Consider the Slavs: Overt Discrimination and Racial Disparities in Rental Housing

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Abstract

Does discrimination lead to racial gaps in economic outcomes? Usually, discrimination is covert, which makes it difficult to study. In this paper I concentrate on the unique market of Moscow rental housing, where landlords discriminate overtly: on average, 20 percent of ads from a major rental website include racial preferences. I document that discrimination generates a racial differential in rents: comparing apartments in the same building with identical observable characteristics, non-discriminatory apartments have a 4% higher price. I also run a correspondence experiment to explore the relationship between overt and subtle forms of discrimination. I find that both forms coexist in the market. The proportion of overt to covert discrimination is stable across neighbourhoods. The average effect is consistent with a random search model with discrimination. However, heterogeneity analysis contradicts some predictions of the model. I show how adding neighbourhood sorting to the model can explain spatial heterogeneity of the racial rent differential.

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1 Introduction

Racial discrimination is usually hidden from public view. Aiming to reveal the very fact of discrimination, economists mainly resort to one of two approaches: studies that estimate racial gaps in various economic outcomes, and field experiments that uncover the differential treatment. As a result, both racial gaps and discrimination are well-documented in many markets and countries[1]. However, there are few pieces of evidence on the link between the two, so it is still under discussion: to what extent does discrimination generate racial gaps?

Economists have repeatedly questioned the contribution of discrimination to racial gaps, pointing out to the premarket factors (education, social capital, culture) as the main drivers (Neal and Johnson, 1996; Heckman, 1998). At the same time, the systematic evidence on this link is hard to obtain mainly due to the private nature of discrimination. The rare exception is Fryer et al. (2013) who show that under specific conditions at least one-third of the black-white wage gap can be attributed to discrimination.

While it is rare nowadays, overt discrimination has been widespread in the past. Writing on the United States before the Civil Right Act of 1964, Arrow (1998) noted:

> The presence of racial discrimination throughout American society was, to use the words of Samuel Johnson, a fact *too evident for detection and too gross for aggravation.* To establish the existence of discrimination, estimating wage equations would have been beside the point. Of course, society and scholars would want to know the quantitative implications of discrimination for income as well as other indices of well-being. But the fact of discrimination would not have needed testing.

Today's discrimination is mostly subtle. This makes its impact hard to measure. This paper is trying to overcome this challenge drawing on the unique context of Moscow's

[1]See Bertrand and Duflo (2017) for an extensive review of empirical studies on discrimination. It also discusses the methodological difference between regression decompositions and field experiments, as well as other original lines of research.

rental housing market, where landlords discriminate overtly. They include racial preferences to ads, using phrases like “offer is only for slavic tenants”, where *slavic* denotes ethnically Russian tenants or tenants of ethnically Russian appearance.

More specifically, I investigate how discrimination in the market for rental housing can generate racial rent differentials.

I collect new data on rental ads from the major Russian online real estate marketplace *cian.ru*. The dataset includes all available ads over a period of around six months. I categorise ads by presence of racial preferences and combine it with other observable characteristics of apartments and neighborhoods. Around 20 percent of ads include racial preferences. This setting thus allows me to estimate the effect of discrimination on the racial rent differential. To causally identify this effect, I include building-level fixed effects to the model to absorb any geographic and building-level characteristics.

I find that discrimination generates a significant and sizeable racial rent differential: comparing apartments in the same building with identical observable characteristics, non-discriminatory apartments have a 4% higher price.

This paper also examines the relationship between overt and subtle forms of discrimination. I conduct classic correspondence experiments, sending messages with *non-Russian* and *Russian-sounding* names to a random subset of online ads. This experiment allows me to relate the results obtained from the observational study to the existing body of evidence from the experimental literature. I find that both subtle and overt forms of discrimination coexist on the rental housing market in Moscow. Their relative prevalence is constant across neighbourhoods.

Finally, I borrow a theoretical framework from the literature on labor search with discrimination (Black, 1995) and apply it to the context of rental housing in Moscow. I demonstrate that the search-based model can explain the existence of the racial rent differential. The intuition is the following: when the search is costly and minorities have higher chances of getting rejected, they are more likely than the majority to accept an unfavorable offer. Then non-discriminating landlords who anticipate it will raise the rent price in equilibrium.

However, the standard search-based model cannot explain the results of the heterogeneity analysis. I find that in neighborhoods (and buildings) with a higher share of discriminating apartments the racial rent differential is lower. At first glance, this contradicts the implication of the model, which says that with a larger proportion of discriminating apartments the gap should expand. However, this view assumes that neighborhoods are different and isolated markets, while in fact potential tenants sort (but not necessarily strongly segregate) between neighborhoods. I include a neighborhood choice stage in the search-based model to explain the results obtained in the heterogeneity analysis.

Racial gaps in the housing market are well-documented with most of the research focused on the US (Ihlanfeldt and Mayock, 2009; Bayer et al., 2017; Yinger, 1997; Early et al., 2019). More specifically, for the US rental market Early et al. (2019) show that Blacks pay 0.6 - 2.4 % higher rent price than Whites for identical housing in identical neighborhoods. From the landlord's point of view these results suggest lost profits. There are few papers that investigate the tread-off between decision to discriminate and lost profits. Hedegaard and Tyran (2014) conduct field experiments to measure the sensitivity of discrimination to changes in opportunity cost.

There are numerous studies that document racial discrimination on the housing market with the help of correspondence and audit experiments: Yinger (1986), Carpusor and Loges (2006), Hanson and Hawley (2011) in the US, Ahmed and Hammarstedt (2008) in Sweden, Acolin et al. (2016) in France. When it comes to the labor market, explicit racial preferences are rather rare in Russia: Bessudnov and Shcherbak (2018) conduct a correspondence experiment and document substantial and statistically significant differences in callbacks between majorities and minorities.

This study contributes to an emerging body of literature exploiting user-generated content and text analysis. As an example, Stephens-Davidowitz (2014) uses Google search data as a proxy for racial animus. Closest to my paper is Kuhn and Shen (2012) who study overt gender discrimination in Chinese online job listings, however, they do not estimate the effect on prices, but instead try to determine the causes of discrimination. A detailed review of the methods used for text analysis can be found in Gentzkow et al. (2017).

The link between overt and subtle forms of discrimination is a recurring theme in the sociological literature (Small and Pager, 2020; Pager, 2007). The subtle form has several notable features. First, the discriminating person can either be aware or unaware that he or she is discriminating. *"Unconscious"* discrimination was conceptualised by psychologists and economists as an *implicit discrimination* (Bertrand et al., 2005). Second, the analysis of subtle discrimination blurs the line between statistical and taste-based discrimination: the qualitative studies show that employers narrate their prejudiced attitudes using "statistical" arguments, but fail to update their believes when facing contradicting information (Pager and Karafin, 2009). This also corresponds to the observation that locals in many countries highly overestimate the number of immigrants and perceive imprecisely their characteristics (Alesina et al., 2018).

Overt discrimination is often regarded as a pure manifestation of racial animus. At the same time, anecdotal evidence suggests, that overt discrimination observed in the rental housing in Moscow has a lot in common with typical subtle discrimination, where landlords do not consider their behavior as discriminating[2].

The theoretical section of this paper is related to literature that implements taste-based discrimination to search models. Since the interest of this paper leans towards the impact of discrimination and not its causes, it is reasonable to concentrate on a competitive taste-based framework. Thereby, we leave aside the question of the rationality of landlords' beliefs and assume that landlords have an exogenous distaste of minorities.

A standard Beckerian perfect competition framework (Arrow (1972), Becker (2010)) does not explain the existence of the cost of discrimination. Such an effect would persist if and only if two markets would fully separate between the majorities and the minorities.

[2]See the interview (in Russian) with Irina Radchenko – a realtor and a commentator, who suggests that discrimination in Moscow is not related to xenophobia using arguments resembling the ones outlined in Pager and Karafin (2009)

It implies that the majority rent only discriminating apartments, while discriminating apartments make up only 20 percentage of the rental market. In a more realistic scenario perfect competition leads to a unique price.

Racial discrimination on the labor market has been studied more extensively than discrimination on the housing market[3]. Following insights from the labor literature, I adapt the search model proposed in Black (1995) to the context of rental housing in Moscow. In this model discriminating landlords refuse to accept minorities at any price, which makes search more costly for minorities. Therefore, landlords who do not discriminate increase their rent, since minority tenants with increased search costs tend to accept more expensive offers.

Other important models of random search with discrimination are proposed in Bowlus and Eckstein (2002) and Rosén (1997). Directed search with discrimination is presented in Lang et al. (2005). When it comes to the rental housing market, search models with discrimination are less common. A notable exclusion is an early model proposed by Courant (1978), which has a lot of similarities with Black (1995). Another original mechanism of discrimination during the search, which is called "neighbour discrimination", was proposed by Combes et al. (2018). It captures the situation when landlords who own more than one apartment in a building can discriminate minorities even if they do not have a distaste for them. When a landlord rents an apartment to minority tenants, he or she reduces the attractiveness of his or her other property, because other potential tenants on the market are prejudiced against minorities. There are also several papers that study search and matching on the housing market regardless of the discrimination context: Albrecht et al. (2016), Carrillo (2012); Ngai and Tenreyro (2014).

