Consider the Slavs: Overt Discrimination and Racial Disparities in the 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 a 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 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 a 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: regression decompositions 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 two[2], and question remains open: to what extend 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 driver (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 under specific conditions show that at least one-third of the black-white wage gap can be attributed to discrimination.

Although subtle forms of discrimination are more prevalent today, only the overt forms can be measured directly and used that to investigate the impact on racial gaps. While it is rare nowadays, overt discrimination has been widespread in the past century. 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.

[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.

[2]See Fryer et al. (2013) for discussion

This paper follows the call of Kenneth Arrow and studies the implications of discrimination drawing on a unique context of the rental housing market in Moscow, where landlords discriminate overtly. More specifically, in this paper I investigate how discrimination in the rental housing market can generate racial rent differentials.

I collect new data on rental ads from the Russian major online real estate marketplace *cian.ru*. The dataset includes all available ads over around 6 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 hereby 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, so it absorbs geographic and building-level variations.

I found 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 – the topic overlooked in economic literature. 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 field. I find that both subtle and overt forms of discrimination coexist on the rental housing market in Moscow. Their relative prevalence is constant, keeping the same proportion 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 the 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 majorities to accept an unfavorable offer. Then non-discriminating landlords who understand 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 can oppose discrimination to lost profits. Hedegaard and Tyran (2014) conduct field experiments to measure the sensitivity of discrimination to changes in opportunity cost. To the best of my knowledge there are no studies that estimate racial gaps in housing in Russia using traditional regression decompositions.

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. This paper is the first to conduct a correspondence experiment on the Russian rental housing market – clearly for the reason that discrimination in this market is *"too evident for detection"*. 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. They also portrait complex hierarchy between different ethnicities in the Russian labor market.

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 sociological literature (Small and Pager, 2020; Pager, 2007). Careful analysis of a subtle form of discrimination convincingly shows that possible explanations of discrimination are not exhausted by taste-based and statistical models. 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" augments, but fail to update their believes when facing contradicting information (Pager and Karafin, 2009). This also corresponds to the observation that local 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, the anecdotal evidence suggests, that overt discrimination observed in the rental housing in Moscow has much in common with typical subtle discrimination, where landlords do not consider their behavior as discriminating[3].

The theoretical section of this paper is related to a 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

[3]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)

competitive taste-based framework. Thereby we leave aside the question of the rationality of landlords' beliefs and assume that landlords have nothing but 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. It implies that majorities 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[4]. Following insights from the labor literature, I re-specify the search model proposed in Black (1995) for the context of rental housing in Moscow. In this model discriminating landlords refuse to accept minorities at any price, which makes search for minorities more expensive. 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. 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

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

matching on the housing market regardless of the discrimination context: Albrecht et al. (2016), Carrillo (2012); Ngai and Tenreyro (2014).

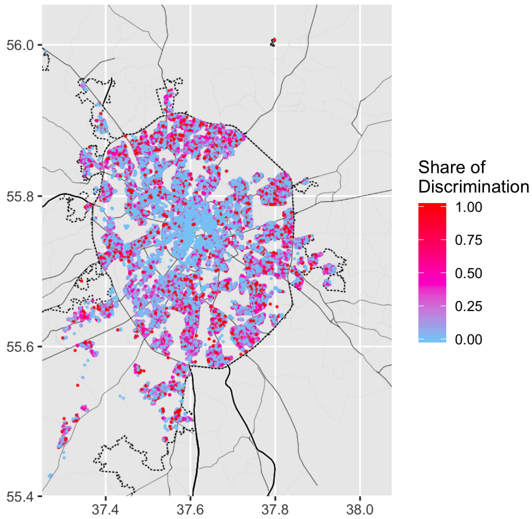
The paper is organized as follows. Section 2 describes the data and background of the online housing marketplace. Section 3 presents major empirical findings on racial rent differentials. Section A describes the results of a correspondence experiment. Section 4 examines a theoretical framework that sheds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

2 Background and Data

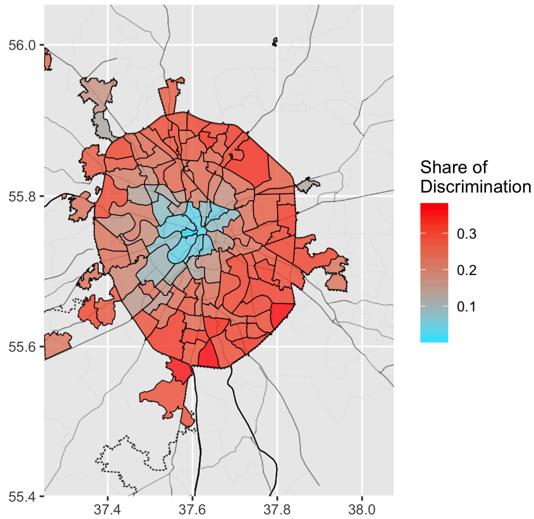
Russia is a multinational state: 19% of the population are not ethnic Russians (Census, 2010). There is also a large population of immigrants. According to the UN data, around 11 millions immigrants resided in Russia in 2019 (8% of the total population), which made Russia a second country in the world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

