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ABSTRACT

Employment Discrimination in a Former Soviet Union Republic: Evidence from a Field Experiment*

We provide the first experimental evidence about ethnic discrimination in the labor market in Georgia. We randomly assign Georgian and non-Georgian, male and female, names to similar resumes and apply for jobs as advertised in help-wanted web sites in Georgia. We find that gender has no effect on the probability of callback, but a job applicant who is ethnic Georgian is twice more likely to be called for a job interview than an equally skilled ethnic non-Georgian (Azeri or Armenian). The almost 100% gap in callbacks is statistically significant and cannot be abridged by having more experience or education. Both taste-based discrimination and statistical discrimination models are consistent with the evidence provided in this study. Labor market discrimination tends to aggravate in economic busts.

JEL Classification: J15, J71, C93, P23

Keywords: employment discrimination, field experiment, former Soviet Union, business cycles

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I. Introduction

Beyond the social and societal damage it inflicts, labor market discrimination, inasmuch as it implies a misallocation of resources, inhibits the productivity, income, and growth of the country. These effects are more remarkable when the country in question is a small transition, developing country like Georgia. Despite them comprising a large share of the population, little is being done to integrate the ethnic minorities living in Georgia into civic life; and discrimination in the labor market contributes to the persistence of this exclusion from the social, economic, and political life.

We study the incidence of discrimination in the Georgian labor market of higher-level jobs, using a similar experimental design that was devised by Bertrand and Mullainathan (2004). In particular, we create a bank of fictitious resumes, to which we randomly assign names of Georgian and non-Georgian (Azeri and Armenian), male and female, job applicants.[1] Using these resumes, we then apply for jobs that are posted on the most popular employment services web sites in Georgia, and record the outcome of each application, whether the applicant received a callback for an interview or not. 550 jobs received a full set of 4-resumes each, resulting in our sample of 2200 job applications.[2] We then analyze the employers' response data to uncover any patterns in the data, and learn about any preferential treatment of different ethnicities or genders in the hiring context which, if exists, is taken as an evidence of labor market discrimination against the group in question.

The seminal work of Bertrand and Mullainathan (2004), carrying out a field experiment to study the effect of discrimination in the U.S. labor market, initiated a wave of similar studies in different countries, for example: Arceo-Gomez and Campos-Vazquez (2014) for Mexico; Kaas and Manger (2012) for Germany; Banerjee et al (2009) for India; Carlsson and Rooth (2007) for Sweden, to name just a few of the recent examples. To the best of our knowledge, this is the first study of this type conducted for a Former Soviet Union

[1] There are other small ethnic minorities in Georgia, but we limit our attention to the largest and distinct ethnic minorities in the country, namely, Armenian and Azeri, who constituted about 12.2% of the population, according to the population census of 2002. This went down to around 11% in 2014, but remained the largest combined minority group; Russians constituted the next largest minority in Georgia, amounting to only 0.7% of the population.

[2] Originally, we had 2208 applications, but we excluded from the analysis all the firms that did not receive a full set of applications (one for each gender-ethnicity combination).

Country. Also, it is one of the rare such studies in a transition context. Baert (2017) provides an extensive list of all correspondence studies since 2005, aimed at evaluating hiring discrimination in the labor market. In this list, the only representation of such studies for transition countries is a study for Poland (Wysienska and Karpinski, 2014), a study for the Czech republic (Bartos et al., 2016), and a couple of studies for China (Maurer-Fazio, 2012; Zhou et al., 2013; Maurer-Fazio and Lei, 2015). Nevertheless, none of these studies is as comprehensive in terms of the dimensions of discrimination measured (across multiple ethnic groups, and across genders) or in terms of the time span studied.

The current study contributes to this literature in different ways. First, we study simultaneous ethnic and gender discrimination in a former Soviet Union labor market, that was not explored before. Georgia is an interesting case to study, because of its exceptional labor market environment. A Former Soviet Union Country, Georgia adopted in 2006 a new liberal Labor Code that eliminated Soviet-era burdens on the freedom to contract and made the cost of employing workers very low. Mandatory minimum wage requirements were kept so low to be clearly not binding[3] and no obligatory overtime costs were implied.[4] At the same time, while the Labor Code explicitly forbids "discrimination of any kind […] during labor relations,"[5] multiple sources confirm the lack of enforcement of such provision.[6] Thus, it is interesting to compare the results obtained in this study with the results from relatively more regulated labor markets, such as the US, Sweden, Germany, and other European countries, as well as from developing countries like India, Mexico, and China.