The paper is organized as follows. Section 2 describes the data and background of the online housing marketplace. Section 3 presents the major empirical findings on racial rent differentials and the results of a correspondence experiment. Section 4 examines a theoretical framework that sheds light on the mechanism of existence of the racial rent

[3]See Lang and Lehmann (2012) for an extensive literature review on the topic of racial discrimination on the labor market

differential and tries to explain the heterogeneity of this effect.

2 Background and Data

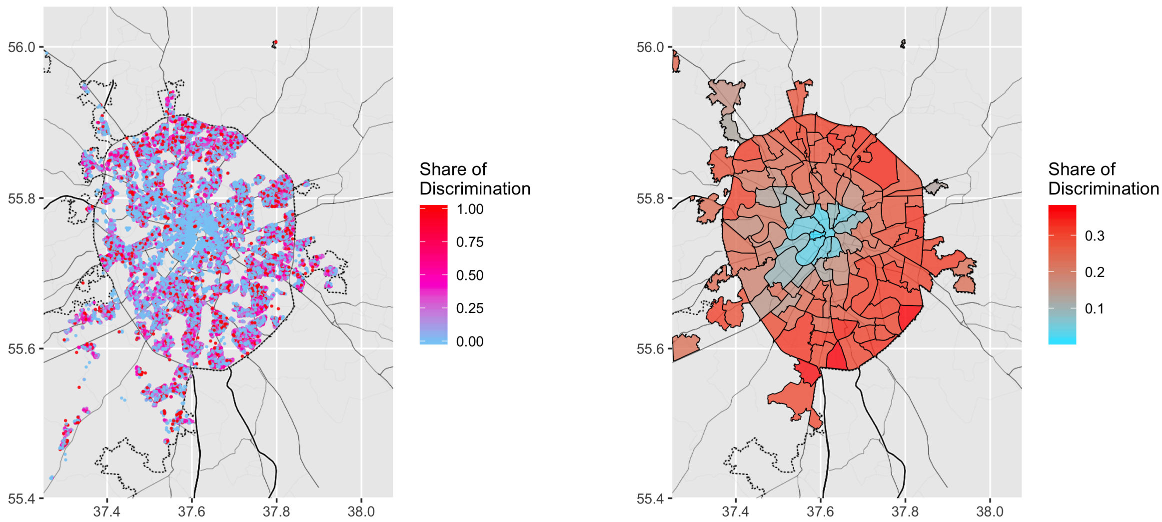
Russia is a multinational state: 19% of the population are not ethnic Russians (Census, 2010). There is also a large population of immigrants. According to UN data, around 11 millions immigrants resided in Russia in 2019 (8% of the total population), which made Russia the second country in the world by the population of immigrants after the US. It is important to note that the overwhelming majority of immigrants residing in Russia are citizens of the former Soviet Union or their descendants. Among the largest "non-slavic" ethnic groups residing in Moscow, there are Tatars, Bashkir, Chuvashs, Chechens, Armenians, Avars, Mordvins, Kazakhs, Azerbaijanis, Uzbeks, Kyrgyz, Tadjiks to name a few.

Xenophobic attitudes are rather common in Russia. According to Russian independent polling organisation Levada Center, 63 percent of Moscow respondents are permissive about discriminating rental advertisements. Every second respondent approve the political slogan "Rossiya dlya Russkikh", which can be translated as "Russia should be for ethnic Russians". These attitudes have historical roots. The Soviet Union pursued a complex and controversial ethnic policy, blending anti-discriminatory and discriminatory interventions, such as: vigorous anti-racism propaganda, harsh control of the population mobility (restrictions on mobility, or, on the contrary, waves of forced migration) and promotion of local languages and cultures (Martin et al., 2001). Dissolution of the Soviet Union stimulated nationalist movements and ethnic violence both among Russian and non-Russian populations.

Modern Russia pursues an ambivalent anti-discrimination policy. On the one hand, the number of those convicted of hate speech has increased from 149 to 604 from 2011 to 2017[4]. On the other hand, the judicial practice is poor when it comes to actual discrimination

[4]According to the Judicial Department at the Supreme Court of the Russian Federation. The statistics was published by newspaper Kommersant

Figure 1: **Geography of discrimination**



(a) Map of discrimination by buildings

(b) Map of discrimination by subdistricts

in the labor and housing markets[5]. In particular, a discriminating landlord does not pay any fees and has no other constraints for including racial preferences in apartments ads.

While people of many ethnicities reside in Moscow, there is no evidence of apparent racial segregation comparable to the one found in American and European cities (Vendina, 2002; Vendina et al., 2019). The census also does not show signs of strong segregation (Figure 4a). At the same time, the share of non-Russian residents is higher in the city center – the more prestigious part of Moscow, where overt discrimination is rare. The lack of strong segregation in Moscow is probably a heritage of the strict housing regulation imposed in the Soviet Union.

The empirical part of this paper benefits from the structure of the Russian housing stock: it allows me to introduce building-level fixed effects to the model. The state of modern mass housing in Russia is largely determined by Soviet post-war housing policy. Two crucial features of this policy should be noted: the housing stock was state-owned and dwelling allocation was state controlled. Since the 1970s, urban development has been focused on 9 and 16-storey buildings. The new private wave of development inherits

[5]For the legal practices on discrimination in Russia see journalistic investigation by online newspaper Meduza

the Soviet housing approach of multi-story community blocks. The data used in this paper shows: the median building is 12-storey with around 200 apartments. In addition, apartments in the same building are usually homogeneous in quality.

2.1 Ads data

Every day the web-site *cian.ru* posts around two thousand rental offers, around two thousand offers disappear from the site, and around 28 thousand offers remain available. According to user statistics *cian.ru* is the biggest online platform to search for long-term rentals in Russia. Over the last decade the property market has almost entirely gone online. Therefore, data collected from *cian.ru* is the most feasible and complete representation of rental supply in Moscow.

Potential tenants get access to the platform through the search interface, where they can specify desired characteristics of the apartment: expected rent price, location, number of rooms, surface area, layout. Then users can browse the list of search results. If a user is interested in the offer, he or she can respond through an online form or call the given phone number.

Each ad consists of the basic apartment's characteristics, a text description and a set of images. Descriptive statistics of ads are reported in Panel A of Table 1. For most apartments, the exact address is indicated. I geocoded addresses, calculated distances between buildings and the city center, distances between buildings and closest metro stations. Location data also allows to group apartments at the building level, district level (12 *okrugs*, according to Moscow administrative division) and subdistrict level (146 *raions* and settlements). Descriptive statistics of buildings, districts and subdistricts characteristics are presented in Panels B, C and D of Table 1.

The main observation period lasted from May 27 to November 11, 2018. There is also a stand alone one-day snapshot, which was collected on April 2, 2017. Data were scraped from the site every midnight Moscow time, when users are supposedly least active. There were few days when it was not possible to collect data – I exclude these days from analysis.

The final dataset consists of 117 daily snapshots. Figure 2 shows that the number of posted ads is a seasonal variable. It varies between 22 thousands and 35 thousands, increases in summer and decreases in autumn. This fluctuation can be explained with seasonality of demand.

Figure 1 (a) reports the map of Moscow, where each dot corresponds to an observed building and the color indicates the share of discriminating apartments in each building. It is clear that discrimination is uneven throughout Moscow. The city center and southwest area are associated with low levels of discrimination, whereas outskirts tend to be most discriminating. The map of discrimination aggregated by subdistricts is presented in the Figure 1 (b). It can be seen that in some subdistricts the share of discriminating apartments can reach as much as 54 %. The spatial pattern of discrimination is highly stable (see Figure 3).

The resulting panel consists of 213 thousands ads that appeared on the site during the observation period. Using this data one can see how rent prices have been changing during the observation period. Two groups of observations stand out: first, around 80 percent of offers that have not changed rent price during the whole period, and, second, the group of offers that decreased the rent price. This pattern motivates the use of the latest rent prices in estimation of the cost of discrimination — these rent prices are closer to equilibrium prices.

The supply side is represented by two types of actors: landlords and agents. They both can directly access the platform. Agents are licensed specialists hired by landlords who take on the job of finding a reliable tenant at an optimal rent price. Anecdotal evidence suggests that, when it comes to ethnic requirements, agents transmit preference of landlords with whom they work. Both agents and landlords leave their phone numbers in rental ads, but it is not always possible to distinguish whether the counterparty is the landlord or the agent.

Using accompanying ads' texts, I was able to identify the presence of racial discrimination. For the baseline analysis, I resorted to a dictionary approach[6] . The algorithm consists of several steps: first, I calculate frequencies of all unigrams, bigrams and trigrams, then examine them manually to reveal the ones related to ethnicity of tenant and, finally, flagged ads containing these n-grams. Discrimination in ads is manifested in a highly uniform way: most of discriminating landlords use the phrase “Slavs only”. The rest of discriminating landlords use words with roots: *slav-*, *russ-*, *caucas-*, *asia-*. For the key phrases, few instances of reversed use were detected and excluded (for example, preceding “not only”, or following “are allowed”). There are also specific inclusive phrases in the data, such as “all ethnicities are allowed”.

