Ethnic Discrimination on an Online Marketplace of Vacation Rentals

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Abstract

We use data from an online marketplace of vacation rentals (Airbnb) to measure discrimination against ethnic-minority hosts. Within the same neighborhood, hosts from minority groups charge 3.2% less for comparable listings. Since ratings provide guests with information about listings quality, we can measure the contribution of statistical discrimination, building upon Altonji and Pierret (2001). We find that an additional review increases the price for minority hosts more than for majority hosts. Statistical discrimination accounts for 2.5 percentage points of the ethnic price gap, half of which could be attributed to erroneous beliefs of hosts about average group quality.

Keywords: ethnic discrimination, statistical discrimination, rental market.
JEL: J15, L85.

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Ethnic discrimination is a pervasive phenomenon and understanding which mechanisms are at work is necessary to design efficient policies. In their recent reviews, Charles and Guryan (2011) and Lang and Lehmann (2012) stress that uncovering discrimination mechanisms is crucial and that empirical attempts are rare and inconclusive. This paper takes advantage of the features of Airbnb, a major online marketplace for short-term rentals to measure how much of the ethnic price gap is accounted for by statistical discrimination on this market.

On Airbnb, hosts list their properties, 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 the prices set by hosts who belong to an ethnic minority and those set by majority hosts. Controlling for a large set of observable characteristics accounts for more than 80% of the raw gap but the "unexplained" gap remains significant[1]. In this paper, we ask whether this unexplained gap 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 gaps vary with the amount of information on the market (Farber and Gibbons, 1996; Altonji and Pierret, 2001). The empirical application of such methods present several challenges. First, employment spells are typically long and worker's productivity evolves over time in a

[1] Edelman and Luca (2014) is the first paper to document a Black-White price gap in New York City on this market.

way that may depend on the quality of the match. Second, there is typically no good measure of the amount of information available to employers. Experience (or age) is usually used to proxy this quantity, which is problematic as human capital also varies with age in a potentially complex and heterogeneous manner.

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

We rely on a simple conceptual framework where properties' quality is partly unobservable. When a property has no reviews, potential guests can only infer unobservable quality using hosts' ethnicity. When a property has reviews, potential guests aggregate the content of reviews and host's ethnicity to form the best possible guess about the property's observable quality. In case 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 reviews. If 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.

Our dataset includes daily prices, characteristics of hosts and properties, as well as associated reviews. We collected the data relating to 400,000 properties, corresponding to apartments to rent in 19 cities in North America and Europe. In total, 20 waves of data collected between June 2014 and June 2015 form an unbalanced panel of 3,500,000 observations. The ethnic minority groups we consider are hosts with Arabic or Muslim first names and hosts with pictures coded as African-American (in North America only).

We find that the within-city raw ethnic price gap is around 16%. The set of observable characteristics about the property (including its precise location) is rich and explains more than 67% of the variance of the price. Controlling for ethnic differences in these characteristics reduces the ethnic price gap to 3.2%. In pooled cross sections, we document that this unexplained ethnic price gap decreases with the number of reviews and is insignificant in the subsample of properties with more than 20 reviews. We then use the longitudinal dimension of our data and show that prices increase faster with the number of reviews when the host belongs to an ethnic minority, as predicted by the theoretical framework. We estimate the parameters of the price equation of the model using longitudinal variations in prices and the number of reviews. Three quarters (2.5 percentage points) of the ethnic price gap can be accounted for by statistical discrimination.

When ratings are not controlled for, the ethnic differential in the slope is smaller but persists. This finding is inconsistent with a model where potential guests formulate correct beliefs about the distribution of quality in the minority group. We expand our theoretical model in order to allow for erroneous beliefs and show that this additional result permits us to empirically separate the part of the gap that corresponds to differences in true expectations from the part that corresponds to erroneous beliefs. We find that roughly half of the 2.5% differential is accounted for by actual differences in the distributions, while half can be attributed to erroneous beliefs.

Our paper contributes to the growing but largely inconclusive literature on the sources of discrimination. On the U.S. labor market, Altonji and Pierret (2001) pioneered the methodology but find little evidence for statistical discrimination in wages on the basis of ethnicity. A related 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.[2]

The amount and nature of information available to discriminatory agents can also be manipulated experimentally. In their correspondence studies on the U.S. and Canadian labor markets, Bertrand and Mullainathan (2004) and Oreopoulos (2011) find that adding information or enhancing resumes do not benefit minority applicants. Conversely, on the online rental apartment market, Ewens et al. (2014) find the response to differential quality varies in a way which is consistent with statistical discrimination. A potential limitation of this approach is related to the critique by Heckman (1998): why would someone conceal a favorable piece of information? Even if the amount of information in the resume is randomized, its absence should be interpreted by employers (or customers) as information.

The heterogeneity in agents' prejudice, whether revealed or assumed, is sometimes used to infer which source of discrimination is more prevalent. Bayer et al. (2012) show that the minority home-buyers pay higher prices on the U.S. housing market regardless of 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.

[2] 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 erroneously believe that Afro-Americans have lower skill levels while Levitt (2004) and Antonovics et al. (2005) find no evidence of discrimination.

Other approaches have been used to separate sources of discrimination. 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. 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. 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 were rather explained by statistical discrimination.[3]

We also contribute to the growing literature on the role of information provided by online market intermediaries on markets' outcomes.[4] 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. Our results are also consistent, in negative, with those obtained by Behaghel et al. (2015), who show that setting up an experimental anonymized-resume policy for some vacancies has counter-productive consequences on the hiring rate of ethnic minorities.

The main contribution of this paper is to provide a quantitative measure of statistical discrimination using a direct method, taking advantage of a context and data that make identification more credible. Our paper is also the first one to isolate the component due to erroneous beliefs in the ethnic price gap. 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

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

[4] See e.g. Autor (2001, 2009); Bagues and Labini (2009); Pallais (2014); Horton (2016); Pallais and Sands (2015); Stanton and Thomas (2015); Brown et al. (2016).

is relevant in itself from an economic point of view: launched in 2008, the website offers more than 3,000,000 listings in 191 different countries and claims to have served over 150 million guests.[5]

The next section presents the context, the data and the first empirical evidence about ethnic price gaps. In the third section, we present our conceptual framework and its predictions. In the fourth section, we provide the empirical results about statistical discrimination. A fifth section provides additional results and discusses alternative explanations. Section 6 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. The information about properties and hosts are displayed to potential guests in a standardized way, in order to ease comparison. 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. the number of accommodates, the type of room, the property type, the 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,

[5] https://www.airbnb.co.uk/about/about-us

a detailed description of the property, a standardized list of the offered amenities, more pictures and detailed reviews from previous guests.[6]

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.[7] A host 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 done and there is no way to modify its terms.[8] 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 diverse 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 below, in the section dedicated to the conceptual framework.

1.2 Data

We collected the information from the publicly available webpages of the marketplace. Specifically, we store all information visible on the first page of the listing: the price that the host asks, the characteristics of the listing,

[6] See Appendix A for a screenshot of a listing.

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

[8] 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. (Forthcoming) for a field study about discrimination against potential guests.

the characteristics of the host and all available reviews and ratings.

We focus on the 19 cities in North America and Europe with the highest number of listings: London, Paris, Madrid, Barcelona, Rome, Milan, Florence, Amsterdam, Berlin, Marseille, Vancouver, Toronto, Montreal, Boston, New York City, Miami, Chicago, San Francisco and Los Angeles.[9] We repeated the collection process every 2-3 weeks between June 2014 and June 2015, obtaining 20 waves in total.[10] Our sample includes 400,000 distinct properties. The panel is unbalanced: some properties enter the system while others exit.