Figure 1: **Geography of discrimination**



(a) Map of discrimination by buildings



(b) Map of discrimination by subdistricts

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[5]. On the other hand, the judicial practice is poor when it comes to actual discrimination in the labor and housing markets[6]. In particular, a discriminating landlord do not pay any fees and have 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). Census (while a limited source of the information on where immigrants live) also does not show a sign of strong segregation (Figure 4a). At the same time, the share of non-Russian residents is higher in the city center – 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 Russian housing stock:

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

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

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 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 2 thousand rental offers, around 2 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 rental in Russia. Over the last decade 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 they can browse the list of search results. If 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. Addresses were geocoded in order to calculate distances between buildings and 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, because the site was down. I exclude these days from analysis. Final dataset consists of 117 daily snapshots. Figure 2 in Appendix shows that the number of posted ads is a seasonal variable. It varies between 22 thousands and 35 thousands, increase in summer and decrease in autumn. This fluctuation can be explained with seasonality of demand.

Figure 1 (a) reports the map of Moscow, where each dote corresponds to observed building and 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 associate with low level 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 share of discriminating apartments can reach as much as 54 percent. Surprisingly, spatial pattern of discrimination is vastly sustainable (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. On the histogram in Figure **??** two groups of observations stand out: first, around 80 percent of offers that have not changed rent price during the whole period, and, second, group of offers that decreased the rent price. This picture motivates the use of the latest rent prices in estimation of the cost of discrimination — these rent prices can be interpret as an equilibrium prices in the spirit of theoretical predictions presented in Section 4.

There are two types of "sellers" on this market: landlords and agents. They both can directly access the platform after creating personal account. Agents are licensed specialists hired by landlords who take on the job of finding reliable tenant at an optimal rent price. In the baseline analysis, I abstract away from the difference in the behavior of landlords and agents. Many agents from the market claim that, when it comes to ethnic requirements, agents only transmit preference of landlords with whom they work. Sellers and their potential types can be identified with help of ids and phone numbers. I explore the difference between agents and landlords as well as influence of such mediation on main results in Robustness Section **??** in Appendix.

Using accompanying ads' texts, I was able to identify the presence of ethnic or racial discrimination. For the baseline analysis, I resorted to a dictionary approach[7] . The algorithm consists of several steps: first, I calculate frequencies of all unigrams, bigrams and trigrams, then examine them manually to reveal ones related to ethnicity of tenant and, finally, marked up ads containing these n-grams. Discrimination in ads is manifested in highly uniform way: most of discriminating landlords use phrase "Slavs only". The rest of discriminating landlords use words with roots: *slav-*, *russ-*, *caucas-*, *asia-*. For these key phrases, few instances of reversed use were detected (for example, preceding "not only", or following "are allowed") and excluded. There are also specific inclusive phrases in data, such as "all ethnicities are allowed". Despite the fact that declaratively inclusive ads are quite rare, they were employed in extended analysis. For more details see Section **??** in Appendix.

In each specification controls for the individual characteristics of apartments are added. Surface area, layout, floor number are explicit characteristic of apartment. To proximate more ambiguous characteristics, I construct two variables: length of announcement in symbols and number of photos attached. I also construct more complex measure of quality of apartment with help of bag-of-words approach — results of this analysis can be found in Section **??** in Appendix.

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

2.2 Other data

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

In Section A I report design and findings of correspondence experiment which compares discrimination in ads with discriminative behavior. I respond to sample of ads through the online form and manipulate the names of potential tenants such that some of them could be perceived as "russian" and some of them as "non-russian". In this design I follow Bertrand and Mullainathan (2004). Since in Russia there are no common data on birth names, I construct approximate ranking of names using data from Russian popular social network *vk.com*. I use the data on the city of residence to make a rating of the 10 most popular names in Moscow and the 10 most popular names in Makhachkala — multi-ethnic city where Russians make up only 5.4 percent.

3 Observational study

3.1 Empirical methodology

The Moscow housing stock consists of high multi-storey buildings with large number of apartments. The median building is 12-storey. Therefore, multiple apartments are often exposed in one building. During the entire observation period in median building 12 vacant apartments appear in exposure. It is also peculiar, that apartments in the same building are usually of a similar quality, and "vertical" or in-building segregation is uncommon in Moscow. Such structure of housing stock is beneficial for my analysis, because it allows to compare apartments within one building. I employ model with fixed effects on buildings level to estimate the cost of discrimination. The baseline specification is:

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

Here observations are all offers that were posted during the observation period. Subscript i denotes posted offer, b is an index of building and τ is an index of day when 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 confounders. Coefficient of interest α is an estimate of the cost of discrimination. It reflects the difference in rent price between discriminating and non-discriminating purified from other influences. With that this specification requires control for apartments individual characteristics. For this purpose model includes set of controls $X_{ib\tau}$. The characteristics of the apartment are divided into two types, which can be denotes as "hard and "soft variables. Examples of "hard easy measurable features are surface area and apartment layout (e.g. share of living room in total surface area). "Soft" features cannot be measured directly and represent such qualities of apartment, 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.[8] It must be emphasized that it is still impossible here to separate landlord's propensity to discriminate and other landlord's personal qualities.

Less conclusive versions of this specification were also tested: model with fixed effects on subdistricts level, model with fixed effects on districts level and cross section model. Each of these specifications includes controls for distance to the city center and distance to the closest metro station.