In each specification controls for the individual characteristics of apartments are added. Surface area, layout, floor number are explicit characteristics of apartment. To proxy for more ambiguous characteristics, I construct two variables: the length of announcement in characters and the number of photos attached.

2.2 Other data

I complement the user-generated data from *cian.ru* with socio-economic data from the Russian Census (2010). Data on population, ethnic composition, level of education, fluency in Russian is grouped on *rayon* (subdistrict) level. I also use electoral statistics from the 2018 Russian presidential elections. This data is provided by the Central Election Commission of the Russian Federation.

In Section A I report the design of a correspondence experiment. I respond to a sample of ads through the online form and manipulate the names of potential tenants such that one group of names could be perceived as “Russian-sounding” and another group as “non-Russian-sounding”. There are no public data on birth names in Russia, so I construct an approximate ranking of names using data from the Russian social network *vk.com.* I use the data on the city of residence to make a rating of the most popular names in Moscow and Makhachkala — a multi-ethnic city where Russians make up only 5.4 percent.

[6]See Gentzkow et al. (2017) for the review of various approaches in text analysis.

3 Empirical analysis

3.1 Estimating equation

The Moscow housing stock consists of multi-storey buildings with large number of apartments. The median building is 12-storey and multiple apartments are often exposed in one building.

When calculated for the entire observation period, the median building has around 12 apartments exposed. Apartments in the same building are usually of a similar quality, and "vertical" or in-building segregation is uncommon in Moscow. This structure of the housing stock is beneficial for my analysis: I employ a model with building level fixed effects to estimate the racial rent differential. The baseline specification is:

$$log(RentPrice_{ib\tau}) = \alpha Discrim_{ib\tau} + X'_{ib\tau}\gamma + \sigma_b + \phi_\tau + \epsilon_{ib\tau} \tag{1}$$

Each observation is an ad that was posted within the observation period. Subscript i denotes a posted offer, b is an index of building and τ is an index of the day when the offer was posted. *Discrim* is a dummy variable of interest that indicates the presence of discrimination in ads text. σ_b and ϕ_τ are building and day of posting fixed effects.

Building fixed effects allow to absorb the spatial and building specific variations. Coefficient of interest α is an estimate of the cost of discrimination. It reflects the difference in the rent prices between discriminating and non-discriminating apartments. I also control for apartments individual characteristics: the set of controls $X_{ib\tau}$. The characteristics of the apartment are divided into two types: one that can be measured directly, such as surface area and apartment layout, and once that cannot be measured directly, such as general cleanliness, quality of repair, lack of dysfunctions. I try to control for these "soft" features using length of advertisement in characters and number of attached photos.

Less restrictive specifications were also tested: the model with *rayon* level fixed effects and the model with *okrug* level fixed effects. Both of these specifications include controls for distances to the city center and to the closest metro station.

This identification strategy holds several assumptions. First, I assume that discrimination in the ad is a direct reflection of real intention of landlord to discriminate. In latter part of this paper I also test the Moscow rental market for the presence of covert discrimination.

Second, I assume that the number of photos and length of text are good proxies for quality of apartment. I include other text-based measures of apartment quality for robustness.

I also explore how the racial rent differential depends on neighborhood characteristics, including the average level of discrimination in the neighborhood. The heterogeneity of the effect is crucial for understanding the mechanism of the racial rent differential – theoretical discussion of the mechanism is presented in Section 4. To do the heterogeneity analysis I interact the discrimination dummy with the share of discrimination in neighborhood and building:

$$log(RentPrice_{ib\tau}) = \alpha Discrim_{ib\tau} + \beta Discrim_{ib\tau} \times DiscrRate_{iu} + X'_{ib\tau}\gamma + \sigma_b + \phi_\tau + \epsilon_{ib\tau} \quad (2)$$

For both neighborhoods and buildings the discrimination rates are calculated as a share of discriminating ads in total number of ads that were posted during the observation period excluding the contribution of interacted observation. Maps of discrimination rate calculated for buildings and subdistricts are shown in Figure 1.

$DiscrimRate_u$ is the surrounding discrimination rate for offer i in the unit u. This specification is tested for discrimination rates on different levels: buildings, *rayons* and *okrugs*.

3.2 Main results

3.2.1 The racial rent differential

Table 2 presents the estimations of the racial rent differential. The extended table can be found in Table B.1 in Appendix. The results bring out a strong and negative effect of discrimination on the price. The first column shows the results of the preferred specification: the one that includes building level fixed effects. I also include to the model time fixed effects (through variables that indicate the day when the ad appeared on the site) which helps to eliminate the impact of seasonality associated with the housing market. This specification also includes controls for individual characteristics of the apartment. Standard errors are clustered at the building level. This result indicates sizeable racial rent differential – around 4% of apartment's rent price.

Column two and three presents the results of the models with *rayon* and *okrug* level fixed effect correspondingly. These specifications also includes controls for logarithms of distances to the city center and the closest metro station. The fourth column presents results of OLS without location-based fixed effects. It can be seen that the coefficient of interest increases from the first to the fourth specification. It can be explained by the fact that on average buildings and districts with less expensive property are also associated with discrimination.

3.2.2 Placebo and robustness

I estimate several placebo regressions that have the same equation as in the main specification presented in column 1 of Table 2. Instead of the discrimination variable I introduce two different text-based variables that also indicate preferences of the landlord: preference for tenants without kids and preference for tenants without pets. Results are presented in the Table B.2. The coefficient for "no kids" variable is not significant, whereas the coefficient for "no pets" is significant, but relatively small – around 0.5% – and positive (unlike the main result obtained for the discrimination dummy). This positive effect for apartments that do not accept tenants with pets can be explained: potentially, landlords that historically did not accept tenants with pets were able to keep their property in better condition. I also repeat the main specification which is presented in the Table 2, but with text-based dummies from the placebo analysis as controls: the main result remains robust. Finally, I estimate the main specification including phone numbers fixed effects to absorb the variation in counterparty identities (however, phone variable does not allow to distinguish between landlords and agents). The coefficient decreases but not drastically – it stays around 3% (Table B.3).

3.2.3 Heterogeneity analysis

The racial rent differential is not uniform across Moscow neighborhoods. To investigate how it changes, I perform heterogeneity analysis. Table 3 indicates that in neighborhoods with higher prevalence of discrimination the rent differential is smaller than in neighborhoods where discrimination is relatively rare. The same is true for the level of building. A higher share of discriminating apartments in a building is associated with a lower rent differential.

When it comes to other socio-economic characteristics of neighborhoods, we observe the following: the racial rent differential is *higher* in neighborhoods with a higher share of non-Russian residents, with a higher selling prices in housing, with a higher share of residents with higher education, with a higher share of votes for presidential candidates in 'opposition' to Vladimir Putin (Table 4).

As a result, we see that both distributions of frequency of discrimination and of the value of racial rent differential have the same center-periphery structure, but other meaningful variables also have a similar spatial distribution: education, population, average rent and purchase price of real estate, share of non-Russian residents.[7]

[7]See maps in Figures 4 and 5

3.2.4 Impact of discrimination on search time

The landlords' disadvantage from discriminating behaviour manifests itself through the increased search time.[8] Extra days spend on the market waiting should naturally be considered as a part of cost of discrimination. Table B.4 presents the estimated effect of discrimination on the number of days offers have been exposed on the platform. The data used in this analysis do not include observations that were available on the first day and observations that stay on the site on the last day of the observation period. Specifications in Table B.4 are similar to the ones from Table 2, but with the logarithm of number of days in exposure in left-hand side. In each regression I control for logarithm of apartment's rent price.[9]

An apartment that do not accept non-slavic tenants remains on the market 10 % longer. This effect is not particularly large if we take into account that for an average ad it turns into one extra day. Though it is a costly delay, but one that landlords suffer only occasionally — in contrast to the monthly rental discount.

3.3 Results of experiment

The design of an experiment is presented Section A in Appendix. Table 5 presents the results of an experiment. Each column presents the outcomes of a probit regression where the dependent variable is an answer dummy: one, if counterparty replied to the message and answered the question, and otherwise – zero. This experiment provides us with several important results. First, indeed, applicants with non-Russian sounding names have significantly lower probability of receiving benevolent response from apartments' accounts that have racial preferences in ads. At the same, it is also true to a certain degree for non-discriminating accounts: non-Russian applicants have a lower chance to receive a reply than Russian applicants even from accounts that have no racial preferences in ads (Table 5). This result speaks in favor of coexistence of overt and subtle forms of

[8]However, despite the fact that it is impossible to observe whether the apartment is really rented out, the date when the offer disappears from the platform can be used as the best possible approximation.

[9]Prices on the last day are used here.

discrimination in the Moscow rental housing. There is another important result, which can be seen in the Table 6. This table presents subsample analysis: it takes ads without racial preferences and splits the sample by neighborhoods. The city center is notable for the low level of overt discrimination, however, one could suggest that landlords in this elite neighborhood switch from overt to subtle discrimination. The experiment's results do not support this hypothesis. Subtle discrimination is more prevalent in the outskirts, so, on the average, subtle discrimination is proportional to neighborhood's overt discrimination.