Table 1 presents the characteristics of the properties and the hosts. The left column displays the mean of each characteristics in the full sample, while the right column focuses on the subsample of listings that have gained at least one review over the observation period. There are no sizeable differences between the two columns. 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. Most places include wireless connection, heating and a washer while some amenities (e.g. cable TV, dryer, or parking space) are less frequent. The presence of a doorman, a gym, a hot tub, or a pool is rare. Most hosts do not allow pets or smoking. 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.[11]

Information about hosts is available on their profile pages. Aside from the first name, a picture and a free-text description, guests know whether they have other properties and when they joined the platform. Most hosts have only one property and have joined the platform recently.

[9] See Table A1 in Appendix B for the number of observations by city.

[10] See the collection dates of each wave in Table A2 in Appendix B.

[11] In the absence of reliable public data on the duration of stays, we consider they last 6 days, and add a sixth of the fee to the price.

Table 1: Summary statistics: Property & host characteristics

	Full Sample	Listings with at least one review
Type of property		
Shared Flat	0.331	0.299
Entire Flat	0.669	0.701
Flat	0.837	0.846
House	0.107	0.103
Loft	0.017	0.019
Size		
Person Capacity	3.114	3.207
# Bedrooms	1.247	1.245
# Bathrooms	1.163	1.153
Terrace or Balcony	0.145	0.171
Type of bed		
Couch	0.006	0.006
Airbed	0.003	0.003
Sofa	0.031	0.032
Futon	0.011	0.012
Real Bed	0.948	0.947
Amenities		
Cable TV	0.348	0.358
Wireless	0.903	0.924
Heating	0.891	0.911
AC	0.373	0.375
Elevator	0.353	0.342
Wheelchair Accessible	0.098	0.101
Doorman	0.103	0.095
Fireplace	0.079	0.081
Washer	0.713	0.716
Dryer	0.393	0.397
Parking	0.181	0.179
Gym	0.071	0.065

(Continued on next page)

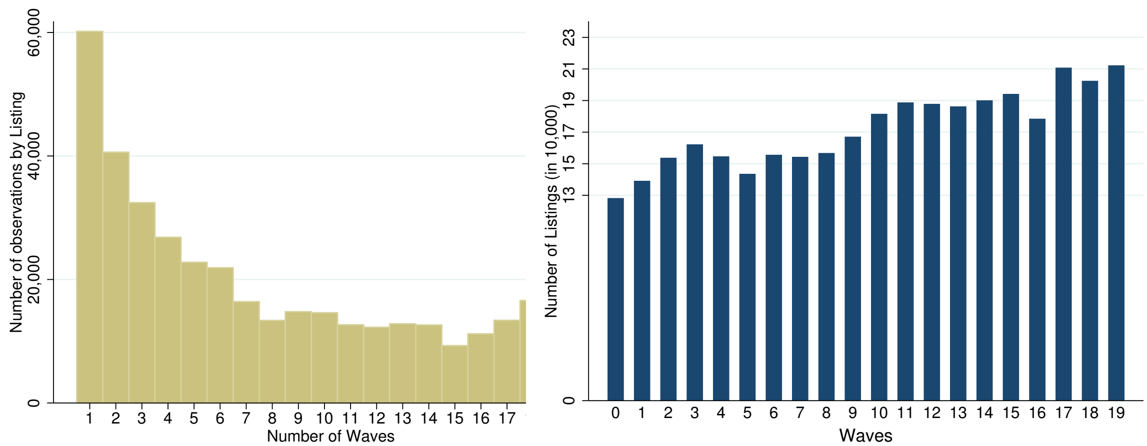
Table 1: Summary statistics: Property & host characteristics

Pool	0.061	0.054
Buzzer	0.378	0.397
Hot Tub	0.073	0.070
Services		
Breakfast served	0.088	0.092
Family/Kids Friendly	0.432	0.455
Suitable for events	0.050	0.054
Rules & Extras		
Additional People	0.533	0.659
Price per Additional People	7.081	8.140
Smoking Allowed	0.142	0.147
Pets Allowed	0.121	0.131
Host Characteristics		
Has multiple properties	0.330	0.344
Member since 2008	0.001	0.001
Member since 2009	0.008	0.009
Member since 2010	0.028	0.033
Member since 2011	0.096	0.108
Member since 2012	0.193	0.213
Member since 2013	0.257	0.270
Member since 2014	0.305	0.297
Member since 2015	0.101	0.063
Number of languages spoken	1.280	1.436
N	404,458	213,740

The distribution of the number of waves during which we observe each property is in the left panel of Figure 1. 11% of listings are observed in all waves and half of listings are observed in more than 6 waves. On average, a property is observed 7 times over the period. The number of listings observed per wave is displayed in the right panel of Figure 1.

Figure 2 shows the distribution of daily prices. There is much variation in prices across properties. To reduce the influence of outliers, we drop 1% of

Figure 1: Number of observations by listing and of listings per wave



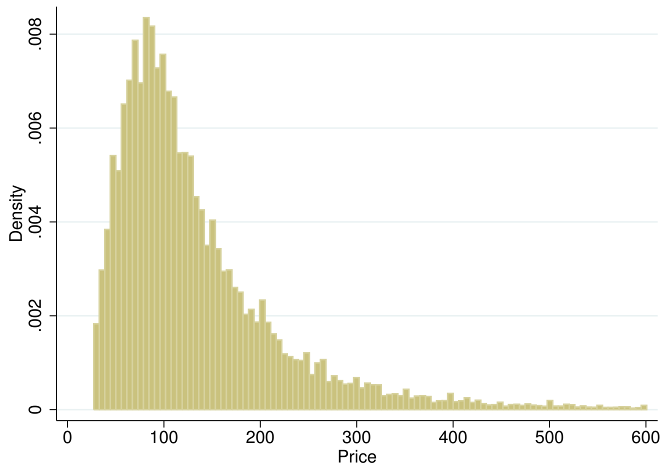
the observations of the top and the bottom of the price distribution. The first quarter is 76 euros, the median 109 euros and the third quarter 164 euros per night. The skewness of the distribution implies that the mean price is 134 euros. The daily price varies across cities and according to the amenities of the listing (number of accommodates, bedrooms, bathrooms...). Table A3 (Appendix B) provides details on how amenities affect the price.

1.3 Ethnic groups and gaps

We consider two groups of ethnic minorities. First, we consider African-Americans, which we identify using the pictures provided on their host profile.[12] This ethnic group is only defined in North America. Second,

[12]Specifically, pictures were coded by workers specialized in this picture-coding task. Workers were asked to code each picture in three categories: (i) whether they thought that at least one person on the picture was African-American, (ii) whether nobody on the picture was African-American, (iii) whether it was impossible to say anything about the ethnicity of anyone on 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

Figure 2: Distribution of daily price



we consider hosts that have a first name associated with Arabic, Muslim or Sub-Saharan African ethnicity (labeled Arabic/Muslim hereafter).[13] We use two different sources to obtain a complete list of names: Jouniaux (2001) and Hawramani (2015).[14] This ethnic group is defined both in North America and Europe.[15]

Table 2 displays the share of ethnic groups in the sample and the within-city-wave raw price gap. African-Americans represent roughly 2% of the observations in the sample, i.e. 5.3% of the North American observations. Compared to their share in total population, it seems that African-

found mistakes at a rate below 5% for this dummy variable.

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

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

[15]One could think of other ethnic minorities than those considered in this analysis. Hispanics are difficult to identify in these data, given that first names used among the group are not necessarily distinguishable and picture characterization is difficult. We replicate our results including individuals coded as Hispanics using first names – for the United States – and present the output in Appendix C. Our findings are qualitatively unchanged.

Americans are under-represented on the website or that some African-American hosts do not display a picture of themselves on the website. Hosts with Arabic/Muslim names in North America represent 1.2% of the sample and those in Europe 2.2% of the sample. Cities have different shares of minorities. NYC has 8% of African-American and 3% 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. Overall, the share of minorities is 5.4%. In the third column of the table, we display the gap between each ethnic group and the majority in daily prices, controlling only for the heterogeneity across cities and waves. The raw price gap is around 5% for Arabic/Muslim hosts in North America and 9% in Europe ; while the gap reaches 31% for African-Americans in North America.