There are several assumptions that accompany the baseline specification. First assumption is that discrimination in ad is a direct reflection of real intention to discrimination and no only some sort of social ritual, normative habit with no other functional purpose behind. The extreme form of this assumption is situation when minority tenant

[8]See Section **??** in Appendix for tests of more complex measures of apartments' quality

will be unconditionally rejected by landlord with discriminating offer and will not be unconditionally rejected by landlord with non-discriminating offer. However, other scenarios are also possible. There can be hidden discrimination on the market. Another possibility is that ritualized discrimination in ad does not translate into active discrimination when landlord is confronted with a minority tenant. I test this assumption with help of correspondence experiment. The results of the experiment and discussion of its interpretations are reported in Section A.

Another assumption is that number of photos and length of text are bad proxies for quality of apartment. I test other measures of apartments' quality in Section **??**.

I also explore how the cost of discrimination varies by different municipal units and how it interacts with surrounding discrimination in municipal unit. This network effect is crucial for understanding of formation mechanism of the cost of discrimination. Black (1995) applied to the context of Moscow rental market predicts not only existence of the cost of discrimination, but also that it should increase with prevalence of discriminative behavior on the market. To test this hypothesis I calculate the effect of interaction between discrimination in ad and discrimination rate in surrounding municipal unit:

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

For each municipal unit discrimination rates are calculated as a share of discriminating ads in total number of ads that were posted during the observation period. Maps of discrimination rate calculated for buildings and subdistricts are shown in Figure 1. Surrounding discrimination rates that are used in models with interaction term exclude contribution of observation they are interacted with. To illustrate this exclusion procedure let us imagine market of two apartments one discriminating and one non-discriminating. Surrounding discrimination rate for the first (discriminating) apartment $DiscrRate_1$ equals 0 and for the second $DiscrimRate_2$ equals 1.

The rest of the model is similar to the baseline model. $DiscrimRate_u$ is surrounding discrimination rate for offer i in municipal unit u. This specification is tested for discrimination rates on different levels: buildings, subdistricts and districts.

The same empirical methodology was used when effect of discrimination on search time was estimated.

3.2 Main results

3.2.1 Cost of discrimination

Table 2 presents the estimations of the cost of discrimination. The extended results with all controls presented can be found in Appendix in Table B.1. The results bring out strong and negative effect of discrimination on price, in other words discrimination is a costly good for landlords. The sign of effect is consistent with theoretical expectations, which are discussed in Section 4. The first column shows the results of model with building level fixed effects. This specification is most restrictive. Other specification do not include building dummies, but include district or subdistricts dummies and control for logarithms of distances to city center and to closest metro stations. The fourth column presents results of most basic model with no geographic dummies. It can be seen that coefficient of interest increases from first to fourth specification. It can be explained by the fact that on average cheaper buildings and districts are also associate with more frequent discrimination. The estimated cost of discrimination is sizeable: it reduces the rent price by 4 percent.

3.2.2 Network effects

As shown above, discrimination is costly for landlords. However, they are not paying the same price. Table 4 indicates that in areas with most flourishing discrimination landlords almost do not lost from such behaviour. The opposite is also true. In central Tverskoy District, where only 2 percent of offers search for “slavic” tenants, the cost of discrimination reaches 13 percent of apartment's rent price — three times more than average cost of discrimination.

This interaction effect, which links the cost of discrimination and the surrounding discrimination, is denoted further the network effect. It exists on building, subdistrict and district levels. The broader geographic unit the bigger value of the network effect: cost of discrimination is more sensitive to what is happening closer to apartment.

Both frequency of discrimination and cost of discrimination have the same center-periphery structure. However, other meaningful variables have similar spatial distribution: education, population, average rent and purchase price of real estate, share of non-Russian residents.[9] Specifications in columns 5 and 6 of extended Table B.2 in Appendix show that cost of discrimination also depends on average selling price of apartments in subdistrict, as well as subdistricts' population density.

In the same time, effects of higher education rate and share of non-Russian residents on cost of discrimination are not statistically significant, despite the fact that the relations between these two parameters and cost of discrimination find some support from theoretical point of view.

The network effect decrease when controlled for other subdistricts' characteristics. However, they remain to be significant and have the same signs and sizeable values. Table B.2 shows that the network effect on district level (column 6) is still bigger than one on building level (column 5).

3.2.3 Impact of discrimination on search time

The landlords' disadvantage from discriminating behaviour manifests itself also through the increased search time.[10] Extra days spend on the market waiting should naturally be considered as a part of cost of discrimination. Table **??** presents the estimated effect of discrimination on number of days offers have been exposed on the platform. The

[9]See maps in Figures 4 and 5

[10]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.

data used in this analysis do not include observations that were available on the first day and observations that remain to be available on the last day of the observation period. Specifications in Table **??** are similar to ones from Table 2, but with logarithm of number of days in exposure in left-hand side. In each regression I control for logarithm of apartment's rent price.[11]

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. It is costly delay, but one that landlords take only once — in contrast to the monthly rental discount.

Increased search time support hypothesis that the cost of discrimination is demand-driven. At the same time, time effect does not quite match the pattern of rent price effect. Table B.4 shows that although search time network exists on building level, it is not statistically significant for the levels of subdistrict and district.