4 Theory

The Beckerian neoclassical framework fails to explain the persistence of the cost of discrimination. In this setting both landlords and tenants are price-takers. Two markets, discriminating and equally accessible, exists with two rents respectively: p_d and p_{nd}.

Assume that predictions of the model are in line with the empirical findings and $p^*_d < p^*_{nd}$. This scenario intends full market segregation. Otherwise, the majority from the discriminating market will move to another market until rents equalize. However, the full segregation is implausible since it means that majority constitutes only 20% of the rental housing market.

Literature on discrimination in the labor market solves this issue by introducing frictional environment. The notable contributions in this direction were made by Black (1995), Rosén (1997), Bowlus and Eckstein (2002), Lang et al. (2005).

4.1 The baseline model

In this section I adapt the random search model from Black (1995) to the context of Moscow rental housing. To take into account the heterogeneous structure of the Moscow housing market, I consider the model with two "neighborhoods" between which potential tenants are sorted.

There are two neighborhoods A and B. Both of them are functioning as independent rental housing markets. There are two types of landlords in both neighborhoods: discriminating (those who refuse to rent an apartment to a *non-slavic* tenant at any price), and non-discriminating (those who are indifferent of tenant's race). The share of discriminating landlords in the neighborhood i is θ_i. I assume that the neighborhood B is more discriminating, i.e. $\theta_B > \theta_A$.

4.1.1 Sorting

There are two types of tenants: *slavic* and *non-slavic*. The share of *slavic* tenants is π, and the share of *non-slavic* tenants is $1-\pi$. Each *slavic* and *non-slavic* tenant chooses the probability of entering the neighborhood A with probabilities q_s and q_{ns} respectively, and of entering the neighborhood B with probabilities $1-q_s$ and $1-q_{ns}$. As a result, the shares of *slavic* tenants in the neighborhoods A and B are:

$$\pi_A = \frac{q_s\pi}{q_s\pi + q_{ns}(1-\pi)}$$

$$\pi_B = \frac{(1-q_s)\pi}{(1-q_s)\pi + (1-q_{ns})(1-\pi)}$$

Slavic and *non-slavic* tenants extract reservation utilities V_s^i and V_{ns}^i respectively from the rental housing market. These reservation utilities will be described below.

In a general setting, when residents decide where to live, they take many factors into account: prices, access to schools, proximity to workplace, amenities and more. While this paper does not aim to model the sorting process in an extensive way, it is still important to introduce to the model motives not related to rental housing. In this stylized model I assume that neighborhood with a lower share of discrimination A is also a central district with rich amenities and better access to work and schooling (which correspond to the Moscow context). Assume, there are shares of both *slavic* and *non-slavic* potential tenants who are attached to the central district A, $\mu_s \leq q_s$ and $\mu_{ns} \leq q_{ns}$. They do not choose between neighborhoods and search apartments in A by default. After mobile tenants choose their neighborhoods, they start apartment search there.

4.2 Search

Within each neighborhood tenants of both types sequentially search for an apartment paying k for each period of the search. When a tenant finds and rents an apartment, he or she stops searching and lives in this apartment forever.

Tenants learn three features during the visit of the apartment online page: how much they value this apartment – α, the type of landlord and the rent p that was set in advance by the landlord. While this mechanism does not fully take into account the informational structure of the online platform, it approximates the search process online: tenants need to invest their time and effort in studying ads. The individual value of apartment α is randomly distributed with distribution function $F(\alpha)$ and density function $f(\alpha)$. Following Black I assume $F(\alpha)$ is strictly log-concave.

There is an important deviation from Black (1995) when it comes to price setting. The main interest of Black's model is the racial wage gap, where employers can set different wages for individual members of minorities and non-minorities. In my model I assume that non-discriminating landlord sets a unique rent price for both *slavic* and *non-slavic* tenants, and a discriminating landlord sets a price for *slavic* tenants and do not accept *non-slavic* tenants at any price.

4.2.1 Tenants' problems

Tenants' equilibrium strategies can be described with reservation utilities such that tenants are indifferent between renting an apartment and continuing the search. Two options available for *slavic* tenants: renting an apartment from a discriminating landlord and renting an apartment from a non-discriminating. This leads to the following dynamic equation:

$$V^s = \theta \mathbb{E} \max\{\alpha - p_d, V^s\} + (1-\theta)\mathbb{E} \max\{\alpha - p_{nd}, V^s\} - k \tag{3}$$

Minorities' problem looks different: with probability θ they meet a discriminating landlord and, therefore, they cannot rent this apartment and receive their reservation utility.

$$V^{ns} = \theta V^{ns} + (1-\theta)\mathbb{E}\max\{\alpha - p_{nd}, V^{ns}\} - k \tag{4}$$

4.2.2 Landlords' problem

Each landlord behaves as a monopsonistic competitor. Therefore, they maximize the rent, considering probabilities of tenants' acceptance. Discriminating landlords rent an apartment if and only if tenant is *slavic*. Thus, their expected utility can be written as:

$$\mathbb{E}u_d = (1 - F(V^s + p_d))p_d \tag{5}$$

Non-discriminating landlords accept tenants of both types and they set a unique price to tenants of both types.

$$\mathbb{E}u_{nd} = p_{nd}(\pi(1 - F(V^s + p_d)) + (1-\pi)(1 - F(V^{ns} + p_{nd})) \tag{6}$$

4.2.3 The Optimal Rents and the Racial Rent Differential in a Separate Neighborhood

Assume that α is drawn from uniform distribution on interval $[0, \beta]$. Then the equilibrium rent prices of both discriminating and non-discriminating apartments are defined by a system of two equations. For a neighborhood $i \in \{A, B\}$ this system can be written as:

$$2k\beta = \theta^i(p_d^i)^2 + (1-\theta^i)(2p_d^i - p_{nd}^i)^2 \tag{7}$$

$$p_{nd}^i = \frac{1-\pi^i}{1+\pi^i}\sqrt{\frac{2\beta k}{1-\theta^i}} + \frac{2\pi^i}{1+\pi^i}p_d^i \tag{8}$$

, where p_{nd}^i and p_d^i are rent prices of discriminating and non-discriminating apartments in neighborhood i, θ^i is a share of discriminating landlords in neighborhood i and π^i is a share of *slavic* tenants in neighborhood i.

Several facts follow from of this system. First, it shows the existence of the racial rent differential presented in the empirical part of this paper (Section 3).

Proposition 1. *$\Delta = p_{nd} - p_d > 0$ for any value of θ and π when non-slavic tenants participate in a search, i.e. $V_d(\theta, \pi) > 0$.*

Second, it can be shown that, consistently with the empirical findings, $\Delta^i(\theta^i, \pi^i)$ is decreasing with an increase of π^i, share of potential *slavic* tenants in the neighborhood i. However, conflicting with the evidence I found, $\Delta^i(\theta^i, \pi^i)$ is increasing with the share of discriminating apartments θ^i.

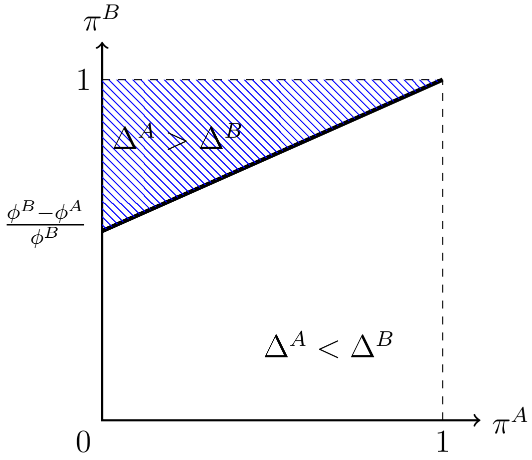
Proposition 2. *For any given $\theta \in (0,1)$ $\Delta(\theta, \pi)$ is decreasing with π. For any given $\pi \in (0,1)$ $\Delta(\theta, \pi)$ is decreasing with θ.*

The interpretation of this relationship is as follows: with an increase of the share discriminating apartment frictions for *non-slavic* tenants increase and non-discriminating landlords respond with increased rent prices, therefore the differential increases.

However, in this setting it is still possible that the neighborhood with a higher share of discriminating apartments has a higher racial rent differential, because the differential also depends on the share of *slavic* tenants in the neighborhood.

4.3 Racial rent differentials in two neighborhoods

Suppose, there are two neighborhoods A and B, such that $\theta^B > \theta^A$. Assume that the shares of discriminating apartments θ^i are exogenous characteristics of a neighborhood. It can be shown that in an interval $\pi^i \in (0,1)$ function $\Delta(\pi^i)$ can be well-approximated with a linear function $\Delta(\pi^i) = -\phi^i(\theta^i)\pi^i + \phi^i(\theta^i)$, where $\phi^i(\theta^i)$ is a coefficient that depends on a share of discrimination in neighborhood θ^i. Therefore, it can be shown that for neighborhoods A and B two spaces consisting of pairs (π^A, π^B) exist: one, for which $\Delta^A > \Delta^B$, and one, for which $\Delta^A < \Delta^B$.



