014); Horton (2017); Pallais and Sands (2016); Brown et al. (2016); Stanton and Thomas (2018).

point of view: launched in 2008, the website offers more than 7,000,000 listings in 220 different countries and claims to have served over 750 million guests.[8]

Section 1 presents the context, the data and the first empirical evidence about ethnic price gaps. Section 2 introduces our conceptual framework. Section 3 presents our empirical strategy and our main results. Section 4 provides additional results and discusses alternative explanations. Section 5 concludes.

1 Context and Data

1.1 Description of the platform

Airbnb connects hosts looking for opportunities to let their properties and potential guests looking for a place to stay. Both types of users have to register and provide a large set of information about themselves. Hosts also have to provide information about their properties. In practical terms, potential guests usually start by typing the city where and when they want to stay on the search engine. They can filter the results of the search according to the price, or other characteristics (e.g., accommodation capacity, room type, property type, number of bedrooms). At that stage, potential guests obtain a list of results with basic information, among which the daily price, a picture of the property, a thumbnail photo of the host and the overall rating (presented in stars and defined as the average rating over the reviews of the listing). When they click on one of the listings, they have access to more detailed information, notably the first name of the host, a detailed description of the property, a standardised list of the offered amenities, more pictures and detailed reviews from previous guests.[9]

Hosts can revise the price of their properties at any moment. The potential guest decides which place she prefers among those available during the period selected and commits by clicking on the "Book It" button. The decision is then in the hands of the host. She can accept or reject the guest, without any justification.[10]

[8] https://news.airbnb.com/fast-facts/

[9] See Figure A1 for a screenshot of a listing corresponding to the period of the data we use.

[10] Rejections are frequent; see Fradkin (2017).

A guest who gets rejected receives an email encouraging her to look for another place. The rejection is not reported on her profile. If the host accepts the guest, the deal is concluded and there is no way to modify its terms.[11] The potential guest may decide to cancel her booking. In this case, the terms of the cancellation policy (specified on the listing) apply: depending on the flexibility of the policy, penalties of different amounts are charged. The host may also decide to cancel the deal. In this case, there is no financial penalty, but there is a reputation cost: the website records on the host's profile that she has cancelled a deal.

We consider hereafter that potential guests are price-takers. Using a simple model of supply and demand, we consider that the existence of discrimination towards hosts, which triggers a shift in demand, should translate into lower prices. We formalize this idea in the section dedicated to the conceptual framework.

1.2 Data

We collect data from publicly available webpages of the marketplace. We store all information visible on the first page of the listing: the price asked by the host, the characteristics of the listing, the characteristics of the host and the last 10 reviews and ratings. We focus on the 19 cities in North America and Europe with the highest number of listings.[12] We repeat the collection process every 2-3 weeks between June 2014 and June 2015, and add a last wave in November 2017, obtaining 21 waves in total.[13] Our sample includes 663,090 distinct properties. The panel is unbalanced: some properties enter the system and others exit.[14]

[11]While the acceptance/rejection decision would in itself be of interest as regards discrimination, we do not have the necessary data to study that side of the market. See Edelman et al. (2017) for a field study about discrimination against potential guests.

[12]The cities are: London, Paris, Madrid, Barcelona, Rome, Milan, Florence, Amsterdam, Berlin, Marseille, Vancouver, Toronto, Montreal, Boston, New York City, Miami, Chicago, San Francisco and Los Angeles. See Appendix Table A1 for the number of observations and listings by city.

[13]See the collection dates of each wave in Appendix Table A2. The last wave was added because we wanted to increase the longitudinal depth of our dataset.

[14]We check the possibility of differential attrition between ethnic groups. In Appendix C, we show that the probability to leave the market is the same for minority and majority groups, after controlling for property characteristics, ratings and neighbourhood fixed-effects.

We restrict our analysis on the sub-sample of listings that have gained at least one review over the observation period. The motivation behind this restriction is to work with active listings, where there has been established transactions and feedback from the guests. This restriction reduces the sample size from 663,090 to 220,939: most Airbnb listings do not get any review during that period (or exit before they do). The distribution of the number of waves during which we observe each property is in Appendix Figure A2: 13% of listings are observed in at least 20 waves and half of listings are observed at least 11 waves.

For each property, we know the main characteristics: the type of property, the size, the type of bed, amenities, services and rules. Most properties are apartments and the entire place is let in 70% of cases. Properties are rather small, with 1.2 bedrooms on average, and they can host on average three guests. Some properties add a cleaning fee and charge for additional people. We count the cleaning fee directly into the price in order to obtain the final price paid by the guest.[15] We also obtain some information about the hosts on their profile pages. Aside from the first name, a picture and a free-text description, potential guests know whether hosts have other properties and when they joined the platform. Most hosts have only one property and have joined the platform recently. See the full list of characteristics of the properties and the hosts in Table A3 in Appendix.

Figure 1 shows the distribution of daily prices. There is much variation in prices across properties. To reduce the influence of outliers, we drop 1% of the observations at the top and the bottom of the price distribution. The first quarter is \$75, the median \$107 and the third quarter \$160 per night. The skewness of the distribution implies that the mean price is \$130. The daily price varies across cities and according to the amenities of the listing (number of accommodates, bedrooms, bathrooms...). Appendix Table A4 provides details on how amenities affect the price.

In order to identify statistical discrimination, we need to have enough variability in the number of reviews and we need reviews to be informative about listings' quality. Appendix Figure A3 displays the distribution of reviews across the observations of our sample (left panel) and the variation of the number of reviews

[15]We assume guests stay on average six days, and add a sixth of the fee to the price.

between the last and the first observations (right panel) and shows that the sample offers a decent amount of heterogeneity in the number of reviews.

For each property, we use the last observed rating, which represents the average of all ratings received over its lifetime on Airbnb. Ratings can vary between 1 and 5 stars (with half-star increments), and the distribution is skewed towards good ratings, as documented in Fradkin et al. (2018). If we consider the last rating observed for each property of our sample, 44% of observations have 5 stars and 39% 4.5 stars. By contrast, only 4% have 3.5 stars or less (see Appendix Table A5).

1.3 Ethnic groups and gaps

We consider two groups of ethnic minorities. First, we consider Blacks, which we identify using the pictures provided on their host profile.[16] Second, we consider hosts that have a first name associated with Arabic, Muslim or Sub-Saharan African ethnicity (labeled Arabic/Muslim hereafter).[17] We use two different sources to obtain a complete list of names: Jouniaux (2001) and Hawramani (2015).[18]

Table 1 displays the share of ethnic groups in the sample and the price gap, controlling for interacted dummies for the city and the wave of observation (i.e. within-city-wave price gap). Blacks living in North America represent 2% of the observations and those living in Europe 0.9%. Hosts with Arabic/Muslim names in North America represent 1.3% of the sample and those in Europe 2.1% of the sample. Compared to their share in total population (both in North America &

[16] Specifically, pictures were coded by workers specialised in this picture-coding task. Workers were asked to code each picture in three categories: (i) whether they thought that at least one person in the picture was African-American, (ii) whether nobody in the picture was African-American, (iii) whether it was impossible to say anything about the ethnicity of anyone in the picture or the picture was not showing any human being (pictures of flats, pets, furniture, landscape...). We created one dummy variable equal to one in the first case. In order to check their results, we selected random samples and found mistakes at a rate below 5% for this dummy variable. In Appendix D, we provide suggestive evidence that minority hosts do not seem to strategically obfuscate their skin colour.

[17] See Rubinstein and Brenner (2014) for an example of discrimination based on names.

[18] The list of Arabic/Muslim names we used is available upon request.

Europe), ethnic minorities seem to be under-represented on the website. A possible explanation is that only those with a fairly good-quality property may attempt to rent on Airbnb, which would induce a positive selection. Overall, the share of minorities is 6.2%, but this share varies across cities. NYC has 9.8% of African-American and 3.7% of Arabic/Muslim observations. London and Paris both have around 5% of Arabic/Muslim observations, while this group represents less than 1% of the observations in Milan and Rome. The raw price gap for Arabic/Muslim hosts, controlling only for the heterogeneity across cities and waves, is around 5% in North America and 7% in Europe. For Blacks, the raw gap reaches 31% in North America and 26% in Europe.

Table 2 shows the ethnic price differential for several specifications. The first column displays within-city-wave raw differential in daily log-prices: only differences in cities and waves are taken into account, no differences in characteristics. The raw ethnic gap is large (17%) and highly significant. Accounting for ethnic disparities in property observable characteristics reduces the gap to 11% (column 2), which shows that ethnic minorities have on average properties of lower observable quality. Characteristics include all information provided by the host concerning her listing and her profile. The overall number of pictures and the number of pictures taken by professionals are also taken into account in our estimation.[19] Observable characteristics explain a large part of the variance: the adjusted R-squared jumps to .63 in the second column.

A major source of heterogeneity across listings is their location. Airbnb does not publicise the exact coordinates of a given listing, but rather a .3 mile-radius circle. We build a grid of blocks that are .6 miles large for all cities and assign each listing to the block where the centroid of its circle is located. On top of this, Airbnb assigns listings to the neighbourhood they belong to. In total, we work with 6,700 squared blocks and 1,500 neighbourhoods. Throughout the paper, controlling for the listing's location means that we control for both the block and the

[19]We identify the number of "verified photos" on each listing. Verified photos mean a professional Airbnb photographer visited the listing, captured and uploaded the photos. Airbnb contracts the photographers and the photography service is free for hosts. More information can be found at https://airbnb.com/info/photography

neighbourhood where the listing is located. Appendix Table A6 shows the number of neighbourhoods and blocks per city. The ratio of blocks per neighbourhood mainly depends on the area and the density of the city.

Including neighbourhood and block fixed-effects reduces the ethnic price gap from 17% to 7% (column 3) and the adjusted R-squared increases from .15 to .36. Finally, in the fourth column, both location and property characteristics are included in the regression: the residual ethnic price gap is reduced to 3.2% but is still very significant. The adjusted R-squared is high in this last specification, equal to .73. Compared to the unexplained ethnic wage gaps found on labour markets, a figure of 3.2% may look small. To make sense of it, one has to compare it to the average surplus that hosts realise on Airbnb. Working on the 50 largest US cities, Farronato and Fradkin (2018) find that hosts enjoy an average of $26 in surplus per night booked for an average price of $136. A 3.2% ethnic price gap represents a loss of $4.4 per night, i.e. a 17% ethnic differential in surplus.[20]

Table 3 shows the coefficient associated to the ethnic minority dummy in a regression of the log-price on property characteristics, neighbourhood dummies and ratings, on several subsamples defined by the number of reviews. We find that the point estimates differ across subsamples: from 3.4% for listings with no reviews to an insignificant 2% for listings with more than 49 reviews. These results are suggestive of the existence of statistical discrimination if reviews bring information that help offset the ethnic price gap. However, there are two caveats about this interpretation. First, we don't have the statistical power to reject the null hypothesis that all five coefficients are equal. Second, there is a potential sample bias: properties with no reviews are likely to be different from those with more than 49 reviews. In the remainder of the paper, we introduce a conceptual framework leading to an empirical test of statistical discrimination that leverages the longitudinal dimension of our data.