3.2.4 Subsample analysis

Table B.5 presents results of subsample analysis, where network effects are estimated separately for districts with average selling price of apartments below and above median. The same separation is produced for such characteristics of districts as share of residents with higher education and share of non-Russian residents. The estimations show that network effect is mostly driven by districts with above median level of education and selling prices. It is also rather not sensitive to the presence of non-Russian residents in district. This result resembles network effect documented above, but between subdistrict and building levels.

This hierarchical chain of effects probably reflects the structure of demand for (non)-discriminating apartments.

[11]Prices on the last day are used here in the same way as when the cost of discrimination was estimated.

3.2.5 Electoral Analysis

Non-discriminating environments associate with pro-democratic values. Lower share of discriminating apartments in overall number of available apartments predicts higher vote shares of pro-democratic candidates in 2018 Russian presidential elections. Most importantly, this result cannot be explained with segregation, high income or education, which can be seen in Table ??. There were eight candidates in this election. Table ?? presents results with outcomes of five of them, votes for which totaled 95 percent. I combined the vote shares of Ksenia Sobchak and Grigory Yavlinsky, who used pro-democratic rhetoric during the election.

This finding suggests that non-discriminating communities can be attractive not only for minorities. Some tenants can deliberately avoid areas with high rates of discrimination, because these areas are associate with markedly different values and social norms. Together with previous results the electoral analysis support the idea that the cost discrimination is demand-driven and related to preference of some of potential tenants against discrimination. All the emprircal results presented here are brought together in theoretical Section 4 of the paper to suggest a potential mechanism of the cost of discrimination.

3.3 Results of experiment

Table 6 presents results of experiment. Each column gives the results of a probit regression where the dependent variable is the answer dummy. It can be seen that applicants with non-Russian sounding names have significantly lower probability to receive benevolent response from apartments' accounts with discrimination in ads: 40 percent less likely on average. At the same time, there is no such effect for Russian sounding names. However, applicants with non-Russian names are also less likely to receive a response from the landlords without discrimination in the ads.

4 Theory of the racial rent differential

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 goes along with an empirical findings and $p^*_d < p^*_{nd}$. This scenario intends full market segregation. Otherwise, majorities from 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 labor market solves this issue by introducing frictional environment. The most noticeable contributions in this direction were made in Black (1995), Rosén (1997), Bowlus and Eckstein (2002), Lang et al. (2005).

In this section I adjust simple random search model from Black (1995) to the context of Moscow rental housing. This model can explain existence and sign of the cost of discrimination, but it should be extended to fit with other empirical findings.

4.1 The baseline model

There are two types of tenants: *slavic* and *non-slavic*. The share of *slavic* tenants is π. All tenants sequentially search for an apartment paying k for each period of search. When tenant finds and rents an apartment, he or she stops searching and live in this apartment forever.

There are two types of landlords: those who refuse to rent apartment to a *non-slavic* tenant at any price, and those who are indifferent of tenant's race. The fraction of prejudiced landlords is θ and fraction of unprejudiced landlords is $1-\theta$. For the simplicity I assume that landlords value their own property identically and this value equals zero.

Tenants learn three features during the visit: how much they value this apartment α, type of landlord and the rent p that was set in advance by landlord. This assumption contradicts the idea of online platform that provides users with all information before the visit. The boundaries of this stylization and possible improvements are discussed in the following sections.

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's model when it comes to price setting. The main interest of Black's model is racial wage gap, this is why in this model employers are allowed to set different wages for minorities and majorities. In context of Moscow rental housing there is unique rent for discriminative apartments and unique rent for non-discriminative, so I assume that unprejudiced landlord can only set unique rent for both *slavic* and *non-slavic* tenants.

4.1.1 Tenants' problem

Tenants' equilibrium strategies can be described with reservation utilities such that tenants are indifferent between renting apartment and continuing the search. Two option available for *slavic* tenants: renting apartment from discriminating landlord and renting apartment from non-discriminating. This leads to 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 in a way that with probability θ they meet prejudiced landlord and therefore, receive their reservation utility.

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

These problems can be rearranged such that (3) and (4) respectively are:

$$k = \theta \int_{V^s + p_s}^{\infty} (\alpha - p_d - V^s) f(\alpha) d\alpha + (1-\theta) \int_{V^s + p_{nd}}^{\infty} (\alpha - p_{nd} - V^s) f(\alpha) d\alpha \tag{5}$$

$$\frac{k}{1-\theta} = \int_{V^{ns}+p_{nd}}^{\infty} (\alpha - p_{nd} - V^{ns}) f(\alpha) d\alpha \tag{6}$$

Then assume that α is drawn from uniform distribution on interval $[0, \beta]$. While losing in generality, this assumption greatly simplifies the solution. The equation can be rewritten as:

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

$$V^{ns} = \beta - p_{nd} - \sqrt{\frac{2\beta k}{1-\theta}} \tag{8}$$

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.

4.1.2 Landlords' problem

Each landlord behave as a monopsonistic competitor. Therefore they maximize the rent, considering probabilities of tenants' acceptance.