Proposition 3. *The city economy can reach such equilibrium that* $\Delta^A > \Delta^B$ *when*

$$(\pi^A, \pi^B) = \left(\frac{\mu_s \pi}{\mu_s \pi + \mu_{ns}(1 - pi)}, \frac{(1 - \mu_s)\pi}{1 - \mu_s \pi + (1 - \mu_{ns}(1 - \pi)} \right)$$

In this case, both *slavic* and *non-slavic* mobile tenants will sort to the neighborhood B. For such equilibrium to appear we should assume sufficiently large share of non-mobile *non-slavic* tenants, which in reality can be interpret as either high attachment to services accessible in the city center or high attachment to non-discriminating environment.

Despite the fact that this model is highly stylized, it still shows how heterogeneous effects found in empirical section of this paper can emerge. It also corresponds to the fact that the share of non-Russian residents is higher in the Moscow city center than on the outskirts, according to the Census (2010).

5 Conclusion

Racial discrimination can generate significant racial disparities in economic outcomes: I find that an apartment with a discriminatory ad has 4% lower rent price than an identical, but non-discriminating apartment in the same building. This result complements well-established theoretical insights on how differential treatment can generate racial differentials in the housing market. While there are many channels through which racial differentials can occur, pure discrimination in the market remains important and requires further research.

This paper touches on the uncovered topic of the relationship between overt and subtle forms of discrimination. I analyse unique data from the Moscow rental housing, where landlords do not hide there racial preferences. I show that overt and subtle forms of discrimination are closely related. I find that they coexist in Moscow rental housing market and that their relative prevalence is stable across neighborhoods.

Finally, I borrow theoretical framework from the literature on labor search with discrimination and show how the racial rent differential can occur. I do heterogeneity analysis and find that the racial rent differential is higher in neighborhoods with a lower share of discriminating landlords. I show that this result can coincide with a random search model with discrimination by introducing the stylized version of neighborhood sorting.

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Figure 2: **Daily number of ads posted on the platform**

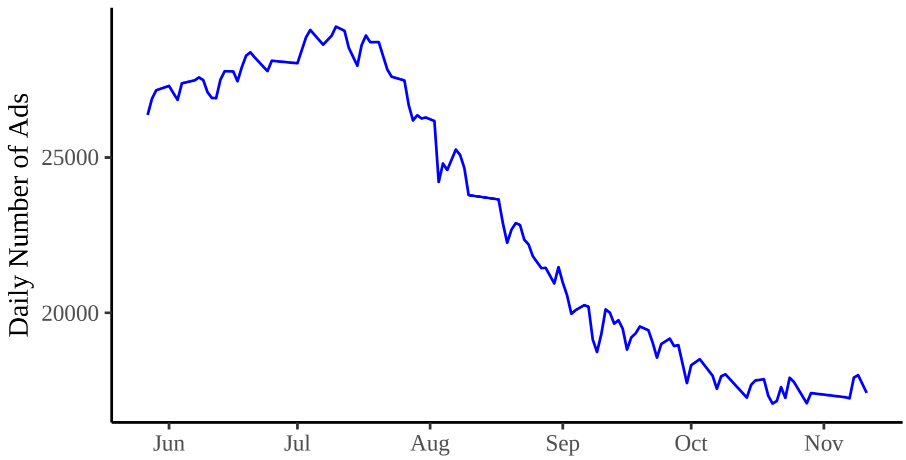


Figure 3: **Share of discrimination by neighbourhoods on the first and last days of the observational period**

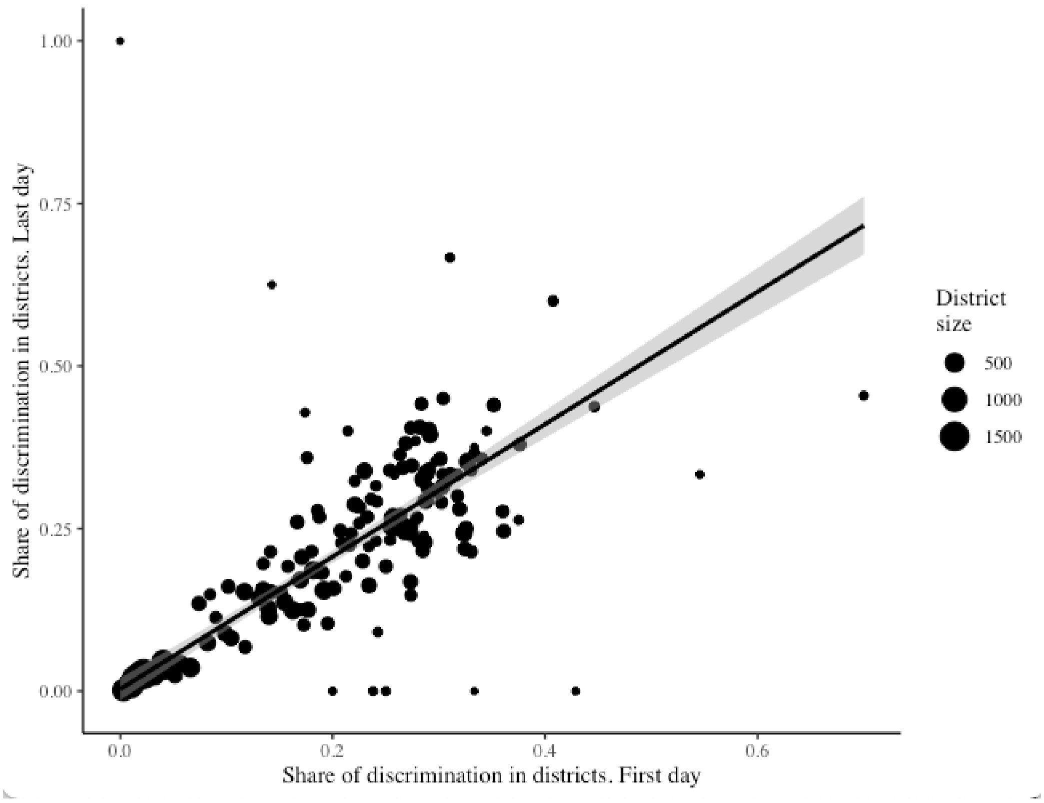
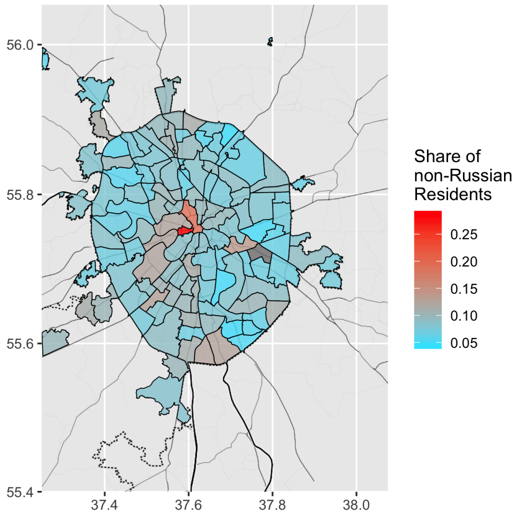
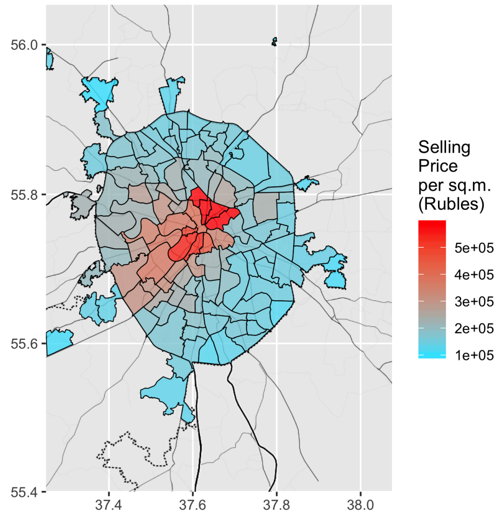


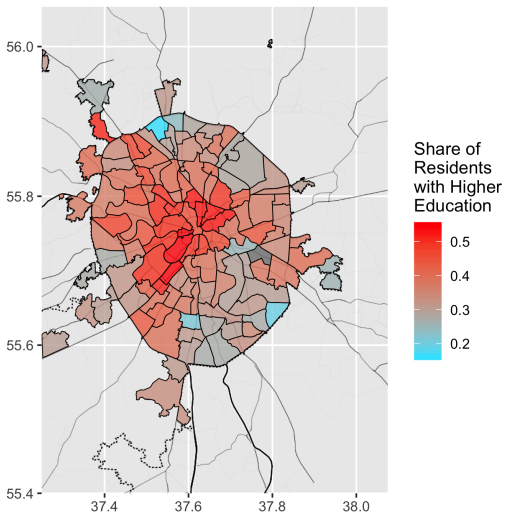
Figure 4: **Characteristics of districts (*rayons*)**



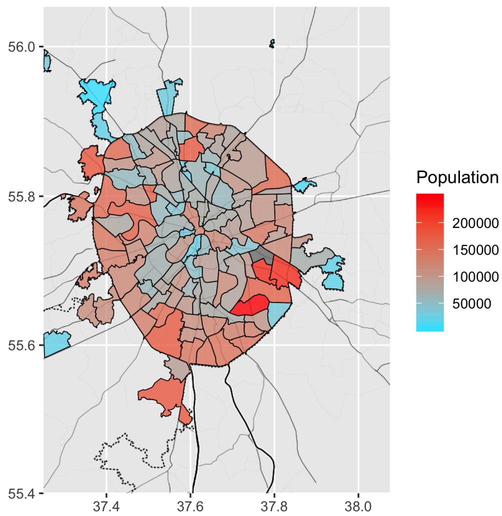
(a) Share of Non-Russian Residents



(b) Rent Price per sq. m.