Table 2: Raw price gaps by ethnic groups

	Sample size	Share	Within-city-wave gap
Majority	3,255,597	94.6%	-
African-American (US/Can)	67,046	2.0%	31.4%
Arabic/Muslim (US/Can)	42,142	1.2%	4.9%
Arabic/Muslim (Europe)	76,164	2.2%	9.4%

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 3 displays 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 (16%) and highly significant. Accounting for ethnic disparities in property observable characteristics reduces the gap to 10% (column 2), which shows that ethnic minorities have on average properties of lower observable quality. Because we observe the neighborhood where the listing is located, we can control for the heterogeneity of locations within cities. In total, there are 2,845 neighborhoods. Including neighborhood fixed-effects instead of city fixed-effects reduces the ethnic price gap from 16% to 7% (column 3). This indicates that ethnic-minority hosts tend to live in neighborhoods that are less valued by potential guests. Finally, in the fourth column, both neighborhood and property characteristics are included in the regression: the residual ethnic price gap is reduced to 3.2% but is still highly significant. Note that the adjusted R-squared is high in this last specification, equal to .67. Observables are found to explain the largest part of the variance, as the adjusted R-squared is equal to .60 in the second column.[16]

Table 3: Ethnic price gap, by specification

	Log daily rate			
	(1)	(2)	(3)	(4)
Minority	-0.161	-0.102	-0.070	-0.032
	(0.007)	(0.005)	(0.006)	(0.004)
city-wave FE	Yes	Yes	Yes	Yes
Neighborhood FE	No	No	Yes	Yes
Property characteristics	No	Yes	No	Yes
Adj R^2	0.15	0.60	0.31	0.67
N obs.	3,440,949	3,332,844	3,440,949	3,332,844

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 A3. Robust standard errors clustered at the property level.

[16]Stratifying this analysis by ethnicity shows that African-Americans start from a higher raw gap than Arabic/Muslim hosts but end up with a lower price when location and characteristics are controlled for: 1.3% vs. 4.1%.

2 Conceptual framework

In this section, we introduce a simple conceptual framework to explain how we expect to separate the different mechanisms behind the ethnic price gap. We show that, under some assumptions, we can separate statistical discrimination from the other mechanisms. Conversely, taste-based discrimination and differentials in characteristics that are observed by potential guests but not by the econometrician are found to be observationally equivalent, given our data. Our framework also allows us to test whether ethnic minorities set lower prices because they have lower outside options.

2.1 Prices and demand as a function of quality

At each period (say, a week), a host shares his working time between two activities: renting his property (looking for guests, communicating with guests, cleaning up) or working on a regular job. L is the amount of labor put in renting and $1 - L$ into the regular job. Renting the property is assumed to have decreasing returns to scale: the number of nights supplied is equal to $N = L^{\tilde{\alpha}}$, 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:

$$p = p_0 + \lambda \alpha w + \lambda \beta q - \lambda \gamma m$$

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 Unobserved quality

Quality q is not perfectly observable by potential guests or the econometrician. Everyone observes x. ζ is the part of the information that is available to the guests but not to the econometrician and is orthogonal to x. ν is the part of the information that is revealed by the reviews and is orthogonal to x and ζ. u is the part of the information that not available to anyone and is orthogonal to x, ν and ζ. We assume that the distribution of $\nu|m$ is a $\mathcal{N}(\bar{\nu}_m, \sigma_\nu^2)$.[17] We also presume that 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.[18] The average rating over K reviews transmits the signal $\bar{r}$ distributed as a $\mathcal{N}(\nu, \sigma^2/K)$. Denoting $\rho = \sigma^2/\sigma_\nu^2$,

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

Guests observe x, ζ, m, K, and $\bar{r}$. Hosts with an outside option w will set a price:

$$p = p_0 - \lambda\gamma m + \lambda\alpha w + \lambda\beta(x + \zeta) + \lambda\beta\frac{K\bar{r} + \rho\bar{\nu}_m}{K + \rho}$$

[17] In Appendix D, 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).

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

We normalize ζ, ν and u so that they have zero mean in the majority group and denote δ_ζ, δ_ν and δ_u the difference in the expectations of these variables between the majority and the minority groups. In the absence of reviews, the best guess about ν is its expectation conditional on the host's group. Statistical discrimination arises when $\delta_\nu > 0$.

The econometrician observes p, K, m, a proxy for $\bar{r}$ as well as a vector of characteristics X from which x has to be inferred. Denote δ_w the difference between the mean of $\log w$ in the majority and the minority groups. The best possible prediction of the log-price based on what is observed by the econometrician is:

$$p = p_0 + \lambda\beta x - \lambda\left(\gamma + \beta\delta_\zeta + \beta\delta_u + \alpha\delta_w\right) m + \lambda\beta\frac{K\bar{r}}{K+\rho} - \lambda\beta\frac{\rho\delta_\nu}{K+\rho} m \quad (1)$$

From equation (1), we see that the sign of δ_ν, the parameter relating to statistical discrimination, can be identified by comparing observations of the same listing with different number of reviews. On the other hand, the parameters $\gamma, \delta_\zeta, \delta_u$ and δ_w, relating to taste-based discrimination, unobservables and outside options cannot be distinguished from each other using equation (1).

2.3 Prices and reviews: Empirical evidence

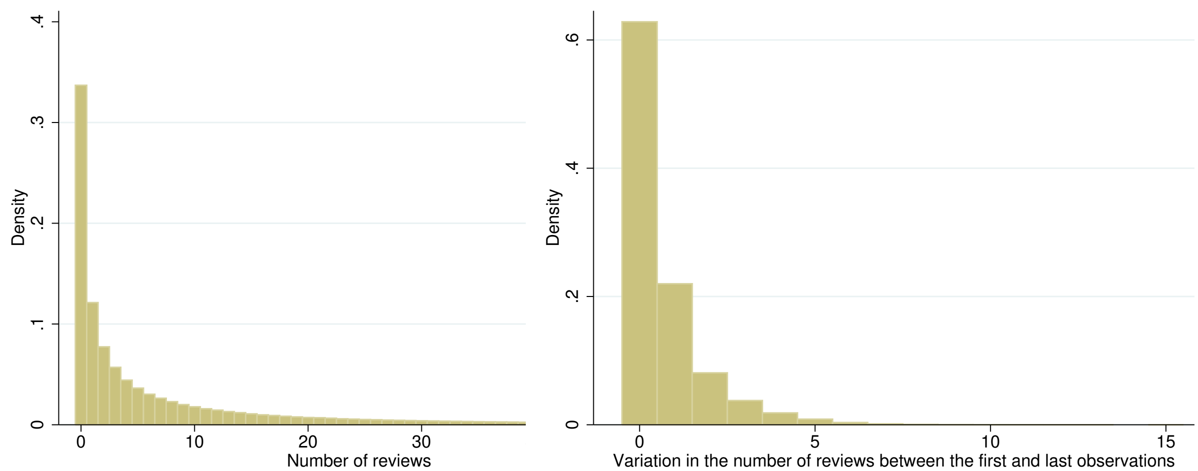
In order to be able to identify statistical discrimination, we need to have enough variability in the number of reviews and we need reviews to be informative about listings' quality.[19]

First, we assess how the number of reviews varies in our sample. Figure 3 shows the distribution of reviews across the observations of our sample (left panel) and the variation of the number of reviews between the last and the first observations (right panel). The sample offers a decent amount of

[19] See Fradkin et al. (2017) for details about the reviewing system of Airbnb.

heterogeneity in the number of reviews, the empirical distributions being quite similar to that of a Poisson random variable.