Prejudiced landlords are ready for a deal only if tenants are *slavic*. Thus, their expected utility can be written as:

$$\mathbb{E}u_d = (1 - F(V^s + p_d))p_d \tag{9}$$

Unprejudiced landlords accept tenants of both types, but they are limited to set unique price.

$$\mathbb{E}u_{nd} = p_{nd}(\pi(1 - F(V^s + p_d)) + (1-\pi)(1 - F(V^{ns} + p_{nd})) \tag{10}$$

First order conditions for (9) and (10) are respectively:

$$p_d = \frac{1 - F(V^s + p_d)}{f(V^s + p_d)} \tag{11}$$

$$\pi(p_{nd} - p_{nd}F(V^s + p_{nd}) + (1 - \pi)(p_{nd} - p_{nd}F(V^{ns} + p_{nd})) = 0 \tag{12}$$

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

$$p_d = \frac{1}{2}(\beta - V^s) \tag{13}$$

$$p_{nd} = \frac{1}{2}(\beta - (\pi V^s + (1 - \pi)V^{ns})) \tag{14}$$

4.1.3 Optimal Rents and Cost of Discrimination

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.

$$2k\beta = \theta p_d^2 + (1 - \theta)(2p_d - p_{nd})^2 \tag{15}$$

$$p_{nd} = \frac{1 - \pi}{1 + \pi}\sqrt{\frac{2\beta k}{1 - \theta}} + \frac{2\pi}{1 + \pi}p_d \tag{16}$$

It can be shown that there is unique positive solution of this system and rent differential is positive in optimum ($p_{nd} - p_d > 0$) for any values of parameters. This result is consistent with our empirical findings. However, rent differential in optimum increases with share of discriminating apartments θ, which contradicts our regression results.

4.1.4 Extension. Preference for non-discriminating communities

As can be seen, basic setup of the model predicts network effect with sign opposite to my empirical findings. However, small modification of the model leads to results that better fits the data. In this section I endogenize share of *non-slavic* tenants $1-\pi$ by introducing entry decision stage into the model.

Let us assume that entry decision precedes the search process. On this stage *non-slavic* tenants can decide whether they want or do not want to enter this segment of rental housing market.[12]. Their benefit from participation equals to equilibrium reservation utility on this market V^{ns}. Let us also assume that *non-slavic* tenants have disutility that positively depends on share of discrimination on the market. I denote it as $\phi(\theta)$, such that $\phi'(\theta) > 0$. Then their utility from entry equals to:

$$u_{ns}^{entry}(\theta, \pi) = V^{ns}(\theta, \pi) - \phi(\theta) \tag{17}$$

Reservation utility V^{ns} negatively depends on share of *non-slavic* tenants $1-\pi$. *Non-slavic* tenants from continuum of tenants will enter this segment of market until marginal *non-slavic* tenant will be indifferent between entering and not entering. Then optimal share of *slavic* tenants is defined by equation.

$$u_{ns}^{e}(\theta, \pi) = V^{ns}(\theta, \pi) - \phi(\theta) = 0 \tag{18}$$

Let us assume that from this equations the function $\pi = \pi(\theta)$ can be obtained. In order to find the derivative of this function, the implicit function theorem can be applied.

$$\frac{d\pi}{d\theta} = -\frac{\partial u_{ns}^{e}(\theta, \pi)}{\partial \theta} / \frac{\partial u_{ns}^{e}(\theta, \pi)}{\partial \pi} \tag{19}$$

[12]It is important to note here that I treat segments of market in isolation. Even though such partial approach does not give a complete picture, it can serve as a useful device for illustration of the network effect

$$\frac{\partial u_{ns}^{e}(\theta,\pi)}{\partial\theta}=\frac{\partial V^{ns}(\theta,\pi)}{\partial\theta}-\frac{\partial\phi(\theta)}{\partial\theta}<0 \tag{20}$$

$$\frac{\partial u_{ns}^{e}(\theta,\pi)}{\partial\pi}=\frac{\partial V^{ns}(\theta,\pi)}{\partial\pi}>0 \tag{21}$$

Thus, share of *slavic* tenants π positively depends on share of discrimination θ when disutility from surrounding discrimination is assumed:

$$\frac{d\pi(\theta)}{d\theta}>0 \tag{22}$$

Now, let us see how cost of discrimination behaves with different increasing functions $\pi(\theta)$. For this I run a simple numerical exercise, results of which can be found on Figure **??**.

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

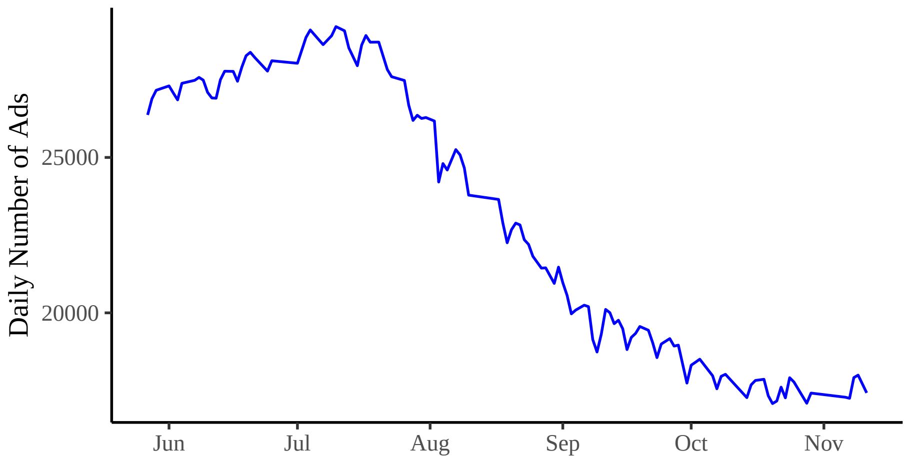


Figure 3: **Share of discrimination by neighbourhoods on the first and last days of the observational period**