Second, since the study spans over the whole year, we can relate to the relationship between unemployment and discrimination. Third, along with our experimental data, we use existing household survey data to both explore the representativeness of the experimental sample, and thus the external validity of the results based on its analysis, and to point out directions in which existing observational survey data can be used

[3] The mandatory minimum wage does exist but it is as if it didn't – 20 GEL (less than 8 USD) per month for private employees and 115 GEL (43 USD) for public employees (the subsistence level in 2016 for an "average consumer" was 142 GEL).
[4] Even if the 2006 Labor Code did mention the existence of overtime, it also stated that the "Terms of the overtime labor are defined upon consent of the parties." The current provision is not very different: "Overtime work shall be compensated by the hour based on increased pay rate. The amount of the above compensation shall be determined by agreement between the parties." (Labor Code of Georgia, 2013 - article 17).
[5] Article 2 comma 3. Labor code of Georgia, 2013.
[6] http://www.state.gov/j/drl/rls/hrrpt/humanrightsreport/index.htm?year=2015&dlid=252849 (last accessed 1.2.2017)

for causal inference.

We find extremely large ethnic differences in callback rates, larger than any such gap observed in the previous studies, in all the countries. In particular, ethnic Georgian job applicants, whether males or females, receive about 100% more callbacks than their non-ethnic-Georgian (henceforth non-Georgians) counterparts. To receive one callback, a non-Georgian applicant needs to send 16 job applications, whereas a Georgian applicant needs to send only about 7 applications.

This stark difference is highly statistically significant, and cannot be abridged by improvement in human capital variables like experience or education; because, once accounted for ethnicity, no other variable or credential has any statistically significant effect on the likelihood of a callback. Ethnicity is the single most important variable in hiring decisions—rendering both statistical discrimination models and taste-based employer discrimination models equally suitable for explaining the causes of the callback gap.[7]

Within the non-Georgian ethnic group, that is between Armenian and Azeri applicants, there is no evidence of discrimination in hiring. Discrimination in hiring in the Georgian labor market does not seem to be motivated by gender, either. In fact, within each ethnicity, female applicants apparently receive more callbacks per application than male applicants—but this difference is not statistically significant. Also, we note that during economic busts employers are reluctant to hire new staff, but more so for non-Georgian job applicants, resulting in higher discrimination rates during high-unemployment periods. When unemployment increases by 1% the gap in the probability of a callback between Georgians and non-Georgians increases by 0.02.

Notwithstanding the clear and significant findings, it is important to note that our experimental data suffer from the same weaknesses acknowledged in this literature, first by Bertrand and Mullainathan (2004), like the use of ethnic-sounding names rather than actual ethnicity input, using a callback in lieu of a real job offer or wage per offer, and using a specific channel for job ads can be limiting.

[7] Baert and De Pauw (2014) showed, in a vignette experiment, that ethnic hiring discrimination might be motivated by worker-induced or customer-induced taste-based discrimination.

The rest of the paper is organized as follows. In section II we describe the data collection procedure and steps, as well as the experimental and research design. In section III we report the main results of the study, and relate to different related issues like using observational survey data to study similar questions, and studying the relationship between the macro economy and ethnic discrimination. Section IV concludes.

II. Research Design and Data

We use experimental design to study the hiring decisions of employers inasmuch as that is affected by the ethnic background of job seekers. Experimental design, in particular correspondence testing, cannot be utilized in all the sectors of the Georgian labor market, because workers' recruitment procedures are different across sectors, and not all are susceptible of a formal application by correspondence. In most blue-collar positions, for example, workers are recruited through the social network, by asking friends and relatives, rather than by sending resumes; or, otherwise, interested candidates are advised to visit the potential employer in-person. It is, therefore, important to identify the sectors to which job applications and resumes are to be sent.

To facilitate the implementation of the correspondence testing, therefore, and since the opportunity cost of discrimination in hiring is larger in higher-level jobs, we direct our attention to this type of jobs. In low-skill jobs, on the other hand, prejudice (and asymmetric information) play no major role. Furthermore, unemployment does not seem to differ in this type of jobs by gender or ethnicity, so it is less of a concern in low-skill jobs. For all these reasons, focusing on the higher-level jobs is both interesting and important.

It is of no consequence, however, to the particular choice of a specific sector. After all, we cover a wide array of industry types which includes, among others: administrative, financial, technical, and sales jobs. Moreover, the Georgian context is suitable for this kind of experimental design as far as a sophisticated short-listing software has not been implemented, which would not allow for controlling the ethnicity and gender of the candidate.