[20]Our framework (*see infra*) allows the remaining 3.2% gap to be explained by the uneven distribution of unobservables across ethnic groups. Thus, we refrain from using a test à la Altonji et al. (2005).

2 Conceptual framework

In this section, we present a simple conceptual framework where ethnic price gaps can be due to statistical discrimination, taste-based discrimination, ethnic differentials in characteristics unobserved by the econometrician but observed by potential guests, and ethnic differentials in outside options.

2.1 Prices and demand as a function of quality

At each period (say, a week), a host shares her working time between two activities: renting her property (looking for guests, communicating with guests, cleaning up) or working on a regular job. L is the amount of labour dedicated to renting and $1 - L$ to the regular job. Renting the property is assumed to have decreasing returns to scale: the number of nights supplied is equal to $L^{\tilde{\alpha}}$, with $\tilde{\alpha} \in (0,1)$. The regular job has constant returns to scale. Given the price of a night P and the wage of the regular job W, the revenue of the host over the period is: $PL^{\tilde{\alpha}} + W(1 - L)$.

From the point of view of potential guests in a particular market, properties differ in three dimensions: quality Q, price P and the ethnicity of the host m (equal to 1 if the host belongs to an ethnic minority, 0 otherwise). Demand D for a particular property is assumed to increase with Q, decrease with P. Taste-based discrimination is embedded in this framework: demand is assumed to be divided by $\Gamma > 1$ when $m = 1$, relatively to $m = 0$. Assuming β and κ are strictly positive, we write demand as:

$$D = \frac{Q^{\beta}}{P^{\kappa}\Gamma^{m}}$$

Taking Q and m as given, hosts can set the price P and the effort L they dedicate to renting to maximize their profit, under the demand constraint:

$$\max_{P} PD(P) + (1 - D^{1/\tilde{\alpha}}(P))W \text{ with } D(P) = \frac{Q^{\beta}}{P^{\kappa}\Gamma^{m}}$$

Solving the program, hosts will set the log-price such that:

$$p = p_0 + \lambda\alpha w + \lambda\beta q - \lambda\gamma m \tag{1}$$

where $p = \log P$, $w = \log W$, $q = \log Q$, $\gamma = \log \Gamma$, $\alpha = \frac{\tilde{\alpha}}{1-\tilde{\alpha}}$, $\lambda = (\kappa + \alpha)^{-1}$, $p_0 = \lambda\alpha \log(\frac{\tilde{\alpha}(\kappa-1)}{\kappa})$.

2.2 Imperfectly observed quality

Potential guests cannot observe quality perfectly. They have an information set which contains everything that the website displays about the listing (description, pictures, host ethnicity, and ratings, if any). We assume that quality q is the sum of two components orthogonal from each other: $q = \zeta + \nu$. ζ is immediately observable in the listing by potential guests, while ν is unobservable when the listing has no reviews but perfectly observable when it has an infinite number of reviews.

We assume that the distribution of the quality component inferred from reviews conditional on ethnicity $\nu|m$ is a $\mathcal{N}(\bar{\nu}_m, \sigma_\nu^2)$.[21] Each review transmits a signal, which is a random draw around ν in a normal distribution, the error on a single review being of variance σ^2.[22] Potential guests observe r, the average signal transmitted by the set of K existing reviews, which is distributed as a $\mathcal{N}(\nu, \sigma^2/K)$. Denoting $\rho = \sigma^2/\sigma_\nu^2$, the expected ν for a listing with average r, K reviews and host ethnicity m is the weighted average between the prior $\bar{\nu}_m$ and the signal r:

$$\mathbb{E}(\nu|r, K, m) = \frac{Kr + \rho\bar{\nu}_m}{K + \rho}$$

From the point of view of potential guests, the expected quality of a listings with K reviews, a signal r, a host ethnicity m and observable characteristics ζ is:

$$\mathbb{E}(q|\zeta, r, K, m) = \zeta + \frac{Kr + \rho\bar{\nu}_m}{K + \rho}$$

In a context where quality is not perfectly observed, the host will combine the expected quality conditional on the information set of potential guests with equa-

[21] In Appendix E, we show that we can obtain a similar expression for the expectation of the price when we assume, more realistically, that ν follows a non-normal prior distribution (beta distribution).

[22] This assumption is not obvious. Reviews may depend not only on the quality but also on prices. We abstract from this aspect to simplify.

tion (1) to form the price-setting rule:

$$p = p_0 - \lambda\gamma m + \lambda\alpha w + \lambda\beta\zeta + \lambda\beta\frac{Kr + \rho\bar{v}_m}{K + \rho} \tag{2}$$

3 Empirical strategy and results

In this section, we first derive empirical predictions from the theoretical framework in order to identify statistical discrimination from the other mechanisms. Second, we show how we can separate the part of the statistical-discrimination ethnic price gap that corresponds to differences in true average unobservable quality from the part that corresponds to inaccurate beliefs. Finally, we present the estimation results.

3.1 Identification strategy when beliefs are accurate

We assume that the econometrician observes for each listing i a sequence of prices p_{it} at different dates t, the associated number of reviews K_{it}, listing characteristics X_{it}, the host's ethnicity m_i, and the last known average rating $\bar{r}_i$. We assume that, conditional on a listing fixed-effects and X_{it}, the variability in prices over time does not come from variations in features ζ, or the outside option w.

Prediction 0 (accurate beliefs). Under the previous set of assumptions, our main empirical prediction is that the non-linear regression with listing fixed effects specified in equation (3) will allow the econometrician to identify $\beta_m = \lambda\beta(\bar{v}_1 - \bar{v}_0)$, the ethnic price gap that can be attributed to statistical discrimination, as well as ρ, the number of reviews that is necessary to make up for half of the gap due to statistical discrimination. Proofs are in Appendix F.

$$p_{it} = \sum_{\bar{r} \in Supp(\bar{r})} \beta_{\bar{r}} \mathbb{1}\{\bar{r}_i = \bar{r}\} \frac{K_{it}}{K_{it} + \rho} - \beta_m m_i \frac{K_{it}}{K_{it} + \rho} + \mu_i + X_{it}\beta_x + \varepsilon_{it} \tag{3}$$

Once we control for the time evolution of prices that corresponds to listings of quality $\bar{r}_i$ (where $Supp(\bar{r})$ is the set of all possible values of $\bar{r}_i$), the specific time evolution of prices of listings of minority hosts reveals the extent of statistical discrimination. If minority hosts have on average listings that have worse unobservables than majority hosts, $\bar{v}_1 < \bar{v}_0$, we have $\beta_m < 0$. Intuitively, all minority hosts have to post lower prices initially to compensate for lower expectations from the demand side. Within bins of listings of the same quality, the price of listings belonging to minority hosts will increase faster with the number of reviews than those belonging to majority hosts. As information about ν becomes more accurate, the price of minority-host listings will catch up and converge towards the price of their majority-host counterparts.

Note that, within this framework, we cannot disentangle the other possible channels causing ethnic price gaps. Differences in unobservables that do not evolve with reviews (ζ), differences in outside option (w), and taste-based discrimination (γ) are pooled together and absorbed by the listing fixed effects.

3.2 Identification strategy when beliefs are inaccurate

So far, we have assumed that potential guests have accurate beliefs and that statistical discrimination exists because the average quality of the listings proposed by minorities is lower than those proposed by the majority ($\bar{v}_1 < \bar{v}_0$). Here, we relax the assumption that guests have accurate beliefs about the average quality $\bar{v}$ in each group. For simplicity, let us assume that potential guests make no mistake on the average quality $\bar{v}_0$ of listings held by majority hosts. However, their prior on the average quality $\tilde{v}_1$ might differ from the true average quality $\bar{v}_1$. For instance, guests might wrongly believe that minority listings are worse on average than they actually are ($\bar{v}_1 - \tilde{v}_1 > 0$).

When beliefs are allowed to be inaccurate, we can decompose the term $\bar{v}_0 - \tilde{v}_1$ that we attribute to statistical discrimination into two components. The first one $\bar{v}_0 - \bar{v}_1$ is due to the difference in the true average unobservable quality across groups. The second one $\bar{v}_1 - \tilde{v}_1$ is due to the difference between the average true unobservable quality and the (potentially inaccurate) beliefs that potential guests hold about it.

Predictions 1 and 2 (inaccurate beliefs). Under this new, more general, set of assumptions, our first empirical prediction is that the regression specified in equation (3) will allow the econometrician to identify $\beta_m = \lambda\beta(\tilde{v}_1 - \bar{v}_0)$, the ethnic price gap that can be attributed to statistical discrimination, as well as ρ.

Our second empirical prediction is that the non-linear regression with listing fixed effects in which we do not include the interaction terms between ratings dummies $\mathbb{1}\{\bar{r}_i = \bar{r}\}$ and the evolution in the number of reviews $\frac{K_{it}}{K_{it}+\rho}$, as specified in equation (4), will allow the econometrician to identify $\tilde{\beta}_m = \lambda\beta(\tilde{v}_1 - \bar{v}_1)$, the ethnic price gap that can be attributed to inaccurate beliefs, as well as ρ. Proofs are in Appendix F.

$$p_{it} = \beta_k \frac{K_{it}}{K_{it} + \rho} - \tilde{\beta}_m m_i \frac{K_{it}}{K_{it} + \rho} + \mu_i + X_{it}\beta_x + \varepsilon_{it} \tag{4}$$

Whenever beliefs are correct ($\tilde{v}_1 = \bar{v}_1$), the estimate of $\tilde{\beta}_m$ in equation (4) should be equal to 0, while the estimate of β_m in equation (3) will be equal to $\bar{v}_1 - \bar{v}_0$. When $\tilde{v}_1 = \bar{v}_1$, potential guests are right, on average, about the property quality in each group. When we do not control by the price evolution specific to ratings' levels, the prices of minority-owned listings will evolve at the same pace as those of the majority.

On the contrary, when both groups have the same true average quality ($\bar{v}_1 = \bar{v}_0$) but potential guests have inaccurate beliefs ($\tilde{v}_1 < \bar{v}_1$), the estimate of β_m in equation (3) and the estimate of $\tilde{\beta}_m$ in equation (4) should be equal to each other and strictly positive. In the empirical subsection below, we will report β_m, the total statistical-discrimination gap, $\tilde{\beta}_m$ the ethnic gap due to inaccurate beliefs and $\beta_m - \tilde{\beta}_m$ the ethnic gap due to differences in the true average quality.

Where could inaccurate beliefs come from? Listings on Airbnb are a selected subset from all homes. Most likely, hosts self-select into Airbnb based on the quality of their homes, and it is possible that minority listings are even more selected, given that ethnic minorities tend to live in areas and properties that are less valued by guests. This differential selection may induce a gap between the guests' beliefs about unobservables and actual quality for minority listings. This hypothesis is consistent with the fact that the share of minorities on Airbnb is smaller than their share in the whole population. Another way to explain why potential guests, who are primarily from the majority group, have unduly low beliefs about the quality of minority hosts' listing is provided by the model of stereotypes in Bordalo et al. (2016).