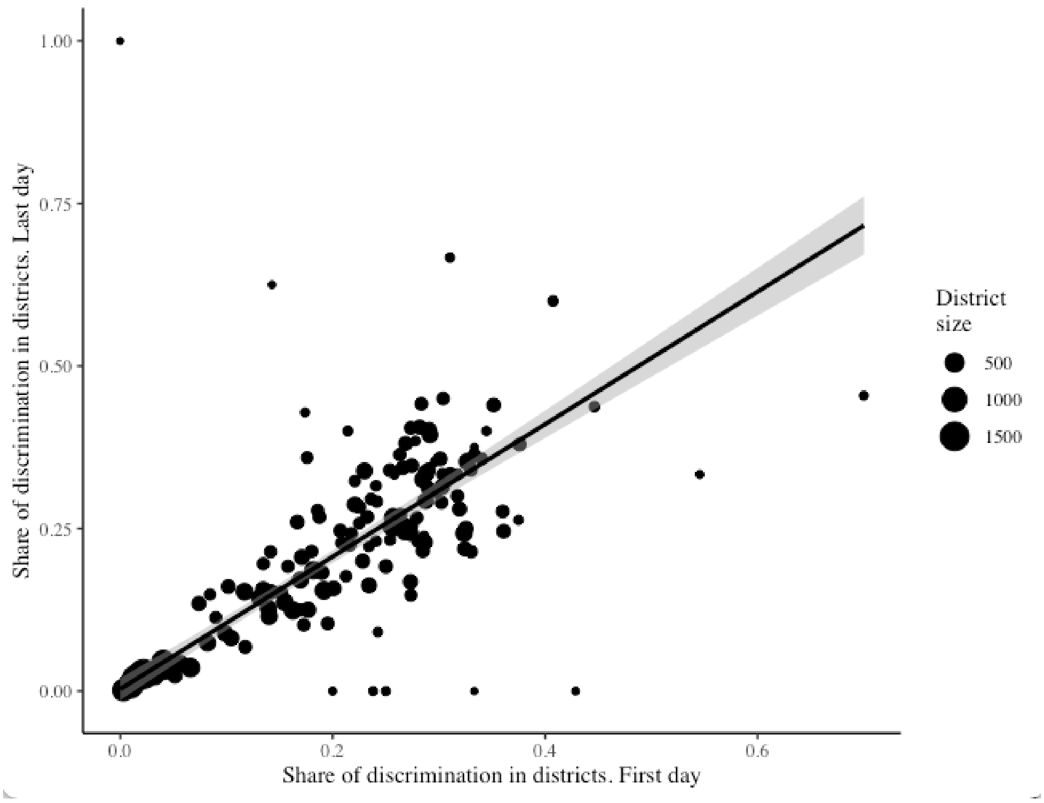
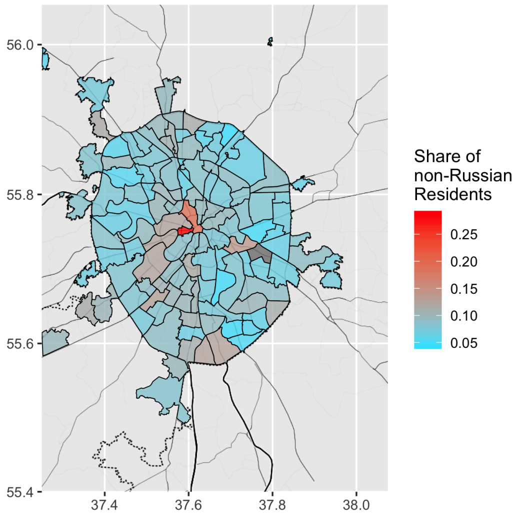
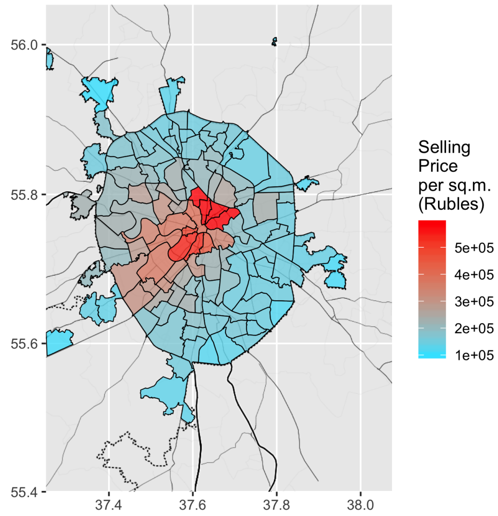