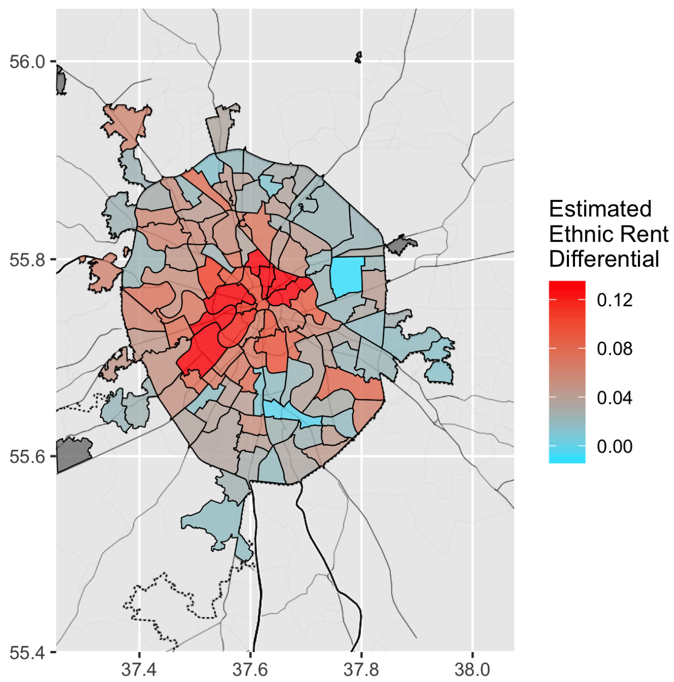


(c) Share of Residents with Higher Education



(d) Population (thousands)

Figure 5: **The racial rent differential by districts(*rayons*)**



6 Tables

Table 1: **Descriptive statistics**

Panel A. Apartments exposed during the observation period					
	Obs	Mean	Std. Dev	Min	Max
Price (rubles)	139,965	72,190	92,962	14,500	1,024,106
Kitchen area (sq.m.)	139,965	10.27	5.42	1	160
Living area (sq.m.)	139,965	38.14	27.58	.9	450
Total area (sq.m.)	139,965	62.65	41.00	10	500
Floor number	139,965	7.06	5.74	1	85
Days in exposure	139,965	18.48	29.76	0	168
Length of text (symbols)	139,965	800.19	527.51	52	3743
Number of photos	139,965	12.09	7.59	0	50
Declare descrimination	139,965	.20	.40	0	1
Declare inclusivity	139,965	.005	.07	0	1
Panel B. Buildings' characteristics					
Number of floors	20,417	10.27	5.42	1	160
Distance to city center (km)	20,417	11.59	5.85	.24	59.80
Distance to closest metro (km)	20,417	1.36	2.21	.005	55.89
Share of discriminating apartments	20,417	.24	.28	0	1
Panel C. Subdistricts' characteristics[a]					
Share of discriminating apartments	140	.23	.08	.009	.54
Population (thousands)	125	92	43	3	247
Share of non-Russian	125	.08	.02	.04	.28
Share of Central Asian population	124	.007	.006	.002	.03
Share of North Caucasian population	122	.004	.002	.001	.02
Share of Jewish population	125	.005	.003	.0008	.02
Price per sq. m. (rubles)	140	886	267	443	1863
Panel C. Districts' characteristics					
Share of discriminating apartments	12	.23	.06	.05	.33

[a]Panel C presents data from the Russian Census of 2010.

Table 2: Main result: The Racial Rent Differential

	Dep. Var.: Logarithm of rent price			
	(1)	(2)	(3)	(4)
Discrimination dummy	-0.0409***	-0.0638***	-0.0670***	-0.0743***
	(0.001)	(0.004)	(0.008)	(0.003)
Observations	139,965	139,965	139,965	139,965
Building FE	Yes			
Subdistrict FE		Yes		
District FE			Yes	
Day of posting FE	Yes	Yes	Yes	Yes
Controls (apartment char.)	Yes	Yes	Yes	Yes
Controls (building char.)		Yes	Yes	Yes

Note: Estimation of the effect of overt discrimination in the ad on the rent price. Each observation is an individual ad posted on the website *cian.ru* during the observation period from May 27 to November 11, 2018. Standard errors are clustered on the building, *rayon* and *okrug* levels in specifications (1), (2) and (3) correspondingly. Standard errors in parenthesis.
** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Heterogeneous effects: the Racial Rent Differential and the Share of Discrimination in Neighborhood

	Dep. Var.: Logarithm of Rent Price			
	(1)	(2)	(3)	(4)
Discrimination dummy	-0.0409***	-0.0488***	-0.1009***	-0.1030***
	(0.001)	(0.002)	(0.006)	(0.007)
Discrimination dummy × *Share of discrimination in building*		0.0339***		
		(0.007)		
Discrimination dummy × *Share of discrimination in subdistrict*			0.2463***	
			(0.022)	
Discrimination dummy × *Share of discrimination in district*				0.2660***
				(0.029)
Average of interacting variable		.074	.052	.050
Maximum of interacting variable		1	.52	.33
Observations	139,965	139,965	139,965	139,965
Building FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Estimation of the heterogeneous effect of overt discrimination in the ad on the rent price. Interaction terms are dummy for discrimination interacted with shares of discrimination in buildings, subdistricts and districts. Each observation corresponds to an individual ad posted on the website *cian.ru* during the observation period from May 27 to November 11, 2018. Standard errors are clustered on the level of buildings. Standard errors in parenthesis.
** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Heterogeneous Effects: Interactions with Characteristics of Neighborhood

	Dependent variable: Logarithm of rent price			
	(1)	(2)	(3)	(4)
Discrimination dummy	0.7024***	0.0214***	0.0112**	-0.0168***
	(0.061)	(0.007)	(0.005)	(0.006)
Discrimination dummy × *Housing selling price in district*	-0.0613***			
	(0.005)			
Discrimination dummy × *Higher education in district*		-0.1739***		
		(0.021)		
Discrimination dummy × *Votes for 'liberals'*			-0.5560***	
			(0.053)	
Discrimination dummy × *Share of 'non-Russians'*				-0.2927***
				(0.069)
Observations	139,965	139,965	139,965	139,965
Building FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Estimation of the heterogeneous effect of overt discrimination in the ad on the rent price. Interaction terms are dummy for discrimination interacted with characteristics of neighborhoods. Each observation corresponds to an individual ad posted on the website *cian.ru* during the observation period from May 27 to November 11, 2018. Standard errors are clustered on the level of buildings. Standard errors in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Experiment: Main Results

	Dependent variable: Reply rate (dummy)		
	All ads	Ads without discrimination	Ads with discrimination
	(1)	(2)	(3)
Non-Russian name	-0.5511***	-0.3596***	-0.7631***
	(0.091)	(0.130)	(0.130)
Order dummy	Y	Y	Y
Text dummy	Y	Y	Y
Price (log)	Y	Y	Y
Total area (log)	Y	Y	Y
Length of text (log)	Y	Y	Y
Ground floor	Y	Y	Y
Last floor	Y	Y	Y
Observations	874	444	430

Note: Each column gives the results of a probit regression where the dependent variable is the answer dummy: one denotes benevolent reply from agent/landlord and zero denotes non-response (while message has been read) or refusal. Robust standard errors in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Experiment: **Subset of ads without overt discrimination**

	Dependent variable: Reply rate (dummy)		
	All districts	Less discriminating districts	More discriminating districts
	(1)	(2)	(3)
Non-Russian name	-0.3596***	-0.3079*	-0.4923**
	(0.130)	(0.168)	(0.209)
Order dummy	Y	Y	Y
Text dummy	Y	Y	Y
Price (log)	Y	Y	Y
Total area (log)	Y	Y	Y
Length of text (log)	Y	Y	Y
Ground floor	Y	Y	Y
Last floor	Y	Y	Y
Observations	444	272	172

Note: Each column gives the results of a probit regression where the dependent variable is the answer dummy: one denotes benevolent reply from agent/landlord and zero denotes non-response (while message has been read) or refusal. The sample consists of only ads without overt discrimination. Robust standard errors in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

A Design of Correspondence Experiment

Moscow landlords and agents explicitly discriminate against minorities in rental ads. However, it is not entirely clear whether discrimination in ads really turns into active discrimination in marketplace. This type of repetitive communicative pattern can serve as a device for enhancing trust among some groups — be part of social ritual with no real consequences for minorities. It is also not evident that landlords, who do not use language of discrimination, do not discriminate privately. In this section I explore these possibilities with help of correspondence experiment.

Since seminal paper by Bertrand and Mullainathan (2004) economists extensively use approach of correspondence study to reveal racial, ethnic or gender discrimination on various markets.[10] This approach is based on direct manipulation of applicants characteristics, specifically names, when it comes to the subject of racial discrimination. In this way, Bertrand and Mullainathan randomly assigned African-American sounding names to job applicant's resumes, send these resumes to real employers in Boston and Chicago and compared call backs rates of two racial groups. This study revealed that applicants with African-American names have statistically and economically significantly lower probability of call back.