Figure 3: Distribution of the number of reviews (left) and of the longitudinal variation in the number of reviews within a property (right)

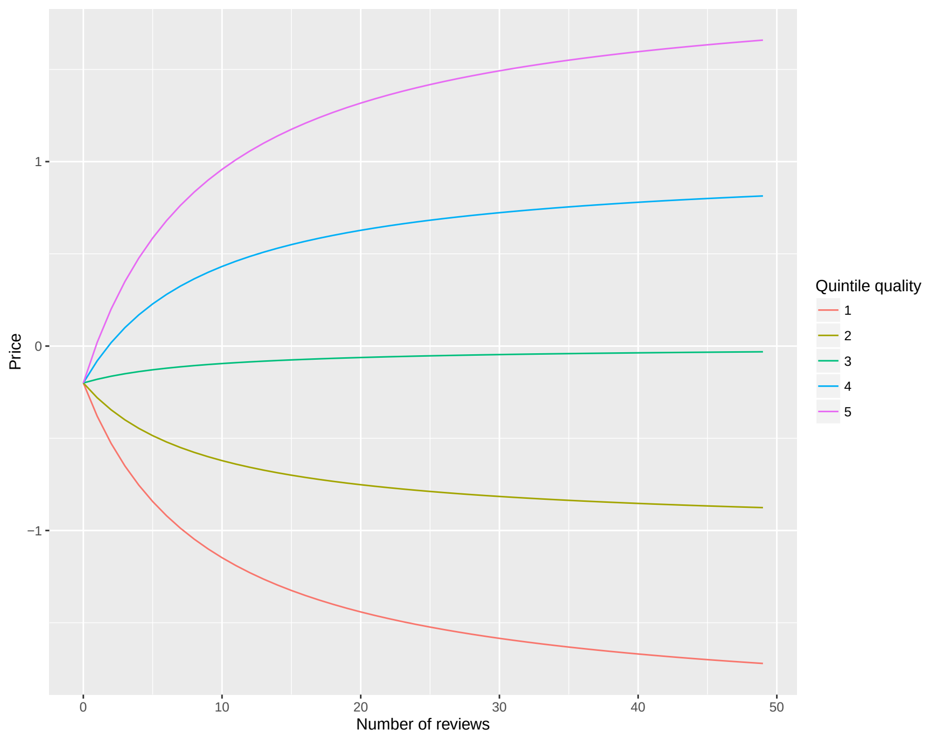


While ratings can vary between 1 and 5 stars (with half-star increments), the distribution of ratings is disproportionately skewed to good ratings, as documented in Fradkin et al. (2017). If we consider the last rating observed for each property of our sample, 49% of observations have 5 stars and 34% 4.5 stars. By contrast, only 4% have 3.5 stars (see Table A4 in Appendix B). Moreover, 75% of properties have a different price in the first and the last observations.

According to our conceptual framework, hosts should update their prices as new information is available about the quality of their properties, i.e. as the number of reviews increases. The amount of information in the marginal review being decreasing, the model predicts a concave relationship between the price and the number of reviews, converging to some value when the number of reviews tends to infinity. The impact of new information on prices depends on the unobservable quality of the listing.

High-quality properties will benefit from new information while prices of low-quality properties are expected to decrease. Figure 4 provides a qualitative illustration of this Bayesian-updating phenomenon from a simulation of our model.

Figure 4: Illustration of the conceptual framework: Prices with the number of reviews, by unobservable quality



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

Do we observe such a pattern in our data? We use as a proxy for unobservable quality the more recent rating of the properties, which is computed as the mean of all reviews received up to the last time the property appears in the data and is the most reliable measure of unobservable quality we observe. This last rating is rounded and takes four values: 5, 4.5, 4, and

3.5 stars and less. We regress the log-price on splines of the number of reviews interacted with the last rating and the full set of characteristics of the properties. The spline specification allows us to flexibly accommodate a hypothetical concavity in the relationship between prices and number of reviews without forcing it.

$$p_{it} = \sum_{r=3.5}^{5} 1\{\bar{r}_i = r\} s_r(K_{it}) + X_{it}\beta_x + \eta_i + \varepsilon_{it} \quad (2)$$

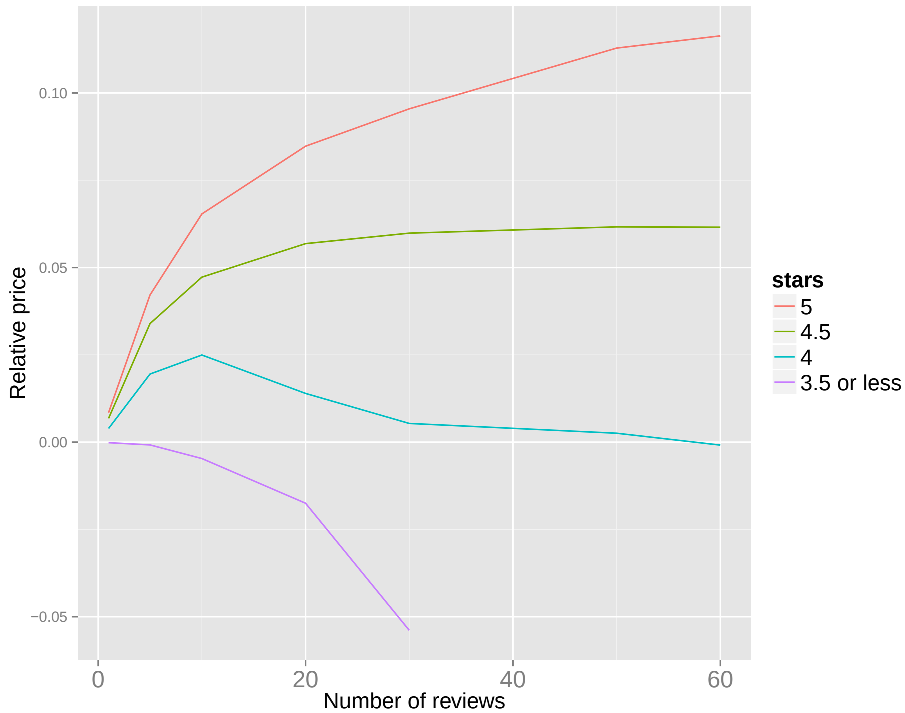
where p_{it} is the log-price of property i at wave t, K is the number of reviews, X are observable characteristics of the property and the host, $s_r(.)$ are linear splines for each level of the last rating r and η are property fixed-effects. The results of the estimation are displayed in Figure 5. The figure shows that, depending on the last rating, the prices diverge in a way that is close to the way predicted by our conceptual framework. This result shows that (i) reviews provide information to potential guests, (ii) hosts use reviews and information to update their prices, and (iii) the last rating is a satisfactory proxy for the unobservable quality of the listing.

3 Ethnic price gaps and statistical discrimination

We first document how the unexplained ethnic price gap changes with the number of reviews. Table 4 shows the coefficient associated to the ethnic minority dummy in a regression of the log-price on property characteristics, neighborhood dummies and ratings, on several subsamples defined by the number of reviews. We find that the ethnic gap changes across subsamples: from 3.3% for listings with no reviews to an insignificant 1% for listings with more than 20 reviews.[20]

[20] We check that our results are not sensitive to the way we control for geographic unobserved heterogeneity. Instead of neighborhood dummies, we build 5000 squared blocks using longitude and latitude of listings. Controlling for block fixed-effects instead of neighborhood fixed-effects does not affect the results at all. See Appendix E.

Figure 5: Estimated prices with the number of reviews, stratified by the most recent rating



Notes: Equation (2) 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.

While this pattern could be interpreted as suggestive evidence of statistical discrimination, it might be subject to selection issues. Potential guests could accept to be hosted by minorities only if the quality of the property was extremely good, and be less demanding for majority-host listings. In this case, the ethnic gap would be reduced, not because of the existence of statistical discrimination, but simply because the minority-host listings

Table 4: Ethnic price gap, for several segments of the number of reviews

	Log daily rate				
	(1)	(2)	(3)	(4)	(5)
Minority	-0.033	-0.030	-0.024	-0.012	-0.011
	(0.007)	(0.006)	(0.007)	(0.011)	(0.017)
Nb reviews	0	1-4	5-19	20-49	50+
Minority share	5.4%	5.3%	5.4%	5.4%	5.3%
Adj R^2	0.64	0.72	0.76	0.77	0.77
N obs.	1,035,731	959,097	830,436	353,160	154,420

Notes: OLS regressions of the daily log-price on the minority dummy, controlling for neighborhood FE, property characteristics and ratings (for properties with at least one review). See the list of all property and host characteristics in Table A3. Robust standard errors clustered at the property level.

with many reviews are relatively much better than those with less reviews. In this case, we would observe a drop in the share of minority listings with the number of reviews. Table 4 reports the share of minority-host listings in each subsample and shows it remains stable, at 5.3%-5.4%.