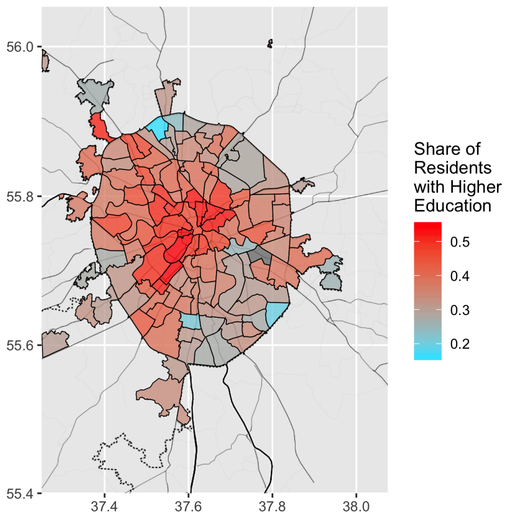
Figure 4: **Characteristics of districts (*raions*)**



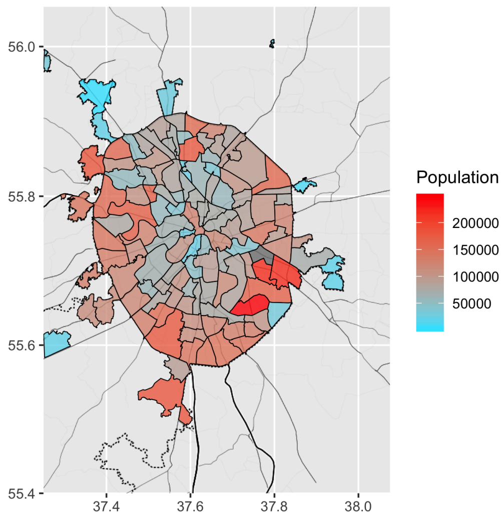
(a) Share of Non-Russian Residents



(b) Rent Price per sq. m.

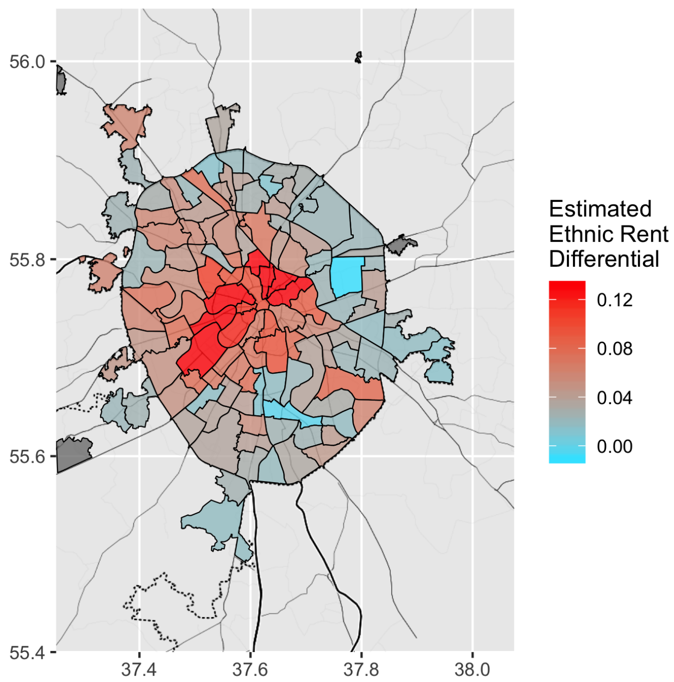


(c) Share of Residents with Higher Education



(d) Population (thousands)

Figure 5: **Cost of discrimination by Subdistricts**



5 Tables

Table 1: **Descriptive statistics**

Panel A. Apartments exposed during the observation period	Obs	Mean	Std. Dev	Min	Max
Price (rubles)	213,057	72,190	92,962	14,500	1,024,106
Kitchen area (sq.m.)	207,371	10.27	5.42	1	160
Living area (sq.m.)	213,057	38.14	27.58	.9	450
Total area (sq.m.)	213,057	62.65	41.00	10	500
Floor number	213,037	7.06	5.74	1	85
Days in exposure	213,057	18.48	29.76	0	168
Length of text (symbols)	213,057	800.19	527.51	52	3743
Number of photos	206,439	12.09	7.59	0	50
Declare descrimination	213,057	.20	.40	0	1
Declare inclusivity	213,057	.005	.07	0	1
Panel B. Buildings' characteristics					
Number of floors	28,597	10.27	5.42	1	160
Distance to city center (km)	26,849	11.59	5.85	.24	59.80
Distance to closest metro (km)	24,658	1.36	2.21	.005	55.89
Share of discriminating apartments	28,597	.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: Cost of discrimination (average)

	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)
Observations	146,684	139,964	139,965	139,967
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
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Extended table B.1 in Appendix

Table 3: Network effect: Cost of Discrimination and Share of Surrounding Discrimination

	Dependent variable: 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)
Observations	146,684	146,684	146,684	146,684
R-squared	0.952	0.952	0.953	0.953
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Extended table B.2 in Appendix

Table 4: Heterogeneity analysis: other variables

	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	146,684	141,483	143,170	141,483
Building FE	Yes	Yes	Yes	Yes
Controls	Yes	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 5: Experiment 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	0.0954	0.2450*	-0.0265
	[0.091]	[0.131]	[0.130]
Text dummy	0.3222***	0.3576***	0.3538***
	[0.043]	[0.070]	[0.061]
Price (log)	0.8338***	0.8801***	0.4360*
	[0.155]	[0.228]	[0.241]
Total area (log	-0.3950*	-0.4686	-0.4626
	[0.214]	[0.300]	[0.331]
Length of text (log)	0.0483	0.1105	0.0269
	[0.070]	[0.094]	[0.120]
Ground floor	0.1286	0.5336**	-0.1616
	[0.161]	[0.264]	[0.228]
Last floor	-0.3490**	-0.9818***	-0.0511
	[0.165]	[0.259]	[0.209]
Observations	874	444	430