I conduct correspondence experiment using online contact form which is available on the platform and which allows to reach a person behind the ad. I use design of paired-matched applications and send couples of short messages with Russian and non-Russian identities. Experiment was conducted in two separate rounds.

A.1 Messages

The platform provides users who are looking for apartments, two alternative ways to contact landlords or agents: via a public mobile phone or through an online form. The second is intended to ask the landlord or agent a short clarifying question about the proposal. The online form was chosen as the communication device for the experiment for technical reasons.

Following the way the online form is organized, I built two simple questions that were used as the basis for the intervention. Translations of these two questions are following:

> ***Q1.*** *Hello, I'm interested in your apartment. May I contact you tonight? [First name]*
>
> ***Q2.*** *Good afternoon, your offer interested me. I would like to ask a clarifying question. When could one move to an apartment? [First name]*

As can be seen, the topics of the questions are not related to the topic of ethnic discrimination. The sole purpose of these questions is to enable landlords (or agents) to react to the name of the applicant. The online form is not the main means of communication: its role is to be an intermediate stage before a telephone conversation, which in itself is an intermediate stage before a personal visit to the apartment. As a rule, the online form is not used to conclude transactions or discuss conditions. Therefore, the experiment was designed in such a way that the landlords could ignore the messages of the applicants with non-Russian names and, thus, disrupt the interaction at the first stage.

[10] See Baert (2018) for review of correspondence experiments

A.2 Names and identities

When the applicant submits his message through the form, the landlords can observe only the message itself. Despite this, separate accounts with realistic email addresses were created for each identity.

The variation of perceived ethnicity of names is a treatment of the experiment. Two rounds of experiment were conducted. They are different in terms of name selection approaches. It is important to note here that in Russia there is no common dataset on birth names. For the first round of the experiment, only two names were chosen: the Russian-speaking name Andrei and the Turkic name Arslan. Both names are popular and recognisable in Russia.

In the second round, a more rigorous approach to names selection was used. Between the first and second stages of the experiment, I created an original set of data on names in Russia, using account statistics collected from the popular Russian social network *vk.com*. Ratings of names by popularity for each Russian city was constructed.

Two cities were selected among the entire set: Moscow and Makhachkala. The first is a city in which the majority of the population is Russian: around 90 percent according to 2010 Russian Census. The second is plural city with only 6.3 percent of Russian residents. The largest ethnic groups in this region are among the most discriminated groups in the Moscow housing market and labor market.[11] Most of the representatives of these ethnic groups are citizens of Russia.

I take the 10 most popular names in Moscow and the 10 most popular names in Makhachkala, excluding the first places in the ranking and the names used in the first round of the experiment. The resulting set of names was used in the second round.

A.3 Sending messages

The experiment was conducted in two rounds: June 20-21, 2018 and December 13-14, 2019. The design of the second round was changed due to the fact that statistics on names became available. In this section, I describe the procedure and schedule of the first round of experiment and difference between first and second round.

The sample was constructed from the set of new offers that become available on the platform during the night 19-20 June, 2018. To identify these offers, I select those ones that appeared this night and were not available on previous days.

The next step, I randomly remove from the sample all offers with duplicate phone numbers, except one. Landlords or agents with duplicate phone numbers are coordinating the rental processes of more than one apartment. By design of experiment it is necessary not to contact one person through several different offers' pages. Such messages can be perceived as conspicuous and can bias results of experiment.

At this stage, 291 new discriminating offers were obtained. I randomly select other 291 offers among non-discriminating set. The resulting 582 observations become the sample of the first round of experiment.

As a final preparatory phase, texts of messages and identities for the first request were randomly independently attached to each offer. For the second paired message another text and alternative identity were used.

Finally, during the day of June 20, I manually sent the first message through the form of each offer. The process of sending messages is difficult to automate, because the platform prevents such interventions. The next day, requests with alternative texts and names were sent via forms

[11] Bessudnov and Shcherbak (2018) find that Chechen job seekers have one of the lowest callback rates. Given that the set of names of largest ethnic groups in Dagestan intersects widely with the set of Chechen names, this result is valid for the most popular names of Makhachkala residents.

with the same offers. The one day period was chosen as long enough to be realistic and short enough to decrease the number of cases when offers are no longer available to the time of second message.

Thanks to the randomization of the order and message texts, the influence of these two factors do not influence results.

During the second round names of two groups were randomized.

A.4 Classification of responses

Landlords or agents can reply in free form, however several basic types were identified. Classification is following:

1. Answer question or ask to call
2. Ask extended identification of potential tenant/ explicitly ask about ethnicity
3. "Already rented"
4. Message was not read
5. Read, but not answered
6. Rejects, motivating this with the tenant's ethnicity
7. Rejects, motivating this with the tenant's gender

Landlords or agents do not have other ways to communicate with potential tenant, therefore there are no other possible response ways to be coded.

In analysis of experiment's outputs, this classification was simplified. Point 1 was considered as "likely non-discriminating', points 2, 3, 5, 6, 7 is combined in on category "likely discriminating". Observations with point 4 replies were excluded from the analysis.

B Appendix: Empirical Results

Table B.1: The Racial Rent Differential: Extended Table

	Dependent variable: Logarithm of rent price			
	(1)	(2)	(3)	(4)
Discrimination dummy	-0.0409***	-0.0638***	-0.0670***	-0.0743***
	(0.001)	(0.004)	(0.008)	(0.003)
Log total surface	0.7091***	0.8817***	0.8972***	0.9204***
	(0.007)	(0.025)	(0.052)	(0.010)
LivingArea / TotalArea	0.1964***	0.1918***	0.2224***	0.2023***
	(0.013)	(0.037)	(0.027)	(0.026)
Number of floors		0.0095***	0.0101***	0.0106***
		(0.001)	(0.000)	(0.001)
Ground floor	-0.0198***	-0.0078	-0.0022	-0.0040
	(0.003)	(0.005)	(0.007)	(0.006)
Last floor	0.0139***	0.0057	0.0062	0.0060
	(0.003)	(0.005)	(0.004)	(0.005)
Log dist. to center		-0.2741***	-0.3069***	-0.3383***
		(0.029)	(0.018)	(0.006)
Log dist. to metro		-0.0296***	-0.0400***	-0.0390***
		(0.005)	(0.005)	(0.003)
Log(number of photo + 1)	0.0084***	0.0134***	0.0144***	0.0168***
	(0.001)	(0.002)	(0.002)	(0.001)
Log length of text (10 chars)	0.0280***	0.0432***	0.0443***	0.0468***
	(0.001)	(0.002)	(0.003)	(0.002)
Log days in exposure	0.0148***	0.0217***	0.0217***	0.0229***
	(0.001)	(0.001)	(0.003)	(0.001)
Constant	7.7410***	7.4413***	7.4171***	7.3820***
	(0.023)	(0.141)	(0.260)	(0.037)
Observations	139,965	139,965	139,965	139,965
R-squared	0.952	0.890	0.882	0.876
Building FE	Yes			
Subdistrict FE		Yes		
District FE			Yes	
Day of posting FE	Yes	Yes	Yes	Yes

Note: The sample consists of all ads posted on the web-site during the observation period. Standard errors are clustered on the level of buildings, subdistricts and districts in specifications (1), (2) and (3) correspondingly. Standard errors in brackets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.2: Placebo: Other Preferences of Landlords

	Dependent variable: Logarithm of rent price		
	(1)	(2)	(3)
No animals	0.0050**		0.0164***
	(0.002)		(0.002)
No kids		-0.0020	0.0048**
		(0.002)	(0.002)
Only for Slavs			-0.0430***
			(0.001)
Observations	139,965	139,965	139,965
Building FE	Yes	Yes	Yes
Day of posting FE	Yes	Yes	Yes
Controls (apartment char.)	Yes	Yes	Yes

Note: Standard errors are clustered on the level of buildings. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.3: Robustness: Phone Numbers Fixed Effects

	Dependent variable: Logarithm of rent price			
	(1)	(2)	(3)	(4)
Discrimination dummy	-0.0315***	-0.0483***	-0.0506***	-0.0547***
	(0.002)	(0.003)	(0.005)	(0.002)
Observations	130,179	125,191	125,192	125,194
Building FE	Yes			
Phone FE	Yes	Yes	Yes	Yes
Subdistrict FE		Yes		
District FE			Yes	
Day of posting FE	Yes	Yes	Yes	Yes
Controls (apartment char.)	Yes	Yes	Yes	Yes
Controls (building char.)		Yes	Yes	Yes

Note: Standard errors are clustered on the level of buildings, subdistricts and districts in specifications (1), (2) and (3) correspondingly. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.4: Increased Search Time: Discrimination and Number of Days before Ad Removed