For the sake of concreteness and simplicity we limit ourselves to two groups of ethnic minorities, Azeri and

Armenians, which are the biggest ethnic minority groups in Georgia (6.5% and 5.7%, respectively)[8] and have easily recognizable last names, which sound completely different from Georgian. Rather than sending two different quality resumes,[9] we send only normal quality, four similar in qualifications resumes, assigning them ethnic Georgian and ethnic minority sounding names and gender. For the same reason, we also reply to the openings only in the capital of Georgia, Tbilisi, to avoid the geographic heterogeneity of discrimination. It is not a major limitation as far as the vast majority of the vacancies announced is based in the capital city.

Internet-based job-posting agencies are the main source of employment ads we use in our study. The most popular web sites where higher level job openings are announced are: www.jobs.ge and www.hr.com.ge.

We build a bank of fictitious resumes, using the resumes of real applicants, after changing the names and modifying different components to match some of the job requirements as listed in the employment ads. The slight changes we introduce, moreover, serve to rule out identification of real applicants.

A. Detailed Data Collection Procedure

After the job opening being announced we prepare the relevant set of four resumes, initially creating the new ones, but subsequently drawing from the resumes previously created for similar announcement and slightly altering it. Then we randomly assign ethnic Georgian and ethnic minority sounding last names and female and male specific names to resumes. The names are drawn from the pool of the names and surnames created in advance from the actual election voters list for 2008. We also include real email address and mobile number, different for two ethnic groups and gender and send to the designated email address. In case we receive the call backs on either phone number, we make sure to identify the vacancy we are called back for, the company and politely refuse the offer.

When applying for the announced job opening we create a detailed database of the vacancies we are applying for such as: type of the company, industry, ownership of the company (foreign or domestic), position and detailed requirements of the opening on the one hand and on the other hand we also create the database of the

[8] The population census of 2002, National Statistics Office of Georgia.
[9] As in Bertrand and Mullainathan (2004).

applicants and their characteristics and qualifications including age, gender, type and years of education, experience, computer skills.

B. Data Collection (March 2009 to February 2010)

We start replying to vacancies in March 2009. We continue this process, on a monthly basis, until February 2010. Overall, we reply to 552 job announcements.[10] In Table 1 we report the number of vacancies listed in the aforementioned sites, as well as the number of resumes we sent and the number of callbacks we received, for each month of the study period.

[TABLE 1]

The vast majority of the companies are private (87.5%), domestic (58.7%) firms. We divide the companies in five industries: Financial, which includes banks, insurance companies, accounting and other financial institutions; Marketing includes sales, distribution, market research and analysis, etc.; Service sector includes all other services, such as hotels, cleaning, hospitals, educational entities, etc.; Production, which is small part of the all companies, includes wine producing firms, pharmaceutical companies, bakeries, etc. The last smallest group includes some miscellaneous companies that do not fall under any categories described above.

Positions announced are also divided into five occupations: Financial, that includes accountants, finance managers, finance assistants, loan experts, etc.; Administrative, such as office managers, assistants, general managers, etc.; Information Technology occupations; Marketing, which includes sales managers, sales workers, researchers, distributors, etc.; Other includes miscellaneous occupations.

C. Econometric set-up

Researchers generally use a simple probit model for estimating the effect of different variables on the probability of callbacks (e.g., Bertrand and Mullainathan, 2004, and similar studies that followed). We,

[10] However, we limit our analysis to 550 job advertisements, that each of which received a full set of applications (four applications: male and female Georgian, and male and female non-Georgian). Including the other two employment ads in the analysis has virtually no effect on the results.

however, use a complementary log-log model to study the effect of ethnicity, as well as applicant and job characteristics, on the probability of receiving a callback. The complimentary log-log analysis is different from traditional probit and logit models in the sense that transformation is not symmetric (it approaches zero slowly, and one fast), thus it is more appropriate in cases where the positive outcome is relatively rare, as is the case in our study. The model we estimate is:

$$\Pr\left(Callback_{ijr} = 1 \middle| X_{ijr}\right) = 1 - \exp\left[-\exp\left(X_{ijr}\beta + \varepsilon_{ijr}\right)\right],$$

where X_{ijr} is the vector of control variables as well as ethnicity, this being Georgian and Armenian (the omitted group is Azeri), of individual i who is applying to job j with job requirements r. The list of individual controls includes: age, experience, squared experience, education, foreign experience, gender, a dummy for being ethnic Georgian, and a dummy for being ethnic Armenian.