Note: Each column gives the results of a probit regression where the dependent variable is the answer dummy. Robust standard errors in parenthesis.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Experiment 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	0.0954	0.2450*	-0.0265
	[0.091]	[0.131]	[0.130]
Text dummy	0.3222***	0.3576***	0.3538***
	[0.043]	[0.070]	[0.061]
Price (log)	0.8338***	0.8801***	0.4360*
	[0.155]	[0.228]	[0.241]
Total area (log	-0.3950*	-0.4686	-0.4626
	[0.214]	[0.300]	[0.331]
Length of text (log)	0.0483	0.1105	0.0269
	[0.070]	[0.094]	[0.120]
Ground floor	0.1286	0.5336**	-0.1616
	[0.161]	[0.264]	[0.228]
Last floor	-0.3490**	-0.9818***	-0.0511
	[0.165]	[0.259]	[0.209]
Observations	874	444	430

Note: Each column gives the results of a probit regression where the dependent variable is the answer dummy. 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.[13] 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.

[13] 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.[14] 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

[14] 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.

A.5 Results of experiment

Table 6 presents results of experiment. Each column gives the results of a probit regression where the dependent variable is the answer dummy. It can be seen that applicants with non-Russian sounding names have significantly lower probability to receive benevolent response from apartments' accounts with discrimination in ads: 40 percent less likely on average. At the same time, there is no such effect for Russian sounding names. However, applicants with non-Russian names are also less likely to receive a response from the landlords without discrimination in the ads.

B Appendix: Empirics

Table B.1: Cost of discrimination: Fixed Effects by Buildings, Subdisctrics and Districs

	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	146,684	139,964	139,965	139,967
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

Short table 2 in body of the text

C Appendix: Theory

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

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

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

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

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:

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

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 there is always one solution for $p_{nd}, p_d > 0$ and for any values of system parameters $p_{nd} - p_d > 0$.

Table B.2: Network effect: Cost of Discrimination and Surrounding Discrimination

	Dependent variable: Logarithm of rent price					
	(1)	(2)	(3)	(4)	(5)	(6)
Discrimination dummy	-0.0409***	-0.0488***	-0.1009***	-0.1030***	0.6272***	0.4443***
	[0.001]	[0.002]	[0.006]	[0.007]	[0.080]	[0.112]
Discrimination dummy × *Share of discrimination in building*		0.0339***			0.0199***	
		[0.007]			[0.007]	
Discrimination dummy × *Share of discrimination in subdistrict*			0.2463***			0.0802**
			[0.022]			[0.038]
Discrimination dummy × *Share of discrimination in district*				0.2660***		
				[0.029]		
Discrimination dummy × *Share of non-russian residents in district*					-0.0513	-0.0565
					[0.064]	[0.071]
Discrimination dummy × *District average apartment selling price*					-0.0650***	-0.0479***
					[0.006]	[0.009]
Discrimination dummy × *District average population density*					0.0114***	0.0077***
					[0.003]	[0.003]
Discrimination dummy × *District share of residents with higher education*					0.0299	0.0234
					[0.027]	[0.025]
Observations	146,684	146,684	146,684	146,684	130,321	141,483
R-squared	0.952	0.952	0.953	0.953	0.953	0.953
Building FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample consists of all ads posted on the web-site during the observation period. Controls for characteristics of apartments and buildings are used in each regression. Standard errors are clustered on the level of buildings. Standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1

Short table 4 in body of the text

Table B.3: 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Short table **??** *in body of the text*

Table B.4: Network effect 2: Cost of Discrimination and Number of Days in Exposure

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

Basic search time effect in table **??** *in body of the text*

Table B.5: Cost of discrimination Interacted on Share of Surrounding Discrimination by Subsamples

	Dependent variable: Logarithm of rent price Subsamples based on subdistricts characteristics:					
	(1) Education below median	(2) Education above median	(3) Share of non-Russians below median	(4) Share of non-Russians above median	(5) Selling price below median	(6) Selling price above median
Discrimination dummy	-0.0404***	-0.0617***	-0.0451***	-0.0548***	-0.0310***	-0.0713***
	[0.002]	[0.004]	[0.003]	[0.003]	[0.002]	[0.004]
Discrimination dummy × *Share of discrimination in building*	0.0172**	0.0489***	0.0281***	0.0388***	-0.0004	0.0598***
	[0.008]	[0.013]	[0.009]	[0.011]	[0.007]	[0.014]
Observations	70,163	71,187	70,408	71,039	71,465	75,154
R-squared	0.891	0.953	0.924	0.959	0.832	0.949
Building FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each observation is ad from the web-site *Cian* on the day before offer closed. The sample consists of all ads posted on the web-site during the observation period. The dummy for discrimination was coded using *Dictionary 1*. Controls for characterstics of apartments and buildings are used in each regression. Standard errors are clustered on the level of buildings. Standard errors in brackets.

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

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