	Dependent variable: # of days before ad removed (log)			
	(1)	(2)	(3)	(4)
Discrimination dummy	0.1060***	0.1025***	0.0996***	0.1002***
	(0.011)	(0.014)	(0.016)	(0.012)
Log total surface	0.1065***	0.1167***	0.1420***	0.1493***
	(0.028)	(0.029)	(0.026)	(0.025)
LivingArea / TotalArea	-0.1014*	-0.0025	-0.0188	-0.0225
	(0.053)	(0.064)	(0.075)	(0.051)
Number of floors		-0.0027***	-0.0033**	-0.0032***
		(0.001)	(0.001)	(0.001)
Ground floor	0.0270	0.0376*	0.0320**	0.0319*
	(0.020)	(0.019)	(0.013)	(0.018)
Last floor	-0.0035	0.0231	0.0221*	0.0224
	(0.017)	(0.016)	(0.011)	(0.016)
Log dist. to center		-0.0506	0.0327	0.0035
		(0.042)	(0.042)	(0.012)
Log dist. to metro		0.0399***	0.0502***	0.0543***
		(0.009)	(0.012)	(0.006)
Log(number of photo + 1)	0.1239***	0.1292***	0.1293***	0.1288***
	(0.006)	(0.007)	(0.007)	(0.006)
Log lenght of text (10 chars)	0.0253***	0.0267***	0.0295**	0.0297***
	(0.005)	(0.006)	(0.010)	(0.005)
Log price	0.6007***	0.5011***	0.4730***	0.4659***
	(0.030)	(0.028)	(0.035)	(0.022)
Constant	-5.1956***	-4.0956***	-4.0736***	-3.9579***
	(0.251)	(0.283)	(0.423)	(0.185)
Observations	116,278	112,497	112,498	112,498
R-squared	0.396	0.211	0.208	0.207
Building FE	Yes	No	No	No
Subdisctrict FE	No	Yes	No	No
District FE	No	No	Yes	No
Day of posting FE	Yes	Yes	Yes	Yes
Controls (apartment char.)	Yes	Yes	Yes	Yes
Controls (building char.)		Yes	Yes	Yes

Note: The Sample consists of ads posted on the web-site during the observation period excluding ads that were available on the first and last days of the observations period. Standard errors are clustered on the level of buildings, subdistricts and districts in specifications (1), (2) and (3) correspondingly.
Standard errors in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.5: Heterogeneity of Search Time Effect: Interaction with Share of Discrimination in Neighborhood

	Dependent variable: Number of days in exposure (log)			
	(1)	(2)	(3)	(4)
Discrimination dummy	0.1060***	0.2455***	0.1090***	0.0768*
	(0.011)	(0.017)	(0.036)	(0.045)
Discrimination dummy × *Share of discrimination in building*		-0.5873***		
		(0.062)		
Discrimination dummy × *Share of discrimination in subdistrict*			-0.0122	
			(0.145)	
Discrimination dummy × *Share of discrimination in district*				0.1250
				(0.186)
Observations	116,278	116,278	116,278	116,278
R-squared	0.396	0.397	0.396	0.396
Building FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: The sample consists of ads posted on the web-site during the observation period. Standard errors are clustered on the level of buildings. Standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.6: Experiments Outcomes

	Slavic names					
Non slavic names	Answer back	Ask id	Is rented	Not read	Read, no answer	Total
Answer back	162	2	0	0	18	182
Ask id	12	1	0	0	3	16
Is rented	0	0	1	0	0	1
Not read	2	0	0	63	3	68
Read, no answer	77	1	3	4	142	227
Reject (due to ethnicity)	13	1	0	0	0	14
Reject (due to gender)	1	0	0	0	0	1
Total	267	5	4	67	166	509

C Appendix: Theory

C.1 Tenants' problems

$$Emax\{\alpha - p_{nd}, V^{ns}\} = P(\alpha - p_{nd} > V^{ns}) \times E(\alpha - p_{nd}) + P(\alpha - p_{nd} < V^{ns}) \times V^{ns} =$$
$$\int_{V^{ns}+p_{nd}}^{\infty} f(\alpha)d\alpha \times E(\alpha - p_{nd}) + (1 - \int_{V^{ns}+p_{nd}}^{\infty} f(\alpha)d\alpha) \times V^{ns} =$$
$$\int_{V^{ns}+p_{nd}}^{\infty} (\alpha - p_{nd} - V^{ns}) f(\alpha)d\alpha + V^{ns}$$

$$V^{ns} - \theta V^{ns} = (1-\theta)(\int_{V^{ns}}^{\infty})(\alpha - p_{nd} - V^{ns}) f(\alpha)\alpha + V^{ns}) - k$$

$$\frac{k}{1-\theta} = \int_{V^{ns}+p_{nd}}^{\infty} (\alpha - p_{nd} - V^{ns}) f(\alpha)d\alpha$$

$$Emax\{\alpha - p_i, V^s\} = \int_{V^s+p_i}^{\infty} (\alpha - p_i - V^s) f(\alpha)d\alpha + V^s$$

Non-slavic tenants' problem when α is distributed uniformly:

$$\frac{k}{1-\theta} = \int_{V^{ns}+p_{nd}}^{\beta} \frac{\alpha - p_{nd} - V^{ns}}{\beta} d\alpha = \frac{(\beta - p_{nd} - V^{ns})^2}{2\beta}$$

Slavic tenants' problem when α is distributed uniformly:

$$2k\beta = \theta(\beta - p_d - V^s)^2 + (1-\theta)(\beta - p_{nd} - V^s)^2$$

C.2 Optimal Rents and Rent Differential in a Separate Neighborhood

Tenants problems can be rearranged such that (3) and (4) respectively become:

$$k = \theta \int_{V^s+p_s}^{\infty} (\alpha - p_d - V^s) f(\alpha)d\alpha + (1-\theta) \int_{V^s+p_{nd}}^{\infty} (\alpha - p_{nd} - V^s) f(\alpha)d\alpha \tag{9}$$

$$\frac{k}{1-\theta} = \int_{V^{ns}+p_{nd}}^{\infty} (\alpha - p_{nd} - V^{ns}) f(\alpha)d\alpha \tag{10}$$

Then assume that α is drawn from uniform distribution on interval $[0, \beta]$. The equations can be rewritten as:

$$2k\beta = \theta(\beta - p_d - V^s)^2 + (1-\theta)(\beta - p_{nd} - V^s)^2 \tag{11}$$

$$V^{ns} = \beta - p_{nd} - \sqrt{\frac{2\beta k}{1-\theta}} \tag{12}$$

With β both mean and variance of α increase. The parameter β can be interpret as likelihood of finding tenant who values the apartment highly.

First order conditions for landlords problems (5) and (6) respectively are :

$$p_d = \frac{1 - F(V^s + p_d)}{f(V^s + p_d)} \tag{13}$$

$$\pi(p_{nd} - p_{nd}F(V^s + p_{nd}) + (1-\pi)(p_{nd} - p_{nd}F(V^{ns} + p_{nd})) = 0 \tag{14}$$

In the same way as in tenants' problems assumption on uniform distribution is imposed. Hence the equations appear as follows:

$$p_d = \frac{1}{2}(\beta - V^s) \tag{15}$$

$$p_{nd} = \frac{1}{2}(\beta - (\pi V^s + (1-\pi)V^{ns})) \tag{16}$$

Four equations (first-order conditions of two tenants' and two landlords problems) contains four unknown variables: prices and reservation values. Therefore, together these equations define equilibrium. With simple rearrangements this system can be reduced to two equations that bind two prices: on discriminating and non-discriminating markets.

$$2k\beta = \theta p_d^2 + (1-\theta)(2p_d - p_{nd})^2 \tag{17}$$

$$p_{nd} = \frac{1-\pi}{1+\pi}\sqrt{\frac{2\beta k}{1-\theta}} + \frac{2\pi}{1+\pi}p_d \tag{18}$$

C.3 Equilibrium

The model can be defined with four equations:

$$\begin{cases} 2k\beta = \theta(\beta - p_d - V^s)^2 + (1-\theta)(\beta - p_{nd} - V^s)^2 \\ V^{ns} = \beta - p_{nd} - \sqrt{\frac{2\beta k}{1-\theta}} \\ p_d = \frac{1}{2}(\beta - V^s) \\ p_{nd} = \frac{1}{2}(\beta - (\pi V^s + (1-\pi)V^{ns})) \end{cases}$$

This can be reduced to the system of two equations that define optimal rent sums:

$$\begin{cases} 2k\beta = \theta(\beta - p_d - V^s)^2 + (1-\theta)(\beta - p_{nd} - V^s)^2 \\ p_{nd} = \frac{1-\pi}{1+\pi}\sqrt{\frac{2\beta k}{1-\theta}} + \frac{2\pi}{1+\pi}p_d \end{cases}$$

The fact that rent differential is positive in optimum ($p_{nd} - p_d > 0$) can be proved geometrically. The first equation is equation of ellipse sloped to the right, and the second equation defines straight line with slope that equals to $\frac{2\pi}{1+\pi}$. For any π this line is less step than line $p_{nd} = p_d$. The point of intersection of ellipse and axis p_{nd} is $\sqrt{\frac{2\beta k}{1-\theta}}$, whereas the point of intersection of straight line given by second equation and axis p_{nd} is $\sqrt{2\beta k}$, which is less than $\sqrt{\frac{2\beta k}{1-\theta}}$. Therefore, for any values of parameters $p_{nd} - p_d > 0$.