We check the possibility of differential attrition between both groups. Minority hosts could be more likely to exit the market than the majority. In Appendix F, we show that it is not the case, the probability to leave the market is the same for both groups, after controlling for property characteristics, ratings and neighborhood fixed-effects.

Still, more sophisticated forms of differential selection could accommodate these findings. In order to deal with selection and unobserved heterogeneity, we take advantage of the longitudinal nature of our data. We estimate a within-listing model linking the evolution of prices to the increase in the number of reviews. Following our conceptual framework, we estimate the following model :

$$p_{it} = \sum_{r=3.5}^{5} \beta_r \mathbb{1}\{\bar{r}_i = r\} K_{it} + \beta_m m_i K_{it} + \mu_i + X_{it}\beta_x + \varepsilon_{it} \tag{3}$$

in which $\bar{r}$ is the overall rating at the last observation and μ_i is a listing-specific fixed effect. For the sake of parsimony, we restrict the relationship to be linear in equation (3) but relax this assumption in some specifications. 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 $\beta_m > 0$.

Table 5 presents the results of the estimation of this model. Column (1) focuses on a subsample restricted to the first and last observations of each property starting with less than 5 reviews. The coefficients on the interactions between the last rating and the number of reviews is consistent with Figure 5. The listings that have a better rating show a higher price slope. The coefficient on the interaction between the minority dummy and the number of reviews is positive and significant. Column (2) widens the sample to all observations of properties starting with less than 5 reviews. All coefficients are lower than in the previous column. This may reflect the fact that hosts do not update their prices immediately. In column (3), we include observations of properties starting with less than 20 reviews and in column (4), we take the full sample. Including observations with a higher number of reviews reduces the magnitude of the coefficients. This is consistent with the assumption of a concave relationship between the number of reviews and prices. To account for concavity, we replace linear relationships by quadratic ones in column (5). The price difference between minority and majority listings exhibits indeed an increase and concave relationship with the number of reviews. These results are consistent with our theoretical framework.

The previous results provide evidence that statistical discrimination contributes to the ethnic price gap but the estimates are not easily translated into magnitudes. In order to quantify the share of the ethnic gap explained by statistical discrimination, we turn back to our conceptual

Table 5: Fixed-Effects Estimation

	log-price				
	(1)	(2)	(3)	(4)	(5)
3.5 stars $\times K/100$	0.042	-0.055	-0.113	-0.122	-0.175
	(0.072)	(0.072)	(0.060)	(0.052)	(0.072)
4 stars $\times K/100$	0.115	0.045	-0.030	-0.055	-0.013
	(0.029)	(0.028)	(0.022)	(0.019)	(0.026)
4.5 stars $\times K/100$	0.269	0.192	0.094	0.032	0.101
	(0.013)	(0.012)	(0.009)	(0.007)	(0.011)
5 stars $\times K/100$	0.401	0.317	0.215	0.124	0.218
	(0.014)	(0.012)	(0.009)	(0.007)	(0.014)
Minority $\times K/100$	0.160	0.102	0.064	0.031	0.099
	(0.043)	(0.038)	(0.038)	(0.026)	(0.036)
3.5 stars$\times(K/100)^2$					0.137
					(0.069)
4 stars$\times(K/100)^2$					-0.044
					(0.022)
4.5 stars$\times(K/100)^2$					-0.060
					(0.007)
5 stars$\times(K/100)^2$					-0.079
					(0.011)
Minority $\times(K/100)^2$					-0.063
					(0.023)
Samples	Min(K)<5 First Last	Min(K)<5 Full	Min(K)<20 Full	- Full	- Full
N obs.	597,455	2,514,783	3,042,103	3,332,844	3,332,844

Notes: OLS regressions with listing fixed effects. Aside from those mentioned in the Table, controls include city-wave FE and property characteristics (see Table A3). Robust standard errors clustered at the property level.

framework and estimate the parameters relating to statistical discrimination $\beta_m = \lambda\beta\delta_v$. We use the last observed review s (taking values 3.5, 4, 4.5, or 5) of each listing as a proxy for $\bar{r}$. We do not observe x and use the vector X of observable characteristics, as well as dummies for the city interacted with the wave in which the listing appeared. We estimate the parameters of the following equation by non-linear least-squares, β_m and ρ being the main parameters of interest. For inference, we bootstrap at the property level.

$$p_{it} = \sum_{r=3.5}^{5} \beta_r \mathbb{1}\{\bar{r}_i = r\} \frac{K_{it}}{K_{it} + \rho} - \beta_m m_i \frac{\rho}{K_{it} + \rho} + \mu_i + X_{it}\beta_x + \varepsilon_{it} \tag{4}$$

We obtain an estimated value of 9 (with a standard error of 0.3) for ρ. 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.

β_m is estimated to be equal to .025 (with a standard error of .005), which means that going from 0 to an infinite number of reviews would increase the prices of minority by 2.5%. This figure is of the same order of magnitude as the ethnic price gap observed in the subset of listings with no reviews (3.3%, see Table 4, column 1). This point estimate suggests that around three quarters of the initial price gap can be accounted for by statistical discrimination.

We perform the whole empirical analysis on several subsamples, according to the continent (North-America vs. Europe), the ethnic minority group (African-American vs. Arabic/Muslim) and the nature of the listing (entire property vs. shared property). Results are in Appendix G. They display some extent of heterogeneity but nothing we can read in a systematic and significant way.

4 Additional results

4.1 Erroneous beliefs

In the conceptual framework introduced in Section 2, the existence of statistical discrimination relies on actual differences in the distribution of quality across groups. On average, minority listings have worse unobservables than majority and the gap is δ_ν. In this section, we add an additional channel for statistical discrimination: hosts may have erroneous priors about the average unobservable quality of each group. Because they revise their priors when new information about a listing is available, we categorise this as statistical discrimination. We also show that we can decompose statistical discrimination into two components: the first one due to actual differences in the unobservable quality across groups, and the second one because potential guests believe erroneously that the average (unobservable) quality of minority listings is lower than that of the majority.

We assume that the true expectation of ν in the minority group is $\bar{\nu}_1$ while guests wrongly believe that it is $\tilde{\nu}_1$. We denote as δ_e the difference $\bar{\nu}_1 - \tilde{\nu}_1$ between the true expectation and the erroneous prior about the expectation. Conditional on x, $\bar{r}$, K and m, the price takes a form similar to equation (1).

$$p = p_0 + \lambda\beta x - \lambda\left(\gamma + \beta\delta_\zeta + \beta\delta_u + \alpha\delta_w\right) m + \lambda\beta\frac{K\bar{r}}{K+\rho} - \lambda\beta\frac{\rho(\delta_\nu + \delta_e)}{K+\rho} m \tag{5}$$

In equation (5), the price penalty suffered by minority listings with no ratings is proportional to $\delta_\nu + \delta_e$, not just to δ_ν. When beliefs are erroneous, the new information provided by the reviews corrects for the gap between the actual quality of the property and the average quality in the group as well as for the erroneous belief.