3.3 Main empirical results

We estimate regressions (3) and (4), using four values for the support of the last observed average rating (5, 4.5, 4, and ≤ 3.5 stars), including listing fixed effects. We use all property characteristics as well as city dummies interacted with the wave in which the listing appears. We estimate the main parameters of interest: β_m, $\tilde{\beta}_m$ and ρ. For inference, we bootstrap at the property level.

We present the estimation results in Table 4. In the first column, we show the results of regression (3). The point estimate for the total ethnic gap corresponding to statistical discrimination is 3.4%. This figure is similar to the ethnic price gap observed in the subset of listings with no reviews (3.4%, see Table 3, column 1). This point estimate suggests that the whole initial price gap can be accounted for by statistical discrimination. In other words, when the number of reviews tends to infinity, the price gap between a property held by a minority host and one of the same quality held by a majority will converge to zero.

In the second column of Table 4, we show the results of regression (4). The component of statistical discrimination corresponding to inaccurate beliefs is estimated to be equal to 2.5%. We interpret this result as evidence that roughly three quarters (i.e., 2.5/3.4) of the gap due to statistical discrimination is driven by inaccurate beliefs, and one quarter (.9/3.4) by differences in average unobservable quality. Potential guests may either be overestimating the average quality of listings by majority hosts, or underestimating the average quality of those held by minority hosts. The true average unobservable quality of minority and majority listings is very similar, and creates a price gap of less than 1%, while the inaccurate beliefs of potential guests is responsible for most of the gap.[23] These

[23] Block-bootstrapping the estimation, we find that the 95% confidence interval of β_m is [0.014,0.054], the CI of $\tilde{\beta}_m$ is [0.005,0.046], and the CI of $\beta_m - \tilde{\beta}_m$ is [0.006,0.010].

inaccurate beliefs are corrected by new information about the quality of listings coming from reviews, which is in practice very different from what taste-based discrimination would generate.

We find that ρ is equal to 14. ρ can be interpreted as the number of reviews necessary to reveal half of the relevant information about the unobservables of a listing. If $\underline{p}$ is the price of a property in the absence of reviews and $\overline{p}$ the price when all the information is revealed, the price $(\underline{p}+\overline{p})/2$ is reached in expectation after ρ reviews. On average, 14 reviews are required to correct the ethnic gap for half of the component due to statistical discrimination.

4 Additional results

In this section, we first present two additional pieces of evidence in support of our main empirical strategy. We show that our results are robust to more flexible or different functional form assumptions on the relationship between log-prices and the number of reviews. Second, we present results by subsamples. Finally, we provide empirical elements that lead us to argue against alternative stories that could explain why minority prices increase faster than majority ones in the absence of statistical discrimination.

4.1 Robustness

In this subsection, we present additional results that do not rely on imposing the $\frac{K}{K+\rho}$ functional form on the relationship between the number of reviews and prices. We estimate a within-listing price model where the number of reviews enters as a linear or a quadratic function.

$$p_{it} = \sum_{\bar{r} \in Supp(\bar{r})} \mathbb{1}\{\bar{r}_i = \bar{r}\}(\beta_{\bar{r},1}K_{it} + \beta_{\bar{r},2}K_{it}^2) - m_i(\beta_{m,1}K_{it} + \beta_{m,2}K_{it}^2) + \mu_i + X_{it}\beta_x + \varepsilon_{it} \tag{5}$$

If reviews matter and ratings provide some information about unobserved quality, we should have $\beta_r > \beta_{r'}$ if $r > r'$, what we have checked above with a more flexible specification. In the presence of statistical discrimination, we should have

$\beta_{m,1} > 0$. The $\frac{K}{K+\rho}$ functional form also implies that the relationship between the number of reviews and prices is concave, so that $\beta_{m,2} < 0$.

Table 5 presents the results of the estimation of this model. Columns (1) and (2) show the estimation results for a linear specification, in which we restrict the sample to observations with less than 40 and 60 reviews. In column (3), we present the results for the quadratic specification. The results are all consistent with those of the previous section. The higher the final rating, the faster prices grow with the number of reviews. The slope of the relationship is higher for hosts belonging to the minority group. The quadratic specification shows that the relationship is indeed concave.

4.2 The relationship between prices and reviews: non-parametric estimation

Another way to support our empirical strategy is to show that the relationship between prices and reviews, irrespective of hosts' ethnicity, is compatible with the function $\frac{K}{K+\rho}$. Do we observe such a pattern in our data? Restricting our sample to properties held by majority hosts, we regress the log-price on splines of the number of reviews interacted with the last rating (5, 4.5, 4, and 3.5 stars and less) and the full set of characteristics of the properties. The spline specification allows us to flexibly accommodate any form of the relationship between prices and the number of reviews.

$$p_{it} = \sum_{\bar{r}=3.5}^{5} 1\{\bar{r}_i = \bar{r}\} s_r(K_{it}) + \mu_i + X_{it}\beta_x + \varepsilon_{it} \tag{6}$$

where p_{it} is the log-price of property i at wave t, K is the number of reviews, X are observable characteristics of the property and the host, $s_{\bar{r}}(.)$ are piecewise-linear splines that are specific to each level of the last rating $\bar{r}$ and μ are property fixed-effects. The results of the estimation are displayed in Figure 2.

The figure shows that, depending on the last rating, prices diverge in a way that is close to the functional form predicted by our conceptual framework, displayed in Appendix Figure A4. This result supports our assumptions that: (i) reviews provide information to potential guests, (ii) hosts use reviews and information to update their prices, and (iii) the functional form between log-prices and the number of reviews conditional on the last rating looks like $\frac{K}{K+\rho}$.

4.3 Heterogeneity

In Table 6, we perform the main analysis on several sub-samples, according to the ethnic minority group (African-American vs. Arabic/Muslim), the continent (North-America vs. Europe), and the nature of the listing (entire property vs. shared property). For each sample or specification, we report in Panel A the estimates of β_m and ρ, from equation (3). Panel B shows the unexplained price gap on the sample of properties with no reviews.

In most cases, the point estimate of β_m is of the same magnitude as the ethnic price gap for non-reviewed listings. According to our model, the ethnic price gap is maximum at zero review and decreases once information is revealed. Statistical discrimination seems to be higher for Black than for Arabic/Muslim hosts. There is no significant difference in the extent of statistical discrimination between Europe and North America. Comparing shared flats with entire flats is intuitively interesting. A possible hypothesis is that shared flats involve a more substantial amount of interaction between hosts and guests than entire flats (where, sometimes, hosts and guests hardly meet). Our analysis show that shared flats tend to have higher statistical discrimination than entire flats. We also find that information is more difficult to collect for shared flats (ρ being roughly twice larger) than for entire flats. This is consistent with the fact that the set of observables is larger (including how friendly the host is, for instance).

4.4 Do ethnic groups compete on the same market?

So far, we have made the implicit assumption that minority and majority hosts compete on the same market. In this section, we investigate whether markets are also segmented: minority hosts receiving almost only guests of their own ethnicities. We first have to extract information about guests' ethnicities. On the website, we observe the first name of the last ten guests leaving reviews on each listing and each wave. Since we do not use the pictures provided on each guest profile, we are not able to identify black guests. To keep a consistent definition for both hosts and guests, we restrict our analysis to the Arabic/Muslim minority group.

For each listing, we regress the share of reviews written by guests with an Arabic/Muslim first name on a dummy for the host ethnicity, controlling for the location and the observable characteristics of the listing. In Table 7, we find evidence for some ethnic matching: a host with an Arabic/Muslim first name is 1 percentage point more likely to have a review from a guest with an Arabic/Muslim first name. While minority hosts seem to receive more minority guests, the magnitude of the difference shows that markets are far from being segregated.

4.5 Are reviews ethnically biased?

Another way to explain our empirical results would involve the combination of taste-based discrimination and ethnically-biased reviews. In this scenario, the initial ethnic gap (among listings with few reviews) would reflect taste-based discrimination. If reviews are ethnically biased, minorities would overall receive lower ratings and worse reviews than majority listings with the same quality. Therefore, minority listings with the same observables and the same ratings would be of higher quality than majority listings. Prices of listings owned by minorities conditional on observable characteristics and ratings would increase faster than prices of majority listings.

A key ingredient of this scenario is that reviews are ethnically biased. In this subsection, we show that minority hosts do not receive significantly better or worse reviews from minority guests than from majority guests. We read this result as an argument against the hypothesis that reviews are biased. To investigate this question, we must build, for each listing i and wave t, the ratings corresponding to the new reviews between t and $t-1$. This step is necessary because the rating we observe at date t, $\bar{r}_{it}$, is the average rating over all the reviews obtained by the listing until date t. We infer $\tilde{r}_{it}$, the average rating over reviews obtained between

$t-1$ and t, from $\bar{r}_{it}$, $\bar{r}_{it-1}$, K_{it} (the total number of reviews at t), and K_{it-1}.

$$\tilde{r}_{it} = \frac{\bar{r}_{it}.K_{it} - \bar{r}_{i,t-1}.K_{i,t-1}}{K_{it} - K_{i,t-1}}$$

We then estimate:

$$\tilde{r}_{it} = \alpha \tilde{g}^m_{it} + \gamma m_i \tilde{g}^m_{it} + X_{it}\beta + \mu_i + \varepsilon_{it}$$

where $\tilde{g}^m_{it}$ is the share of guests between $t-1$ and t that belongs to the minority group and μ_i is a listing-specific fixed-effect. As in Section 4.4, we exclude Blacks from the analysis because we are not able to identify them among the guests. In this regression, γ can be interpreted as the difference between the ratings given by minority and majority guests to minority listings. Restricting the sample to observations with new guests between waves, Table 8 shows that the coefficient of the interaction term is non-significant and small in magnitude: minority guests do not seem to give better reviews to minority hosts.

4.6 Ethnic differences in property upgrading

Minority hosts might react to lower demand by improving the quality of their listing to a larger extent than majority hosts. In this case, we would also observe that minority prices increase faster than majority ones. Hosts can upgrade their property through both observable and unobservable characteristics.

We exploit the information about observable characteristics of a listing and test whether minority hosts tend to change these observables in a way that improves the perceived quality of their listing. First, we estimate a hedonic price regression: we regress the log-price on property characteristics, controlling for location and city-wave fixed effects, on the majority population. We use the estimated coefficients of this regression to predict the log-price corresponding to all properties for each period, as a function of the observables, $\hat{p}(X_{it})$. Second, we use the predicted price $\hat{p}(X_{it})$ as the outcome in the following model:

$$\hat{p}(X_{it}) = \sum_{\bar{r}=3.5}^{5} b_r \mathbb{1}\{\bar{r}_i = \bar{r}\} \frac{K_{it}}{K_{it}+\rho} - b_m m_i \frac{K_{it}}{K_{it}+\rho} + \mu_i + \varepsilon_{it} \quad (7)$$

If minorities upgrade their properties more and sooner than their majority counterparts, b_m should be negative.