The controls for job characteristics include: one-digit industry affiliation, one-digit occupational affiliation, whether the firm is private (as opposed to the public sector), whether it is domestic (as opposed to multinational corporations), and whether it is an NGO. The vector of control variables for job requirements include: whether a foreign language is required, the number of years of experience required, the minimal educational level required, the requirement of technical skills, and the requirements of other skills. The list of job characteristics and requirements is taken from the vacancy announcement.

III. Empirical Findings

A. Main Results

We calculate the percent of callbacks among the different ethnic groups: ethnic Georgians (GE), Armenians (AM), and Azeri (AZ). Defining the combined groups of Armenians and Azeri applicants as "non-Georgians" (NGE), we also calculate the difference in callback rates between Georgians and non-Georgians, as well as within the non-Georgian group (i.e., between Armenians and Azeri). We carry out this analysis for the whole sample of applicants as well as for subgroups defined by age (as old workers, aged 27 or older), by experience (experienced being with 4 or more years of experience), by education (high education defined as holding two master's level degrees or a PhD degree), and by gender. Table 2 reports the results from this analysis.

[TABLE 2]

As is clear from the table, the rate of callbacks for Georgians is more than twice that of either the Armenian or the Azeri (or the whole non-Georgian group combined). In the whole sample, Georgians receive 7.1% more callbacks than non-Georgians, and this difference is statistically significant at all conventional levels. The rate of callbacks is similar between the Armenians and the Azeri in the overall sample: 6.2-6.3%: the difference between these is 0.15% and is not statistically different from zero.

The same picture arises from inspecting the subgroups by age, experience, education, or gender, as shown in the rows 2-6 of the table. For example, older Georgian applicants receive 11.4% callbacks, which is 7.5% higher than the callback rate among older non-Georgian applicants. The difference between callback rates of older Armenian applicants (4.8%) and older Azeri applicants (3.6%) is 1.2% which is statistically not different from zero. Other examples include the highly-educated applicants (with a statistically significant 7.2% difference in callback rates between Georgians and non-Georgians, yet an insignificant difference between callbacks for Armenian and Azeri applicants).

The unconditional estimates in the table provide a first evidence about the discrimination in hiring in Georgia, inflicted by Georgian employers against non-Georgian ethnic groups. The results also imply that this type of blatant discrimination is not limited to a particular demographic group, but is experienced equally among the young and old, the experienced and inexperienced, the more and less educated, and males and females.

Inspecting the distribution of callbacks by job advertisements, rather than by individual applicants, it is possible to distinguish between cases of equal treatment, preferential Georgian treatment, and preferential non-Georgian treatment. Because we can observe the reaction at the employer level, we can count the total number of callbacks to Georgians (G) and that to non-Georgians (N) at the job ad level. Since each employer received four applications (from a supposedly male-Georgian, female-Georgian, male non-Georgian, and female non-Georgian), the possible combinations of callbacks are: zero callbacks to Georgians and zero callbacks to non-

Georgians (“0G+0N”), 1G+1N, 2G+2N—cases referred to as “equal treatment” because Georgians and non-Georgians receive the same number of callbacks; 1G+0N, 2G+0N, 2G+1N—where Georgians are favored, and 1N+0G, 2N+0G, and 2N+1G—where non-Georgians are favored.

Table 3 shows the distribution of callbacks by job ad. It shows the percentage and number of jobs in each category, listing them under equal treatment, Georgians favored, and non-Georgians favored. Following the Urban Institute terminology (Fix, Michael and Struyk, 1993),[11] net ethnic discrimination is defined as the ratio between net Georgian-favored cases to all cases, where net Georgian-favored cases is the difference between Georgian-favored (GF) cases and non-Georgian-favored (NGF) cases: $GF - NGF$; and where “all cases” includes all job ads applied to, even those with no callback at all (0G+0N), here 550 job ads of which 422 cases without any callback. The International Labor Organization (ILO) defines net ethnic discrimination similarly except for the base denominator which excludes the no-callback cases (0G+0N) (Bovenkerk F., 1992, cited in Cediey, E. and Foroni, F. 2008).

The ILO definition of net discrimination excludes the no-callback cases on the grounds that the employers in these cases might have never received the applications in the first place, rather than practicing equal treatment (by equally not replying to all applicants). This definition, therefore, brings about a higher bound estimate of net discrimination. These measures, as well as a test for the null hypothesis that the proportion of Georgians favored equals that of non-Georgians favored, are all reported in Table 3.