When ratings are not included amongst regressors in the price equation, we obtain:

$$p = p_0 + \lambda\beta x - \lambda\left(\gamma + \beta\delta_\zeta + \beta\delta_u + \alpha\delta_w + \beta\delta_\nu\right)m - \lambda\beta\frac{\rho\delta_e}{K+\rho}m \quad (6)$$

Whenever beliefs are correct ($\delta_e = 0$), the price gap should remain constant with the number of reviews when ratings are not controlled for. The intuition is that, while reviews reveal information about which listings among the ones owned by minorities (and the majority) are the best ones, the average quality in each group remains similar. The situation changes when $\delta_e > 0$, because new information improves the average posterior belief about the unobservable quality in the minority group. In this case, the ethnic price gap should decrease in the number of reviews, even when ratings are not controlled for. If $\delta_\nu > 0$, the slope of the price gap with the number of reviews, should still be larger when ratings are controlled for than when they are not.

Table 6 presents the results of the estimation of the same models as Table 4 except that ratings are not controlled for. We see that the decline of the ethnic gap with the number of reviews seems to be slower.

Table 6: Ethnic price gap, for several segments of the number of reviews, without controlling for ratings

	Log daily rate				
	(1)	(2)	(3)	(4)	(5)
Minority	-0.033	-0.035	-0.036	-0.025	-0.023
	(0.007)	(0.006)	(0.007)	(0.011)	(0.018)
Nb reviews	0	1-4	5-19	20-49	50+
Adj R^2	0.64	0.71	0.74	0.76	0.75
N obs.	1,035,731	959,097	830,436	353,160	154,420

Notes: OLS regressions of the daily log-price on the minority dummy, controlling for neighborhood FE, property characteristics *but not ratings*. See the list of all property and host characteristics in Table A3. Robust standard errors clustered at the property level.

Table 7 presents the results of the estimation of the structural model, introduced in equation (4). In the first column, we present the results commented in Section 3: the ethnic gap corresponding to statistical discrimination is equal to 2.5%. The second column shows the results when we do not control by ratings, i.e. by the fact that properties of different quality evolve in a different way. In this case, the coefficient corresponding to β_m decreases to 1.2%, but is still significantly different from zero. We interpret this result as evidence that roughly half of the gap due to statistical discrimination is driven by true differences in expectations, while half may be due to erroneous beliefs.

Table 7: Structural model

	(1)	(2)
5 stars*$f(K)$	0.138	
	(0.002)	
4.5 stars*$f(K)$	0.090	
	(0.002)	
4 stars*$f(K)$	0.030	
	(0.003)	
$\leq$ 3.5 stars*$f(K)$	-0.018	
	(0.006)	
$f(K)$		0.097
		(0.001)
β_m	0.025	0.012
	(0.004)	(0.004)
ρ	0.090	0.090
	(0.010)	(0.010)
N obs.	3,332,844	3,332,844

Notes: Estimations by non-linear least-squares. The outcome is the daily log-price. $f(K) = K/K + \rho$. On top of the covariates included in the table, we include neighborhood FE and property/host characteristics. See the list of all property and host characteristics in Table A3. Inference by block-bootstrap at the listing level.

4.2 Ethnic differences in pricing behavior

A potential explanation for the lower prices of minority-host listings is that minority hosts have on average lower outside options than majority hosts. Going back to our conceptual framework, lower outside options translate into a lower w. Combining the log-demand and the log-price equations and eliminating quality, we obtain a relationship involving only the log-volume of transactions d, the log-price and the outside log-wage:

$$d = \alpha p - \alpha w - (\kappa + \alpha) p_0 \tag{7}$$

A lower outside wage entails a lower price but it should also lead to a higher demand and realized transactions, conditional on price. Unfortunately, we do not have access to the number of days a given listing was occupied. We use the number of new reviews between two waves as a proxy for the volume of transactions. This proxy relies on the assumption that the number of new reviews is proportional to the number of nights the property was occupied. More precisely, we build two outcomes: a dummy for having at least one new review between t and $t + 1$, and the log of the number of reviews.

Table 8 presents the results of the regression of these two outcomes on the log-price (at t), controlling for location and observable characteristics: columns (1)-(2) for the dummy and (3)-(4) for the log new reviews. In columns (2) and (4), lagged prices are included in a more flexible manner (using splines). In all columns, we find that the coefficient of the minority is close to zero and insignificant. These results suggest minority hosts do not get more demand than majority hosts, despite the lower prices. The ethnic price gap does not seem to reflect differences in pricing behavior induced by differences in outside wages.

Table 8: Variation in the number of reviews between two waves as a function of host ethnicity, controlling for prices

	Dummy for any new review		Number of new reviews	
	(1)	(2)	(3)	(4)
Log price	-0.135		-0.175	
	(0.001)		(0.002)	
Minority	-0.000	-0.000	0.005	0.005
	(0.002)	(0.002)	(0.005)	(0.005)
Price functional form	Linear	Spline	Linear	Spline
Adj R^2	0.19	0.19	0.10	0.10
N	3,332,844	3,332,844	934,199	934,199

Notes: OLS regressions. Aside from those mentioned in the Table, controls include city-wave FE, neighborhood FE and property characteristics (see Table A3). Robust standard errors clustered at the property level.

4.3 Do ethnic groups compete on the same market?

In the previous analyses, we have made the implicit assumption that minority and majority hosts compete on the same market. Conversely, it may be that the two markets are segmented: minority hosts receiving almost only guests of their own ethnicities. To investigate this issue, we extract information about guests' ethnicities. We have access to 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 African-American 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 that are 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 9, we find some evidence for a mild 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 be receive more minority guests, the magnitude of the difference show that markets are far from being segregated.

Table 9: 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	0.007
N obs.	240,605

OLS regression. Aside from the dummy Arabic/Muslim Host, controls include city-wave FE, neighborhood FE, property characteristics (see Table A3), log price, number of reviews and ratings. Standard errors are clustered at the property level.

4.4 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 no review) 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:

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

where $\tilde{g}^m_{it}$ is the share of guests between $t-1$ and t that belong to the minority group and μ_i is a listing-specific fixed-effect. As in section 4.3, we exclude African-Americans 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 10 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.

Table 10: Average rating, depending on hosts' and guests' ethnicity

	Average rating over reviews received between $t-1$ and t
Share of minority among new guests	0.010
	(0.007)
Minority host $\times$ Share of minority among new guests	-0.002
	(0.027)
Adj R^2	0.070
N obs.	912,344

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 A3). Robust standard errors clustered at the property level.

4.5 Ethnic differences in property upgrading

If minority hosts reacted to the lower demand by improving the quality of their listing, we would also observe that minority prices increase faster than majority ones. We use the information about the observable characteristics of listings 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 neighborhood and city-wave fixed effects. We use the estimated coefficients of this regression to predict the log-price corresponding to all properties for each period, $\hat{p}_{it}$. Then, we regress the difference $\hat{p}_{i,t+1} - \hat{p}_{i,t}$ of the prediction between two waves on a minority dummy, controlling for property characteristics, neighborhood and city-wave fixed effects. The estimated coefficient on the minority dummy is smaller than .0001, with a T-statistic around 1. This result suggests than minority hosts are not significantly more likely to upgrade their properties, everything else equal.

5 Conclusion

This paper documents that, in a popular online platform of short-term rentals, hosts belonging to an ethnic minority experience a 3.2% price penalty when differences in locations and observable characteristics are accounted for. Taking advantage of the longitudinal nature of our data, we show that statistical discrimination can be considered as the main driver of the ethnic price gap. At least three quarters (2.5 percentage points) of the initial gap can be explained by statistical discrimination. Half of these 2.5 percentage points can be accounted for by differences in the expectations between the unobservable quality in the two groups, while half may be due to erroneous beliefs about the distribution of the unobservables of the minority group.

We can draw several conclusions from this 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, beside the gains in efficiency, improving the feedback system would also contribute to reduce ethnic price gaps.

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, the avenue consisting in concealing more information about actors' identity is likely to 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 incentivize reviewers to provide informative, unbiased and relevant reviews. Further research is required to understand how interventions on information disclosure affects ethnic gaps.

There is no reason to believe that the results of the paper can be directly extended to other platforms or markets. However, we see our results as 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 standardized 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 labor markets.