Upgrading may also come from characteristics that are not directly observable by the econometrician. We test for this by looking at the differential evolution of the word count of the listing description, the number of pictures displayed on the listing's page, and the number of pictures taken by a professional photographer. We run a regression very close to the previous one, except that we now control for observables on the right hand-side.

$$Y_{it} = \sum_{\bar{r}=3.5}^{5} b_r \mathbb{1}\{\bar{r}_i = \bar{r}\} \frac{K_{it}}{K_{it} + \rho} - b_m m_i \frac{K_{it}}{K_{it} + \rho} + \mu_i + X_{it} b_x + \varepsilon_{it} \tag{8}$$

where Y_{it} is the word count or the number of pictures of listing i at date t. Again, we expect b_m to be negative if minority hosts upgrade their properties more than majority hosts.

Table 9 shows the results of the estimations of equations (7) and (8). In column 1, the point estimate of b_m is significantly negative, but very small. This suggests that upgrading on the observable characteristics plays a negligible role in explaining our main results. In all other columns, the point estimates of b_m are small and insignificant. Minority hosts do not seem to have upgraded their listings differentially from majority hosts, in terms of the listing description or pictures.

4.7 Do minority hosts set prices that are too low initially?

Another way to rationalise our results is that minority hosts might be less familiar of this market than majority ones. If minorities are initially more pessimistic about the potential of their listings than majority hosts, they will set up lower initial prices. As information about their quality comes back to them (through reviews or the number of transactions), they would revise their prices up quicker than the majority, which would generate differential dynamics in prices. This would explain our empirical results without the existence of statistical discrimination.

This story entails that minority hosts should get more transactions initially and that demand for ethnic listings should decrease with the number of reviews relative to non-minority listings. We show that it is not the case. As we do not directly observe the number of transactions, we use the number of new reviews between two waves as a proxy. We estimate our non-linear model, using this difference (or the difference in logs), as the outcome.

$$\Delta K_{it} = \sum_{\bar{r}=3.5}^{5} b_r \mathbb{1}\{\bar{r}_i = \bar{r}\} \frac{K_{it}}{K_{it}+\rho} - b_m m_i \frac{K_{it}}{K_{it}+\rho} + \mu_i + X_{it} b_x + \varepsilon_{it} \tag{9}$$

where $\Delta K_{it} = K_{t+1} - K_{it}$. We want to measure whether minorities accumulate more or less reviews (proxy for the number of transactions) as the number of reviews increases. If minorities are over-pessimistic and learn about their type gradually, we should observe that minorities have a more decreasing pattern of the number of transactions per period, compared to majority hosts. In this case, b_m should be positive.

In Table 10, we find that the coefficient associated to minority hosts is negative (which entails a positive b_m), significant and small in the first column, insignificant in the second column. Taken at face value, the magnitude of the first coefficient suggests that minority hosts would initially get .02 reviews more than majority hosts. While the sign of the coefficient is consistent with minorities being pessimistic about their perspectives on the website, the magnitude of the coefficient suggests that it should be a minor contributor to the overall story.

5 Conclusion

This paper documents that Airbnb hosts who belong to an ethnic minority experience a 3% price penalty when differences in locations and observable characteristics are accounted for. Taking advantage of the longitudinal nature of our data, we show that the ethnic gap can be fully explained by statistical discrimination. About one quarter of the gap comes from differentials in average unobservable quality across groups. Three quarters can be attributed to the fact that potential guests hold inaccurate beliefs about the average quality of properties held by minority compared to majority hosts.

We can draw several conclusions from these findings. First, aside from the issues inherent to any online feedback system, the one featured by this online platform is effective in supplying useful information to potential guests. In the absence of such a feedback system, the ethnic price gap would be higher than its current value. Second, aside from gains in efficiency, improving the feedback system would also contribute to reduce ethnic price gaps. Third, minority hosts are still largely penalised by the existence of inaccurate beliefs that potential guests hold against them, even though the review system mitigates their influence.

We believe that the evidence provided in this paper is relevant to the current debate about discrimination on online platforms. While there is no reason to make ethnicity particularly salient on these platforms, policies consisting in concealing more information about actors' identity may backfire if ethnic gaps are due to statistical discrimination. We see our results as advocating another way to reduce ethnic gaps: disclosing more abundant and more reliable information about candidates, sellers or hosts. As discussed by Shaw et al. (2011), it remains to understand how platforms can adequately incentivise reviewers to provide informative, unbiased and relevant reviews. Further research is required to understand how interventions on information disclosure affects ethnic gaps.

On Airbnb, like on many other online marketplaces, interactions between agents are limited. While we have no evidence about how our results can generalise to other platforms, online or not, they are consistent with those obtained by Pallais (2014) and Agrawal et al. (2016) on the online platform ODesk (now Upwork). Pallais (2014) finds that providing public information about workers' abilities has, on average, a positive effect on workers' probability to be hired. Agrawal et al. (2016) find that standardised information about work performed on the platform disproportionately benefits less-developed-country contractors, relative to developed-country ones. The approach we follow in this paper may be adapted to study ethnic discrimination on several other widely-used online platforms, including labour markets.

While our identification strategy allows us to pin down statistical discrimination (and the share of it that is due to inaccurate beliefs), we cannot disentangle other factors like taste-based discrimination, ethnic differentials in characteristics that are observable to potential guests but not to econometricians (e.g., pictures contents), or in hosts' opportunity cost of time. While statistical discrimination (and inaccurate beliefs) appears to explain most of the gap, taste-based discrimination could be offset by differentials in characteristics, for instance. Therefore, we cannot rule out the existence of taste-based discrimination on Airbnb. Another caveat is that the analysis is made conditional on location. Because ethnic minorities tend to live in neighbourhoods that are less valued by potential guests,[24] minority hosts suffer in reality from larger price gaps than those computed conditional on location.

[24]We find that locations where the share of ethnic minority among Airbnb hosts is one-standard-deviation (i.e., 9.6 percentage points) higher are valued 5.5% less in prices.

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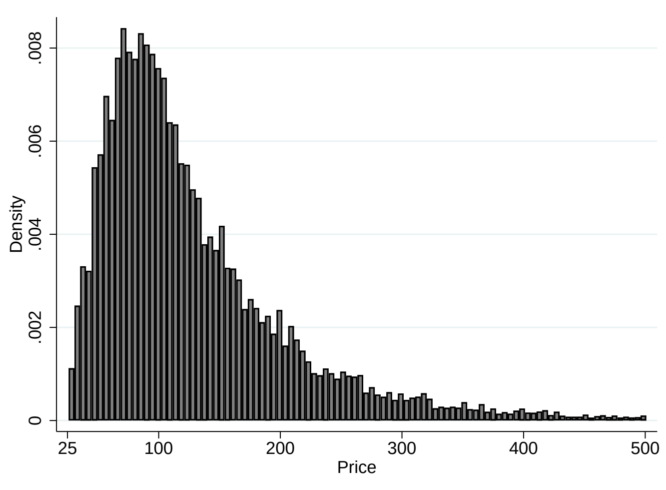
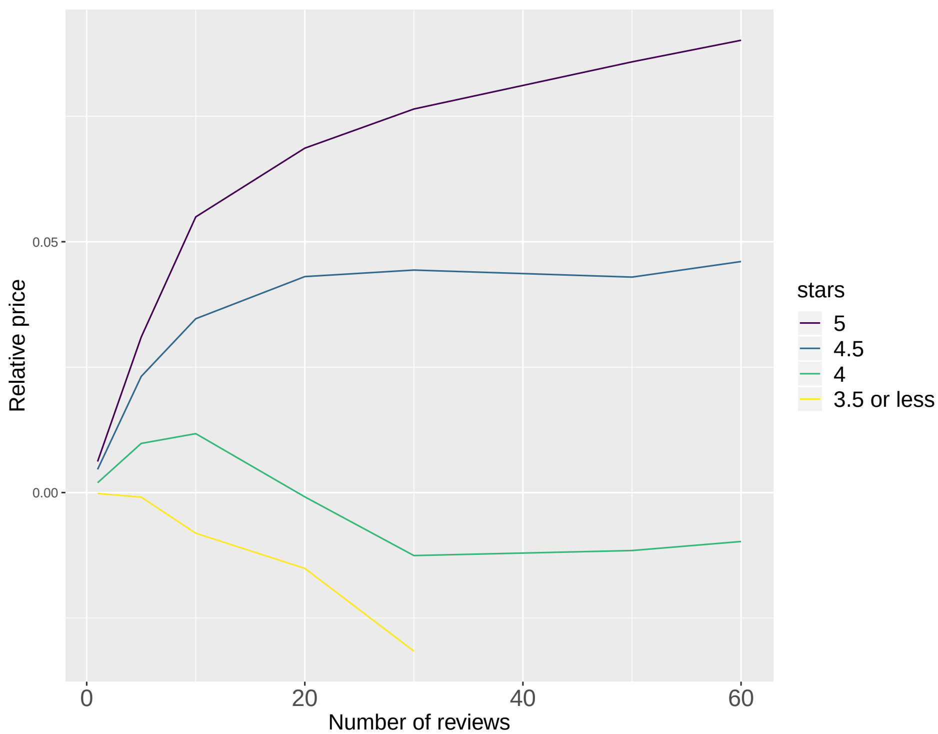
Figure 1: Distribution of daily price



Notes: This figure shows the distribution of the final price (cleaning fees included) represented through 100 bins. The sample is restricted to listings that have gained at least one review over the observation period. The figure is right truncated with a maximum of 500$.

Figure 2: Estimated prices with the number of reviews, stratified by the most recent average rating



Notes: Equation (6) was estimated by linear regression with property fixed effects. We use linear splines with knots at 5, 10, 20, 30 and 50 reviews. The sample is restricted to listings with majority hosts. We plot the estimates $\hat{s}_r(.)$ for all values of r, with the normalization $\hat{s}_r(0) = 0$. The number of observations of properties with ratings 3.5 or lower is very small when the number of reviews is higher than 30 and we do not report the corresponding estimates.

Table 1: Raw price gaps by ethnic groups

	Sample size	Share	Within-city-wave gap
Majority	2,320,285	93.8%	-
Blacks (US/Can)	49,706	2.0%	31.3%
Blacks (Europe)	21,365	0.9%	26.3%
Arabic/Muslim (US/Can)	31,145	1.3%	4.7%
Arabic/Muslim (Europe)	52,050	2.1%	6.8%

Notes: The within-city-wave gaps are obtained as the coefficients on the dummies of each group in a linear regression of the log-price that includes dummies for the interaction of each city and each wave.

Table 2: Ethnic price gap, by specification

	Log daily rate			
	(1)	(2)	(3)	(4)
Minority	-0.169***	-0.111***	-0.067***	-0.032***
	(0.008)	(0.005)	(0.009)	(0.006)
City-wave FE	Yes	Yes	Yes	Yes
Neighbourhood FE	No	No	Yes	Yes
Block FE	No	No	Yes	Yes
Property characteristics	No	Yes	No	Yes
Adj R^2	0.15	0.63	0.36	0.73
N obs.	2,474,551	2,474,551	2,474,551	2,474,551

Notes: OLS regression on the daily log-price on the minority dummy, controlling city-wave fixed-effects. See the list of all property characteristics in Table A4. Robust standard errors clustered at the property level.

Table 3: Ethnic price gap, for several segments of the number of reviews

	Log daily rate				
	(1)	(2)	(3)	(4)	(5)
Minority	-0.034***	-0.026***	-0.023***	-0.022**	-0.021
	(0.009)	(0.007)	(0.009)	(0.011)	(0.015)
Nb reviews	0	1-4	5-19	20-49	50+
Minority share	6.1%	6.2%	6.3%	6.3%	6.1%
Adj R^2	0.72	0.75	0.78	0.79	0.80
N obs.	351,631	808,000	789,798	352,906	172,216

Notes: OLS regressions of the daily log-price on the minority dummy, controlling for neighbourhood FE, block FE property characteristics and ratings (for properties with at least one review). See the list of all property and host characteristics in Table A4. Robust standard errors clustered at the property level.

Table 4: Non-linear model of log-prices as a function of the number of reviews

	(1)	(2)
5 stars $\times f(K)$	0.115***	
	(0.002)	
4.5 stars $\times f(K)$	0.062***	
	(0.002)	
4 stars $\times f(K)$	-0.005	
	(0.003)	
$\leq$ 3.5 stars $\times f(K)$	-0.030***	
	(0.007)	
$f(K)$		0.075***
		(0.001)
Minority $\times f(K)$	0.034***	0.025***
	(0.006)	(0.006)
ρ	13.7	13.7
	(0.30)	(0.30)
N obs.	2,474,551	2,474,551

Notes: Estimations by non-linear least-squares of equations (3) and (4). The outcome is the daily log-price. Stars represent the last known average rating for a listing. Minority is an indicator that identifies the minority host, i.e. $m_i = 1$. $f(K_{it}) = \frac{K_{it}}{K_{it}+\rho}$ where K_{it} is the number of reviews for listing i at time t and ρ is the number of reviews that is necessary to make up for half of the gap due to statistical discrimination. Values in row Minority $\times f(K)$ are estimates of the coefficients on the term $m_i \frac{K_{it}}{K_{it}+\rho}$. Under our assumptions, the interaction $m \times f(K)$ is an estimate of $-\beta_m$ (the total ethnic gap due to statistical discrimination) in column (1), and of $-\tilde{\beta}_m$ (the part of statistical discrimination due to inaccurate beliefs) in column (2). On top of covariates included in the table, we include neighbourhood fixed effects, block fixed effects and property/host characteristics. See the list of all property and host characteristics in Table A4. Inference by block-bootstrap at the listing level.

Table 5: Robustness: Linear and quadratic models of price with listing fixed effects

	log-price		
	(1)	(2)	(3)
3.5 stars $\times K/100$	-0.145**	-0.137***	-0.168**
	(0.058)	(0.052)	(0.085)
4 stars $\times K/100$	-0.133***	-0.132***	-0.134***
	(0.023)	(0.019)	(0.035)
4.5 stars $\times K/100$	0.048***	0.014*	0.133***
	(0.010)	(0.008)	(0.014)
5 stars $\times K/100$	0.185***	0.114***	0.295***
	(0.011)	(0.008)	(0.015)
Minority $\times K/100$	0.090**	0.060**	0.120***
	(0.036)	(0.027)	(0.045)
3.5 stars $\times (K/100)^2$			0.154
			(0.154)
4 stars $\times (K/100)^2$			0.082
			(0.053)
4.5 stars $\times (K/100)^2$			-0.193***
			(0.018)
5 stars $\times (K/100)^2$			-0.315***
			(0.018)
Minority $\times (K/100)^2$			-0.122**
			(0.053)
Samples	K<40	K<60	K<80
N obs.	1,883,500	1,996,554	2,051,820

Notes: OLS regressions with listing fixed effects. Stars represent the last known average ratings and K is the number of reviews. Aside from those mentioned in the Table, controls include city-wave FE and property characteristics (see Table A4). Robust standard errors clustered at the property level.

Table 6: Results on sub-samples

	Full Sample (1)	Arabic Muslims (2)	Blacks (3)	US Canada (4)	Europe (5)	Shared Flat (6)	Entire Flat (7)
	Panel A. Estimation of the main model						
Minority $\times f(K)$	0.034***	0.019***	0.049***	0.029***	0.037***	0.082***	0.013**
	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)	(0.012)	(0.006)
ρ	14	14	12	10	17	22	12
	(0.3)	(0.3)	(0.3)	(0.4)	(0.4)	(0.9)	(0.3)
	Panel B. Unexplained ethnic price gap (non-reviewed listings)						
Minority	-0.034***	-0.036***	-0.25*	-0.020*	-0.049***	-0.034**	-0.038***
	(0.009)	(0.010)	(0.013)	(0.012)	(0.012)	(0.015)	(0.010)
Adj R^2	0.72	0.72	0.58	0.76	0.70	0.59	0.68
Minority share	6.1%	3.8%	3.4%	8.7%	4.8%	7.8%	5.5%
N obs.	351,631	342,988	270,896	119,506	232,125	99,087	252,544

Notes: In Panel A, estimations by non-linear least-squares following the specification adopted in Table 4, column 1. Minority is an indicator that identifies the minority host, i.e. $m_i = 1$. $f(K_{it}) = \frac{K_{it}}{K_{it}+\rho}$ where K_{it} is the number of reviews for listing i at time t and ρ is the number of reviews that is necessary to make up for half of the gap due to statistical discrimination. Values in row Minority $\times f(K)$ are estimates of the coefficients on the term $m_i \frac{K_{it}}{K_{it}+\rho}$. Under our assumptions, the interaction $m \times f(K)$ is an estimate of $-\beta_m$ (the total ethnic gap due to statistical discrimination). On top of covariates included in the table, we include neighbourhood fixed effects, block fixed effects and property/host characteristics. See the list of all property and host characteristics in Table A4. Inference by block-bootstrap at the listing level. In Panel B, OLS regressions following the specification adopted in Table 3, column 1: daily log-price on the minority dummy when the number of reviews is null, controlling for neighbourhood FE and block FE property characteristics.

Table 7: Ethnic matching between Arabic/Muslim hosts and Arabic/Muslim guests

	Share of Arabic/Muslim guests
Arabic/Muslim Host	0.010***
	(0.001)
Adj R^2	0.016
N obs.	220,126

OLS regression. Aside from the dummy Arabic/Muslim Host, controls include city-wave FE, neighbourhood FE, block FE, property characteristics (see Table A4), log price, number of reviews and ratings. Standard errors are clustered at the property level.

Table 8: Average rating, depending on hosts' and guests' ethnicity

	Average rating over reviews received between $t-1$ and t
Share of minority among new guests	0.000
	(0.025)
Minority host $\times$ Share of minority among new guests	0.008
	(0.007)
Adj R^2	0.072
N obs.	954,361

Notes: OLS regressions with listings fixed-effects. The outcome is $\tilde{r}_{it}$, the average rating over reviews obtained between $t-1$ and t. Aside from those mentioned in the Table, controls include city-wave FE, and property characteristics (see Table A4). Robust standard errors clustered at the property level.

Table 9: Differential Upgrading

	Pred. log-price	Word count	Pictures	Pro. Pictures
5 stars $\times f(K)$	0.007***	92.368***	7.516***	5.867***
	(0.000)	(3.028)	(0.105)	(0.102)
4.5 stars $\times f(K)$	0.007***	80.547***	6.400***	4.788***
	(0.000)	(3.183)	(0.097)	(0.094)
4 stars $\times f(K)$	0.005***	55.212***	5.743***	2.714***
	(0.000)	(5.635)	(0.183)	(0.166)
$\leq$ 3.5 stars $\times f(K)$	0.003***	30.629***	5.359***	-0.096
	(0.001)	(8.808)	(0.325)	(0.318)
Minority $\times f(K)$	0.001**	7.503	-0.150	0.283
	(0.001)	(8.419)	(0.299)	(0.287)
Adj R2	0.995	0.218	0.082	0.206
N obs.	2,474,551	2,474,551	2,474,551	2,474,551

Notes: OLS regressions of equations (7) and (8), using the estimated $\hat{\rho} = 13.6$ and $f(K) = \frac{K}{K+\hat{\rho}}$ where K is the number of reviews and ρ is the number of reviews that is necessary to make up for half of the gap due to statistical discrimination. Stars represent the last known average ratings. Minority is an indicator that identifies the minority host, i.e. $m_i = 1$. Values in row Minority $\times f(K)$ are estimates of the coefficients on the term $m_i \frac{K_{it}}{K_{it}+\rho}$. Under our assumptions, the interaction $m \times f(K)$ is an estimate of $-b_m$. In column 1, the outcome is the predicted log-price based on observable characteristics of the listing. In column 2, the outcome is the word count of the listing description. In column 3, the outcome is the number of pictures on the listing profile. In column 4, the outcome is the number of pictures taken by professionals on the listing profile. On top of the covariates included in the table, we include property/host characteristics (except in column 1). Robust standard errors clustered at the listing level.

Table 10: Ethnic differentials in the accumulation of reviews over time

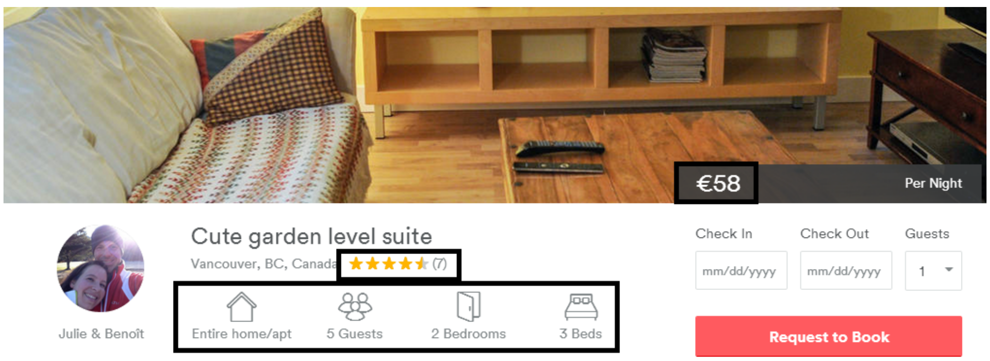
	ΔK	$\Delta \log K$
5 stars $\times f(K)$	0.086***	-2.27***
	(0.002)	(0.026)
4.5 stars $\times f(K)$	0.071***	-2.27***
	(0.002)	(0.023)
4 stars $\times f(K)$	0.030***	-2.52***
	(0.002)	(0.036)
$\leq$ 3.5 stars $\times f(K)$	-0.005*	-3.20***
	(0.003)	(0.073)
Minority $\times f(K)$	-0.018***	-0.103
	(0.005)	(0.068)
Adj R2	0.409	0.199
N obs.	2,253,612	1,901,981

Notes: OLS regressions of equation (9), using the estimated $\hat{\rho} = 13.6$ and $f(K) = \frac{K}{K+\hat{\rho}}$ where K is the number of reviews and ρ is the number of reviews that is necessary to make up for half of the gap due to statistical discrimination. Stars represent the last known average ratings. Minority is an indicator that identifies the minority host, i.e. $m_i = 1$. Values in row Minority $\times f(K)$ are estimates of the coefficients on the term $m_i \frac{K_{it}}{K_{it}+\rho}$. Under our assumptions, the interaction $m \times f(K)$ is an estimate of $-b_m$. In column 1, the outcome is the difference between two dates in the number of reviews. In column 2, the outcome is the difference in the log number of reviews. On top of the covariates included in the table, we include property/host characteristics. Robust standard errors clustered at the listing level.