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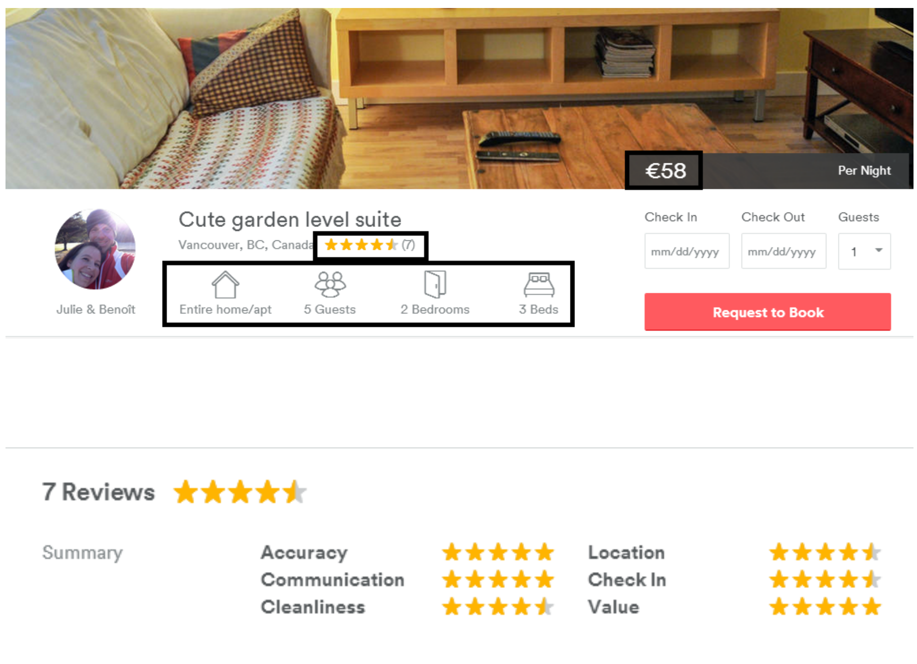
For Online Publication

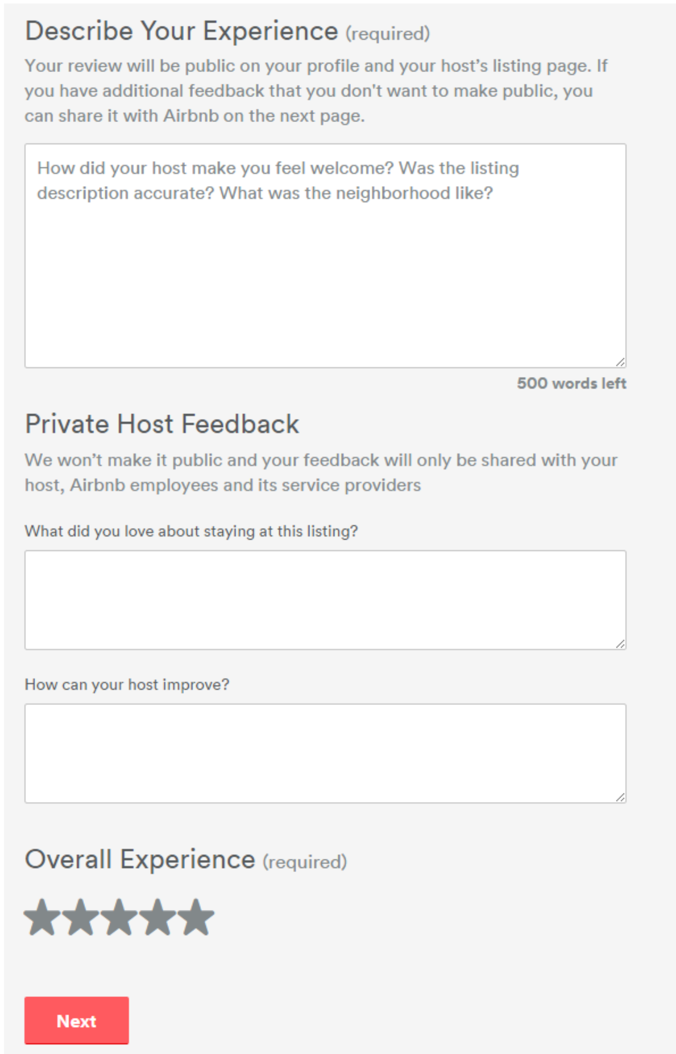
A Online Platform

A.1 Example of listing



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**

A.2 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

B Data

Table A1: Number of observations by city

City	Obs	Share
Amsterdam	135,292	3.93
Barcelona	229,999	6.68
Berlin	209,652	6.09
Boston	51,705	1.50
Chicago	51,698	1.50
Florence	85,174	2.48
London	369,168	10.73
Los Angeles	209,857	6.10
Madrid	92,731	2.69
Marseille	86,077	2.50
Miami	90,726	2.64
Milan	131,603	3.82
Montreal	104,726	3.04
New-York	474,402	13.79
Paris	639,664	18.59
Rome	204,847	5.95
San-Francisco	132,227	3.84
Toronto	81,545	2.37
Vancouver	59,856	1.74

Table A2: Collection dates of waves

Wave	Collection date
0	15 June 2014
1	8 July 2014
2	28 July 2014
3	11 August 2014
4	25 August 2014
5	8 September 2014
6	25 September 2014
7	15 October 2014
8	5 November 2014
9	25 November 2014
10	15 December 2014
11	7 January 2015
12	13 January 2015
13	3 February 2015
14	4 March 2015
15	25 March 2015
16	13 April 2015
17	4 May 2015
18	26 May 2015
19	15 June 2015

Table A3 shows observable characteristics explain a large share of the variance. These covariates are all included in the following regressions. In column (2), neighborhood fixed effects are included in the equation.

Table A3: Log daily rate

	(1)	(2)
Shared flat	-0.789	-0.692
	(0.003)	(0.003)
Person Capacity (> 2)	0.203	0.207
	(0.003)	(0.003)
# bedrooms	0.296	0.313
	(0.009)	(0.008)
# bathrooms	0.096	0.081
	(0.037)	(0.031)
Flat	-0.212	-0.229
	(0.008)	(0.007)
House or Loft	-0.184	-0.100
	(0.009)	(0.008)
Couch	-0.168	-0.143
	(0.014)	(0.013)
Airbed	-0.168	-0.112
	(0.024)	(0.023)
Sofa	-0.166	-0.156
	(0.007)	(0.006)
Futon	-0.161	-0.118
	(0.010)	(0.009)
Terrace or Balcony	0.042	0.055
	(0.003)	(0.003)
Cable TV	0.158	0.118
	(0.003)	(0.002)

(Continued on next page)

Table A3: Log daily rate

Wireless	-0.029	-0.044
	(0.005)	(0.004)
Heating	-0.056	-0.044
	(0.005)	(0.004)
AC	0.163	0.139
	(0.004)	(0.003)
Elevator	0.099	0.088
	(0.003)	(0.003)
Wheelchair Accessible	-0.039	-0.012
	(0.004)	(0.004)
Doorman	0.118	0.056
	(0.005)	(0.004)
Fireplace	0.173	0.134
	(0.005)	(0.005)
Washer	-0.045	-0.012
	(0.003)	(0.003)
Dryer	0.162	0.116
	(0.003)	(0.003)
Parking	-0.126	0.010
	(0.003)	(0.003)
Gym	0.068	0.064
	(0.006)	(0.006)
Pool	0.121	0.132
	(0.007)	(0.006)
Buzzer	0.032	-0.001
	(0.002)	(0.002)
Hot Tub	0.021	0.016
	(0.005)	(0.005)

(Continued on next page)

Table A3: Log daily rate

Breakfast served	-0.003	0.023
	(0.004)	(0.004)
Family/Kids Friendly	0.011	0.026
	(0.003)	(0.002)
Suitable for events	0.094	0.090
	(0.006)	(0.006)
Additional People	-0.046	-0.028
	(0.002)	(0.001)
Price per Additional People	0.001	-0.000
	(0.000)	(0.000)
Cancellation Policy	0.030	0.008
	(0.001)	(0.001)
Smoking Allowed	-0.126	-0.101
	(0.003)	(0.003)
Pets Allowed	-0.029	-0.032
	(0.003)	(0.003)
Host has multiple properties	0.076	0.046
	(0.003)	(0.002)
Member since 2008-2009	0.098	0.085
	(0.012)	(0.011)
Member since 2010-2011	0.072	0.058
	(0.005)	(0.004)
Member since 2012-2013	0.032	0.026
	(0.003)	(0.002)
city-wave FE	Yes	Yes
Neighborhood FE	No	Yes
Adj R^2	0.595	0.674
N obs.	3,332,844	3,332,844

Notes: OLS regression on the daily log-price. Robust standard errors clustered at the property level.