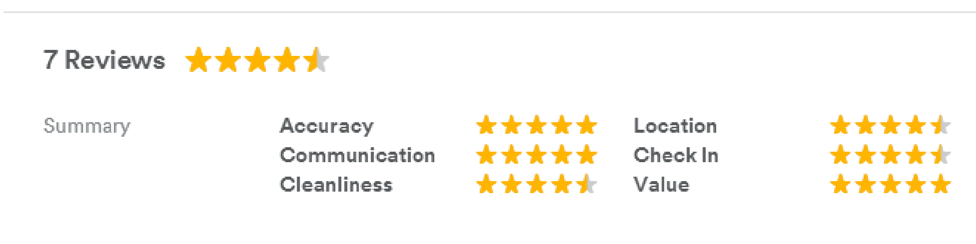
For Online Publication

A Additional Figures

Figure A1: Example of a listing’s dashboard, with the most salient information



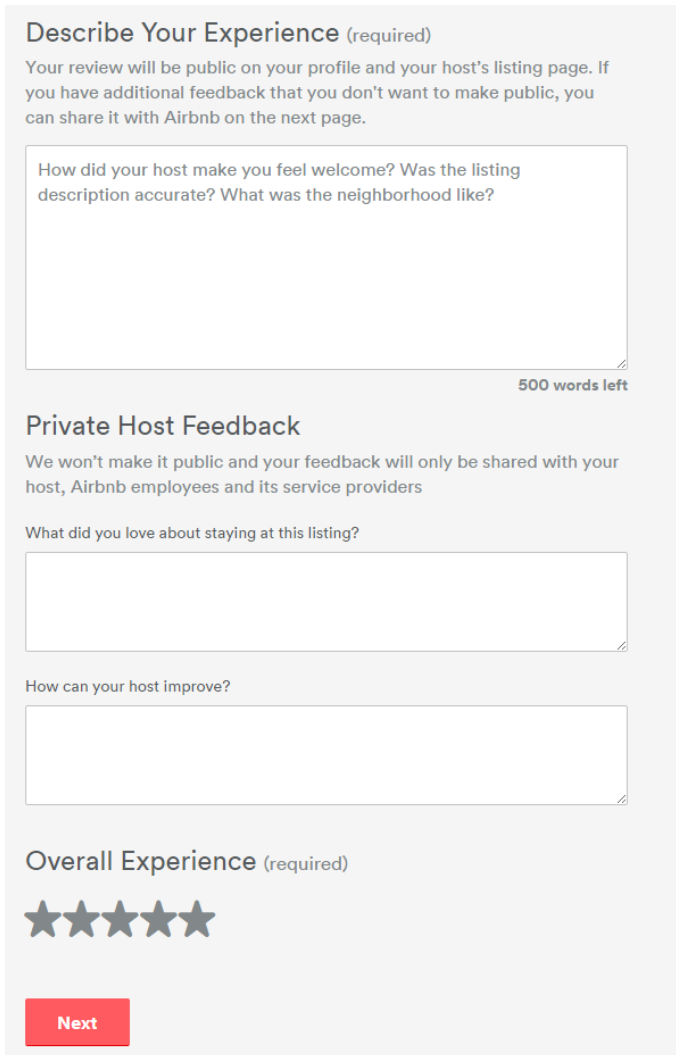
Information on listings’ ratings



Information on listings’ amenities

The Space	Property type: **House** Accommodates: **5** Bedrooms: **2** Bathrooms: **1**	Beds: **3** Check In: **3:00 AM** Check Out: **11:00 AM**
Amenities	**Kitchen** **Internet** **TV** **Essentials** **Heating** ~~Air Conditioning~~ **Washer** **Dryer** **Free Parking on Premises** **Wireless Internet** **Cable TV** ~~Breakfast~~ ~~Pets Allowed~~ **Family/Kid Friendly** ~~Suitable for Events~~	~~Smoking Allowed~~ ~~Wheelchair Accessible~~ ~~Elevator in Building~~ ~~Indoor Fireplace~~ ~~Buzzer/Wireless Intercom~~ ~~Doorman~~ ~~Pool~~ ~~Hot Tub~~ ~~Gym~~ ~~Smoke Detector~~ ~~Carbon Monoxide Detector~~ ~~First Aid Kit~~ ~~Safety Card~~ ~~Fire Extinguisher~~
Prices	Extra people: **No Charge** Security Deposit: **$92** Weekly Price: **$412 /week**	Monthly Price: **$1373 /month** Cancellation: **Moderate**

Peer-reviewing system


Describe Your Experience (required)

Your review will be public on your profile and your host's listing page. If you have additional feedback that you don't want to make public, you can share it with Airbnb on the next page.

How did your host make you feel welcome? Was the listing description accurate? What was the neighborhood like?

500 words left

Private Host Feedback

We won't make it public and your feedback will only be shared with your host, Airbnb employees and its service providers

What did you love about staying at this listing?

How can your host improve?

Overall Experience (required)

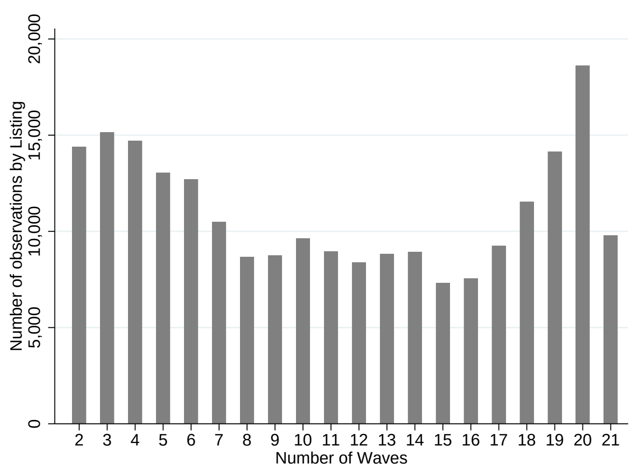
Next

Information on listings' locations

Exact location information is provided after a booking is confirmed.

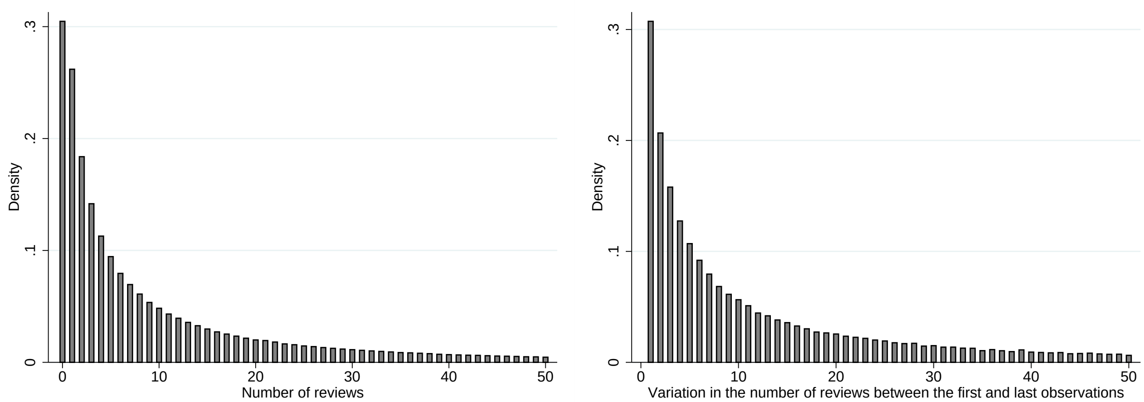
In this example, the listing is shown to be located in the neighbourhood of Pimlico, in London, and the area of the .6-mile-radius circle is almost entirely in that neighbourhood.

Figure A2: Number of observations by listing



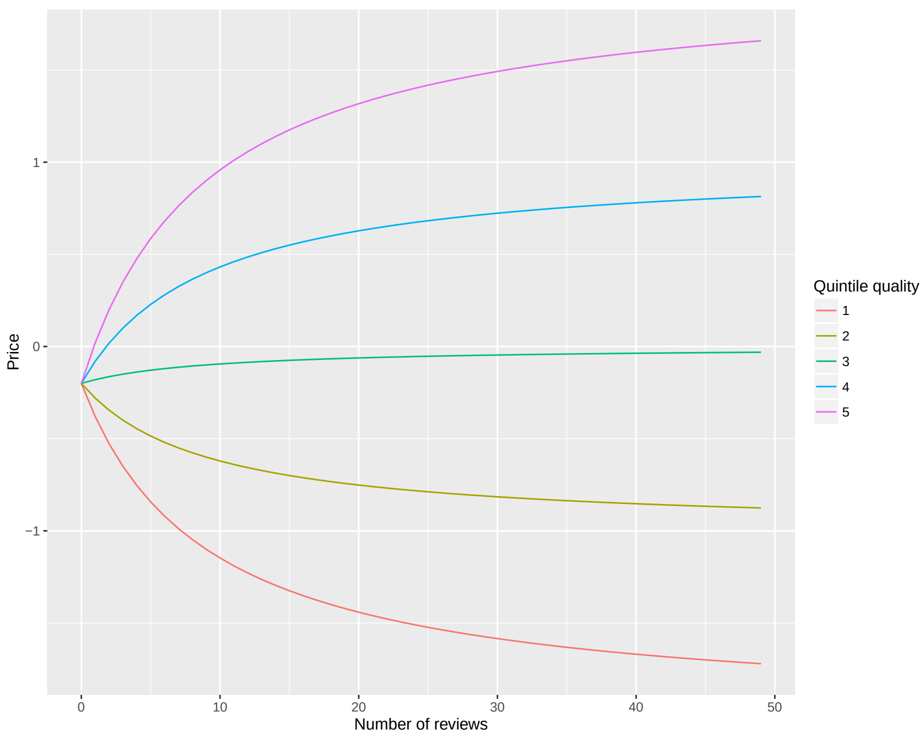
Notes: This figure shows the number of observations by listing depending on the number of waves (x-axis). It starts at 2 waves as we restrict the sample to listings that have gained at least one review over the observation period.