Table A4: Distribution of the last rating

	Obs	Share
3.5 stars	8,796	4.18%
4 stars	25,505	12.12%
4.5 stars	72,209	34.33%
5 stars	103,845	49.37%

Sample: Listings for which last rating is observed.

C Results including Hispanics

In this section, we show the main results including Hispanics in the minority group.

Table A5: Share of Hispanics

	Sample size	Share
Majority	3,157,357	91.76%
Hispanics (US/Can)	103,351	3.00%

.

Table A6: Ethnic price gap, for several segments of the number of reviews

	Log daily rate				
	(1)	(2)	(3)	(4)	(5)
Minority	-0.035	-0.028	-0.019	-0.013	-0.011
	(0.006)	(0.005)	(0.006)	(0.009)	(0.014)
Nb reviews	0	1-4	5-19	20-49	50+
Minority share	8.0%	8.2%	8.4%	8.5%	8.6%
Adj R^2	0.64	0.72	0.76	0.77	0.77
N obs.	1,035,731	959,097	830,436	353,160	154,420

Notes: OLS regressions of the daily log-price on the minority dummy, controlling for property characteristics and ratings (for properties with at least one review). See the list of all property and host characteristics in Table A3. Robust standard errors clustered at the property level.

Estimates (Bootstrap Std. Err.) :

b_m = -0.013 (0.004)

ρ = 9 (0.3)

Table A7: Fixed-Effects Estimation

	log-price				
	(1)	(2)	(3)	(4)	(5)
3.5 stars $\times K/100$	0.044	-0.052	-0.109	-0.120	-0.171
	(0.072)	(0.072)	(0.059)	(0.052)	(0.072)
4 stars $\times K/100$	0.118	0.048	-0.027	-0.053	-0.010
	(0.029)	(0.028)	(0.022)	(0.019)	(0.026)
4.5 stars $\times K/100$	0.271	0.194	0.096	0.033	0.104
	(0.013)	(0.012)	(0.009)	(0.007)	(0.011)
5 stars $\times K/100$	0.402	0.319	0.217	0.125	0.220
	(0.014)	(0.013)	(0.009)	(0.007)	(0.014)
Minority $\times K/100$	0.085	0.045	0.015	-0.000	0.034
	(0.035)	(0.030)	(0.028)	(0.020)	(0.028)
3.5 stars$\times(K/100)^2$					0.136
					(0.069)
4 stars$\times(K/100)^2$					-0.046
					(0.022)
4.5 stars$\times(K/100)^2$					-0.062
					(0.007)
5 stars$\times(K/100)^2$					-0.080
					(0.012)
Minority $\times(K/100)^2$					-0.026
					(0.016)
Samples	Min(K)<5	Min(K)<5	Min(K)<20	-	-
	Min Max	Full	Full	Full	Full
N obs.	597,455	2,514,783	3,042,103	3,332,844	3,332,844

Notes: OLS regressions with listing fixed effects. Aside from those mentioned in the Table, controls include city-wave FE, neighborhood FE and property characteristics (see Table A3). Robust standard errors clustered at the property level.

D 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 which is exactly identical, up to a change in notations, to the one with normal distributions, which looked like this:

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

E Ethnic price gap, for several segments of the number of reviews (with Block Fixed-Effects)

Table A8: Ethnic price gap, for several segments of the number of reviews

	Log daily rate			
	(1)	(2)	(3)	(4)
Minority	-0.032	-0.024	-0.019	-0.015
	(0.007)	(0.006)	(0.007)	(0.009)
Nb reviews	0	1-4	5-19	20+
Adj R^2	0.66	0.74	0.78	0.79
N obs.	1,035,731	959,097	830,436	507,580

Notes: OLS regressions of the daily log-price on the minority dummy, controlling for block FE, property characteristics and ratings (for properties with at least one review). See the list of all property and host characteristics in Table A3. Robust standard errors clustered at the property level.

F 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, 180,616 majority hosts (47.3%) and 11,506 minority hosts (50.6%) leave the platform. We regress q_{it} on a minority dummy, and control for property characteristics, ratings, neighborhood fixed-effects and price.

Table A9 shows that the exit rate is similar for both groups when controlling for property characteristics, ratings, neighborhood fixed-effects, price of the listing and number of reviews.

Table A9: Probability to leave the market at wave t

	(1)	(2)	(3)
Minority host	0.0010	0.0007	0.0006
	(0.0006)	(0.0006)	(0.0006)
Log-price		-0.0112	-0.0125
		(0.0003)	(0.0003)
Number of reviews			-0.0003
			(0.0000)
AdjR2	0.05	0.05	0.05
obs.	3,332,844	3,332,844	3,332,844

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

G Results on sub-samples

We check the robustness of our results by running some of the analyses on several sub-samples. First, we can split the analysis by minority groups (Arabic/Muslims and African-Americans), by continent (Europe and US/Canada) and by type of flats (entire and shared).
Tables A10 and A11 report the results of these robustness checks. For each sample or specification, Panel A shows the unexplained price gap on the sample of properties with no review. According to our model, the ethnic price gap is maximum at zero review and decreases once information is revealed. Panel B shows the result of the estimation of the constrained model. In most cases, the point estimate of b_m is of the same magnitude as the ethnic price gap for non-reviewed listings.

Table A10: Results on sub-samples **(listings that received at least 1 review)**

	Full Sample	Arabic Africans	African Americans	US Canada	Europe
	(1)	(2)	(3)	(4)	(5)
	Panel A. Unexplained ethnic price gap (non-reviewed listings)				
Minority	-0.037	-0.035	-0.040	-0.025	-0.054
	(0.009)	(0.010)	(0.016)	(0.012)	(0.013)
Adj R^2	0.71	0.71	0.74	0.74	0.69
Share Minority	5.3%	3.7%	5.9%	8.6%	3.6%
N obs.	284,253	284,253	82,289	97,341	186,912
	Panel B. Estimation of the constrained model				
b_m	-0.022	-0.014	-0.025	-0.031	-0.010
	(0.005)	(0.006)	(0.008)	(0.009)	(0.009)
ρ	9	9	7	8	10
	(0.2)	(0.2)	(0.5)	(0.5)	(0.4)

Notes: In Panel A, robust standard errors are clustered at the property level. In Panel B, inference is done by bootstrapping with 50 replications.

Table A11: Results on sub-samples **(listings that received at least 1 review)**

	Entire Flat US Canada (1)	Entire Flat Europe (2)	Shared Flat US Canada (3)	Shared Flat Europe (4)
	Panel A. Unexplained ethnic price gap (non-reviewed listings)			
Minority	-0.014	-0.050	-0.043	-0.075
	(0.014)	(0.015)	(0.018)	(0.024)
Adj R^2	0.665	0.644	0.530	0.524
Share Minority	7.8%	3.5%	9.9%	3.9%
N obs.	64,027	140,115	33,314	46,797
	Panel B. Estimation of the constrained model			
b_m	-0.006	-0.017	-0.083	0.009
	(0.009)	(0.009)	(0.012)	(0.022)
ρ	6	8	13	18
	(0.7)	(0.3)	(1.3)	(1.8)

Notes: In Panel A, robust standard errors are clustered at the property level. In Panel B, inference is done by bootstrapping with 50 replications.