Figure A3: Distribution of the number of reviews (left) and of the longitudinal variation in the number of reviews within a property (right)



Notes: The left figure shows the distribution of the number of reviews. The right figure shows the distribution of the longitudinal variation in the number of reviews within a property. Both figures are right truncated with a maximum of 50 reviews. The sample is restricted to listings that have gained at least one review over the observation period.

Figure A4: Illustration of the conceptual framework: Prices with the number of reviews, by unobservable quality



Note: This illustrative graph displays $(K\nu - \rho/5)/(K + \rho)$ as function of K, where ν takes values in $\{-2, 1, 0, 1, 2\}$ and $\rho = 8$.

B Additional tables

Table A1: Number of observations & listings by city

City	Observations		Listings	
	#	share	#	share
Amsterdam	51,189	2.07	6,122	2.77
Barcelona	173,180	7.00	14,529	6.58
Berlin	151,887	6.14	13,948	6.31
Boston	43,637	1.76	4,330	1.96
Chicago	42,990	1.74	4,408	2.00
Florence	67,106	2.71	4,967	2.25
London	264,705	10.70	23,889	10.81
Los Angeles	159,228	6.43	15,182	6.87
Madrid	65,753	2.66	5,359	2.43
Marseille	55,643	2.25	4,921	2.23
Miami	67,373	2.72	6,383	2.89
Milan	85,365	3.45	8,360	3.78
Montreal	69,331	2.80	6,525	2.95
New York City	349,471	14.12	31,717	14.36
Paris	464,493	18.77	39,026	17.66
Rome	152,644	6.17	11,547	5.23
San Francisco	108,144	4.37	10,148	4.59
Toronto	56,843	2.30	5,359	2.43
Vancouver	45,569	1.84	4,219	1.91

Notes: The table shows the number of observations (column 1), its share (column 2) and the number of listings (column 3), and its share (column 4) for each of the 19 cities included in our dataset. The sample is restricted to listings that have gained at least one review over the observation period. The total number of observations is 2,474,551 and the total number of listings is 220,939.

Table A2: Collection dates of waves

Wave	Collection date
1	15 June 2014
2	8 July 2014
3	28 July 2014
4	11 August 2014
5	25 August 2014
6	8 September 2014
7	25 September 2014
8	15 October 2014
9	5 November 2014
10	25 November 2014
11	15 December 2014
12	7 January 2015
13	13 January 2015
14	3 February 2015
15	4 March 2015
16	25 March 2015
17	13 April 2015
18	4 May 2015
19	26 May 2015
20	15 June 2015
21	11 November 2017

Table A3: Summary statistics: Property & host characteristics

	Full Sample	Listings that have gained at least one review over the period
Type of property		
Entire property	0.665	0.705
Flat	0.802	0.843
House	0.064	0.106
Loft	0.016	0.019
Size		
Person capacity	3.148	3.211
Number of bedrooms	1.252	1.244
Number of bathrooms	1.162	1.153
Type of bed		
Couch	0.005	0.006
Airbed	0.003	0.003
Sofa	0.026	0.033
Futon	0.009	0.012
Real bed	0.958	0.946
Amenities		
Cable TV	0.290	0.346
Wireless	0.901	0.899
Heating	0.876	0.887
AC	0.395	0.380
Elevator	0.341	0.340
Wheelchair accessible	0.077	0.098
Doorman	0.080	0.096
Fireplace	0.077	0.080
Washer	0.697	0.697
Dryer	0.402	0.388
Parking	0.200	0.179
Gym	0.072	0.064
Pool	0.063	0.054
Buzzer	0.293	0.386
Hot Tub	0.069	0.069
Services		
Breakfast served	0.111	0.091
Family/Kids friendly	0.466	0.448
Suitable for events	0.045	0.052
Rules & Extras		
Additional people	0.469	0.646
Price per additional people	7.389	7.911

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Table A3: Summary statistics: Property & host characteristics

Smoking allowed	0.133	0.144
Pets allowed	0.125	0.131
Host Characteristics		
Has multiple properties	0.356	0.345
Member since 2008	0.001	0.001
Member since 2009	0.006	0.009
Member since 2010	0.019	0.033
Member since 2011	0.063	0.107
Member since 2012	0.126	0.209
Member since 2013	0.166	0.263
Member since 2014	0.198	0.291
Member since 2015	0.068	0.075
Number of languages spoken	0.851	1.408
Superhost	0.023	0.053
Verified email	0.620	0.960
Verified offline	0.320	0.525
Verified phone	0.281	0.428
Number of Facebook friends	153.567	237.714
Number of words in description	217.000	240.168
Number of words in profile	49.560	49.822
Number of pictures	13.058	13.921
Number of pictures by professionals	0.979	0.703
N	663,090	220,939

Notes: The left column displays the mean of each characteristics in the full sample, while the right column focuses on the sub-sample of listings that have gained at least one review over the observation period (between the first and the last waves).

Table A4: Log daily rate

	(1)	(2)
Shared Flat	-0.828***	-0.715***
	(0.004)	(0.007)
Person Capacity (> 2)	0.164***	0.175***
	(0.004)	(0.005)
# bedrooms	0.273***	0.293***
	(0.003)	(0.004)
# bathrooms	0.167***	0.143***
	(0.004)	(0.005)
Flat	-0.154***	-0.179***
	(0.009)	(0.013)
House or Loft	-0.159***	-0.061***
	(0.010)	(0.014)
Couch	-0.193***	-0.165***
	(0.014)	(0.015)
Airbed	-0.192***	-0.125***
	(0.027)	(0.025)
Sofa	-0.175***	-0.166***
	(0.006)	(0.009)
Futon	-0.158***	-0.116***
	(0.011)	(0.010)
Cable TV	0.141***	0.098***
	(0.003)	(0.004)
Wireless	0.033***	0.021***
	(0.005)	(0.006)
Heating	-0.019***	0.001
	(0.005)	(0.007)
AC	0.134***	0.113***
	(0.004)	(0.006)
Elevator	0.093***	0.084***
	(0.003)	(0.005)
Wheelchair Accessible	-0.039***	-0.007

(Continued on next page)

Table A4: Log daily rate

	(0.004)	(0.005)
Doorman	0.102***	0.036***
	(0.005)	(0.007)
Fireplace	0.158***	0.117***
	(0.005)	(0.005)
Washer	-0.021***	0.020***
	(0.004)	(0.006)
Dryer	0.146***	0.094***
	(0.003)	(0.004)
Parking	-0.133***	0.028***
	(0.004)	(0.005)
Gym	0.062***	0.042***
	(0.007)	(0.009)
Pool	0.083***	0.082***
	(0.007)	(0.012)
Buzzer	0.050***	0.008**
	(0.003)	(0.003)
Hot Tub	0.012**	0.010
	(0.005)	(0.006)
Breakfast served	0.005	0.033***
	(0.004)	(0.005)
Family/Kids Friendly	0.014***	0.033***
	(0.003)	(0.003)
Suitable for events	0.072***	0.062***
	(0.006)	(0.008)
Additional People	-0.034***	-0.013***
	(0.002)	(0.002)
Price per Additional People	0.001***	-0.001***
	(0.000)	(0.000)
Cancellation Policy	0.040***	0.015***
	(0.002)	(0.002)
Smoking Allowed	-0.123***	-0.093***
	(0.004)	(0.004)

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Table A4: Log daily rate

Pets Allowed	-0.024***	-0.027***
	(0.004)	(0.004)
Host has multiple properties	0.050***	0.024***
	(0.003)	(0.004)
Member since 2009	0.145***	0.118***
	(0.019)	(0.021)
Member since 2010	0.121***	0.097***
	(0.015)	(0.016)
Member since 2011	0.098***	0.087***
	(0.014)	(0.015)
Member since 2012	0.077***	0.070***
	(0.014)	(0.015)
Member since 2013	0.076***	0.066***
	(0.014)	(0.015)
Member since 2014	0.051***	0.048***
	(0.014)	(0.014)
Member since 2015	0.052***	0.047***
	(0.014)	(0.015)
Superhost	0.023***	0.014***
	(0.005)	(0.005)
Verified Email	-0.022***	-0.000
	(0.007)	(0.007)
Verified Offline	0.013***	0.005*
	(0.003)	(0.003)
Verified Phone	0.003	0.004
	(0.007)	(0.012)
Nber of Facebook friends	0.000***	0.000
	(0.000)	(0.000)
Nber of words in Description	-0.000***	-0.000***
	(0.000)	(0.000)
Nber of words in Profile	-0.000***	-0.000***
	(0.000)	(0.000)
Nber of Languages	-0.005***	-0.005***

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Table A4: Log daily rate

	(0.001)	(0.001)
Nber of words in Rules	-0.000***	-0.000**
	(0.000)	(0.000)
Nber of pictures	0.003***	0.003***
	(0.000)	(0.000)
Nber of pictures taken by professionals	0.001***	0.002***
	(0.000)	(0.000)
Nber of picture changes	-0.034***	-0.037***
	(0.002)	(0.002)
City-wave FE	Yes	Yes
Neighbourhood FE	No	Yes
Block FE	No	Yes
Adj R^2	0.627	0.733
N obs.	2,474,551	2,474,551

Notes: OLS regression on the daily log-price. In column (2), neighbourhood and block fixed effects are included in the estimation. Robust standard errors clustered at the property level.

Table A5: Distribution of the last rating

	Obs	Share
3.5 stars	9,560	4.39%
4 stars	26,943	12.37%
4.5 stars	85,047	39.06%
5 stars	96,178	44.17%

Notes : The sample corresponds to listings for which last rating is observed. Listings with less than 3.5 stars are included in the first row.

Table A6: Number of neighbourhoods & blocks by city

City	# neighbourhoods	# Blocks
Amsterdam	45	101
Barcelona	70	82
Berlin	88	404
Boston	42	250
Chicago	75	242
Florence	18	102
London	150	838
Los Angeles	115	1267
Madrid	67	166
Marseille	61	615
Miami	80	430
Milan	25	155
Montreal	53	242
New York City	189	527
Paris	64	116
Rome	44	107
San Francisco	169	495
Toronto	115	286
Vancouver	34	307
Total	1,504	6,732

Notes: The definition of neighbourhoods directly comes from Airbnb while blocks are created via the approximate coordinates of the listing.

C Ethnic differences in the exit rate

In this section, we look at the issue of differential selection in the sample across ethnic groups and find that minority hosts are not more likely to leave the market than the majority. We consider that a listing i leaves the market at t if it is present at t, and not present anytime after t, and define $q_{it} = 1$ and 0 for $s \neq t$. Within the period of observation, 65,358 majority hosts (31.6%) and 4,777 minority hosts (33.6%) leave the platform. We regress q_{it} on a minority dummy, and control for property characteristics, ratings, neighbourhood fixed-effects, block fixed-effects and price.

Table A7 shows that the exit rate is similar for both groups when controlling for property characteristics, ratings, neighbourhood and block fixed-effects, price of the listing and number of reviews.

Table A7: Probability to leave the market at wave t

	(1)	(2)	(3)
Minority host	0.0004	0.0003	0.0003
	(0.0005)	(0.0005)	(0.0005)
Log-price		-0.0043***	-0.0053***
		(0.0003)	(0.0003)
Number of reviews			-0.0001***
			(0.0000)
Adj R^2	0.04	0.04	0.04
N obs.	2,474,551	2,474,551	2,474,551

Notes: OLS regressions of the probability to leave the market at wave t. Covariates include, aside from the ones mentioned in the table, neighbourhood fixed effects, block fixed-effects, property characteristics and ratings. Robust standard errors clustered at the property level.

D Pictures from which host ethnicity cannot be measured

Hosts can choose whether to post a picture of themselves on their host profiles. Popular alternative choices are pictures of their properties, pets, furniture, landscapes, etc. We identify pictures for which it was impossible to say anything about the ethnicity of anyone in the picture. In our data, there are 17% of such listings. If minorities are aware of the existence of discrimination on the platform, they might more often obfuscate their skin colour.

In this appendix, we try to understand the choice leading hosts to post or not their pictures. First, is the price set by no-person-picture hosts higher in neighbourhoods where the share of blacks is high? First, how do no-person-picture hosts set their price? Second, does the probability of having a no-person picture depend on the share of Blacks in the neighbourhood?

Table A8 first shows that, controlling for listing characteristics, hosts with a listing located in a neighbourhood with more Black hosts are not more or less likely to post a picture of themselves (Column 1). This result is at odds with a model of strategic hosts anticipating discrimination. Column 2 shows that, controlling for neighbourhoods and characteristics, hosts post very similar prices whether they choose to publish their pictures or not. Column 3 shows that the pattern does not seem to vary much with the ethnic composition of the neighbourhood. If anything, in areas with more Black hosts, the hosts that do not post their pictures have lower prices than those posting their pictures.

Table A8: Behaviour of hosts posting non-person pictures

	Non-person picture	Log-price	
	(1)	(2)	(3)
Local share of Blacks	0.007		
	(0.018)		
Non-person picture		0.002	0.004
		(0.003)	(0.004)
Non-person picture $\times$ share Blacks			-0.078
			(0.064)
Neighbourhood FE	No	Yes	Yes
Adj R^2	0.036	0.713	0.713
N obs.	2,466,726	2,466,726	2,466,726

Notes: OLS regressions. Aside from those mentioned in the Table, controls include city-wave FE, and property characteristics (see Table A4). Specifications in Columns 2 and 3 include neighbourhood FE and block FE, not in Column 1. Robust standard errors clustered at the listing level.

E Using a non-normal prior distribution of quality with a discrete signal

Assume that $\nu \sim \mathcal{B}(\alpha_\nu, \beta_\nu)$ (a Beta distribution). A Beta distribution looks more similar to the measures of quality that we have empirically: it is bounded and can be really skewed.

A single rating being a discrete signal, let's assume that we can model it as a draw in a $Binomial(n, \nu)$, where n depends on how much information a single rating contains (to what extent it is discrete). A rating takes values in $0 \ldots n$.

The pdf of the posterior distribution, given the observation of a rating r can be written as:

$$f(\nu|r) = \frac{P(r|\nu)f(\nu)}{\int P(r|\nu)f(\nu)d\nu}$$

Working on the numerator, we have:

$$P(r|\nu)f(\nu) = \binom{n}{r}\frac{\nu^r(1-\nu)^{n-r}\nu^{\alpha_\nu - 1}(1-\nu)^{\beta_\nu - 1}}{B(\alpha_\nu, \beta_\nu)}$$

where $B(.,.)$ is the beta function. This simplifies to:

$$P(r|\nu)f(\nu) = \binom{n}{r}\frac{\nu^{\alpha_\nu - 1 + r}(1-\nu)^{\beta_\nu - 1 + n - r}}{B(\alpha_\nu, \beta_\nu)}$$

Because $f(\nu|r)$ is a density, we know it is of integral one and thus should be equal to the density of a $\mathcal{B}(\alpha_\nu + r, \beta_\nu + n - r)$. We can also prove it by computing the integral of $P(r|\nu)f(\nu)$ wrt ν and computing $f(\nu|r)$ explicitly.

The expectation of ν conditional on r is therefore equal to:

$$E(\nu|r) = \frac{\alpha_\nu + r}{\alpha_\nu + \beta_\nu + n}$$

Now, suppose that we have K signals instead of just one. I also rescale the signal between 0 and 1 (which is the range of ν) and define $\bar{r} = \sum_k r_k/(nK)$, $\tilde{\alpha}_\nu = \alpha_\nu/n$ and $\tilde{\beta}\nu = \beta\nu/n$. We can show that the expectation depends only on $\bar{r}$:

$$E(\nu|\bar{r}, K) = \frac{\hat{\alpha}_\nu + K\bar{r}}{\hat{\alpha}_\nu + \hat{\beta}_\nu + K}$$

Dividing everything by n rescales the signal between 0 and 1 (which is the range of ν) and we obtain an expression that is exactly identical, up to a change in notations, to the one with normal distributions.

$$\mathbb{E}(\nu|\bar{r}, K, m) = \frac{\rho\bar{v} + K\bar{r}}{\rho + K}$$

with $\alpha_\nu = \rho\bar{v}$ and $\alpha_\nu + \beta_\nu = \rho$.

F Proofs for the identification results

F.1 Accurate beliefs

We start from equation (2). Assuming that we know ρ, the regression line of p_{it} conditional on $\mathcal{I}_{it}$, an information set made of $\frac{K_{it}}{K_{it}+\rho}$, $m_i\frac{K_{it}}{K_{it}+\rho}$, $\bar{r}_i\frac{K_{it}}{K_{it}+\rho}$, characteristics X_{it} and listing fixed effects μ_i:

$$\mathbb{E}(p_{it}|\mathcal{I}_{it}) = \mathbb{E}(p_0 - \lambda\gamma m + \lambda\alpha w_{it} + \lambda\beta\zeta_{it}|\mathcal{I}_{it}) + \mathbb{E}(\lambda\beta\frac{K_{it}r_{it} + \rho\bar{v}_m}{K_{it}+\rho}|\mathcal{I}_{it})$$

By assumption, the first term $\mathbb{E}(p_0 - \lambda\gamma m + \lambda\alpha w_{it} + \lambda\beta\zeta_{it}|\mathcal{I}_{it})$ is equal to a linear combination of the fixed effects and the observable characteristics.

$$\mathbb{E}(p_{it}|\mathcal{I}_{it}) = \mu_i + X_{it}\beta_x + \lambda\beta\mathbb{E}(\frac{K_{it}r_{it}}{K_{it}+\rho}|\mathcal{I}_{it}) + \lambda\beta\mathbb{E}(\frac{\rho\bar{v}_m}{K_{it}+\rho}|\mathcal{I}_{it})$$

At this stage, it is key that $\mathbb{E}(r_{it}|\mathcal{I}_{it}) = \mathbb{E}(r_{it}|\bar{r}_i)$. In particular, r_{it} does not depend on ethnicity conditional on $\bar{r}_i$.

$$\mathbb{E}(p_{it}|\mathcal{I}_{it}) = \mu_i + X_{it}\beta_x + \lambda\beta\frac{K_{it}}{K_{it}+\rho}\mathbb{E}(r_{it}|\bar{r}_i) + \lambda\beta\frac{\rho\bar{v}_0}{K_{it}+\rho} + \lambda\beta\frac{\rho}{K_{it}+\rho}(\bar{v}_1 - \bar{v}_0)m_i$$

As $\frac{\rho}{K_{it}+\rho} = 1 - \frac{K_{it}}{K_{it}+\rho}$:

$$\mathbb{E}(p_{it}|\mathcal{I}_{it}) = \mu_i + X_{it}\beta_x + \lambda\beta\frac{K_{it}}{K_{it}+\rho}[\mathbb{E}(r_{it}|\bar{r}_i) - \bar{v}_0] - \lambda\beta\frac{K_{it}}{K_{it}+\rho}(\bar{v}_1 - \bar{v}_0)m_i$$

Therefore, regressing p_{it} on $\frac{K_{it}}{K_{it}+\rho}\mathbb{1}\{\bar{r}_i = \bar{r}\}$, for all values $\bar{r}$ in the support of $\bar{r}_i$, and $\frac{K_{it}}{K_{it}+\rho}m_i$, conditional on listing fixed effects and characteristics X_{it}, will identify:

- $\beta_{\bar{r}} = \lambda\beta[\mathbb{E}(r_{it}|\bar{r}) - \bar{v}_0]$ for each value $\bar{r}$ in the support of $\bar{r}_i$.
- $\beta_m = -\lambda\beta(\bar{v}_1 - \bar{v}_0)$.

To finish the proof, note that ρ is identified non-parametrically within listing conditional on $\beta_{\bar{r}}$ and β_m. □

F.2 Inaccurate beliefs

The first part of the proof directly follows the one of the case with accurate beliefs. For the second part, we apply the same reasoning, except that we attempt to characterise the regression line of p_{it} conditional on $\mathcal{I}'_{it}$, an information set equal to $\mathcal{I}_{it}$ minus $\bar{r}_i \frac{K_{it}}{K_{it}+\rho}$. The main difference is that Bayesian updating starts from the wrong bias $\tilde{v}_1$ instead of $\bar{v}_1$ for listings held by minority hosts. We obtain:

$$\mathbb{E}(p_{it}|\mathcal{I}'_{it}) = \mu_i + X_{it}\beta_x + \lambda\beta\mathbb{E}(\frac{K_{it}r_{it}}{K_{it}+\rho}|\mathcal{I}'_{it}) + \lambda\beta\mathbb{E}(\frac{\rho(\bar{v}_0 + m_i(\tilde{v}_1 - \bar{v}_0))}{K_{it}+\rho}|\mathcal{I}'_{it})$$

Now, note that $\mathbb{E}(r_{it}|\mathcal{I}'_{it}) = \mathbb{E}(r_{it}|m_i) = \bar{v}_{m_i} = \bar{v}_0 + m_i(\bar{v}_1 - \bar{v}_0)$.

$$\mathbb{E}(p_{it}|\mathcal{I}'_{it}) = \mu_i + X_{it}\beta_x + \lambda\beta\frac{K_{it}}{K_{it}+\rho}(\bar{v}_0 + m_i(\bar{v}_1 - \bar{v}_0)) + \lambda\beta\frac{\rho}{K_{it}+\rho}(\bar{v}_0 + m_i(\tilde{v}_1 - \bar{v}_0))$$

As $\frac{\rho}{K_{it}+\rho} = 1 - \frac{K_{it}}{K_{it}+\rho}$:

$$\mathbb{E}(p_{it}|\mathcal{I}_{it}) = \mu_i + X_{it}\beta_x + \lambda\beta(\tilde{v}_1 - \bar{v}_1)\frac{K_{it}}{K_{it}+\rho}m_i$$

Therefore, regressing p_{it} on $\frac{K_{it}}{K_{it}+\rho}m_i$, conditional on listing fixed effects and characteristics X_{it}, will identify $\tilde{\beta}_m = \lambda\beta(\tilde{v}_1 - \bar{v}_1)$. □