[TABLE 3]

If the no-callback cases are included, we see that 83.5% of all employers practiced equal treatment (76.7% with no callback to either group, 5.1% with one callback for a Georgian and one callback for a non-Georgian, and 1.6% with two callbacks for Georgians and two callbacks for non-Georgians). As Bertrand and Mullainathan (2004) and following similar studies found, most of the equal-treatment cases (91.9%) stem from the no-callbacks records.

[11] As cited in http://www.urban.org/research/data-methods/data-analysis/quantitative-data-analysis/impact-analysis/paired-testing (accessed 1.12.2016)

Of all the employers in the sample, 14.6% favored Georgians (calling them back for an interview more than their non-Georgian counterparts), and 2% favored non-Georgians. Therefore, the net discrimination is estimated at 12.6% (14.6%-2%). Following the ILO definition of net discrimination, excluding the 0G+0N cases, the measure of net discrimination is:

$$ILO\ net\ disc. = \frac{GF - NGF}{at\ least\ one\ response\ cases} = \frac{80 - 11}{550 - 422} = 53.9\%$$

The evidence brought here, at the employment ad level, supports the findings at the individual applicant level: Georgians receive more opportunities for employment than their non-Georgian fellows, and the difference is starker when measured within, rather than across, employers.

Resume Characteristics, Job Characteristics, and Job Requirements

The evidence brought so far established the existence of a large gap in callbacks between Georgians and non-Georgians, albeit within the non-Georgian group there was no evidence of such gap. The large ethnic gap is a clear sign of discrimination at the hiring stage, and can be taken as the reason or the sign for the actual labor market discrimination, observed both in employment and earnings.

The mentioned gap refers to the unconditional gross gap in callbacks. To show whether the callback rates respond to applicant characteristics (age, experience, and education), and whether it changes with job type and characteristics (industry, occupation, private, domestic, etc…) or with the job requirements as listed in the employment ads, we now study the conditional callback rates. Table 4 lists the averages of resume characteristics by gender and ethnic background.

[TABLE 4]

The table shows that the applicant characteristics are comparable and similarly distributed across the four types of applications (Georgian male applicants, Georgian females, non-Georgian males, and non-Georgian females). For example, the average age in the overall sample is 26.6, and it is 26.8, 26.1, 26.9, and 26.5 in the four groups, respectively. Likewise, the average experience lies between 4.2-4.8. Foreign experience or education, and educational levels are identically distributed.

Table 5 shows the main estimation results of this study. In particular, it shows the marginal effects of the different control variables (applicant characteristics, job characteristics, and job requirements) as well as of ethnicity (Georgian and Armenian, versus the Azeri as the omitted group) on the probability of receiving a callback. The marginal effects were calculated from an underlying complementary log-log model, with robust standard errors that are clustered at the job ad level.

[TABLE 5]

Column (1) of Table 5, reports the marginal effects of ethnicity on the probability of callbacks, controlling for gender. Georgians, as shown in the table, are 7% more likely to receive a callback than Azeri or Armenian applicants. This substantial gap is economically and statistically significant. Females, within each ethnic group, are equally likely to receive a callback as male applicants.

The second column controls for applicant characteristics, like age, experience, and education. None of these characteristics has any effect on the probability of callback: the only difference in callbacks stems from being Georgian as opposed to being non-Georgian (whether Azeri or Armenian). The conditional callback differential is 6% and is highly statistically significant at all conventional levels. It is apparent also here that being female does not have any effect on the probability of receiving a callback.

The third and fourth columns of the table add controls for job characteristics and job requirements, respectively, as shown in the table. The conditional difference in callbacks between Georgians and non-Georgians is hardly changed by adding the control variables, and is estimated at the level of 6.2-6.3%.[12]

A 6.2% ethnic differential in callback means that a job applicant with a non-Georgian name would need to send 98.4% more applications to get the same number of callbacks as a Georgian-name applicant. Whereas a Georgian applicant needs to send about 8 applications to get one callback, a non-Georgian needs to send 16

[12] There is a group of discrimination studies that focus on labor market segmentation caused by educational choices. See Asali (2010) to see how we measure such discrimination that is attributable to occupational segregation. However, in our study there is no evidence for such type of discrimination.

applications. This 98.4% gap in callback is statistically significant and, in terms of magnitude, is economically significant, and substantially larger than all such gaps found in the previous studies that we are aware of (for a wide range of countries and races and ethnicities), with the exception of the gap found in China by Maurer-Fazio (2012) for women of Tibetan ethnicity (with respect to women of Han ethnicity), exceeding 120% (Table A1).

The gap is more remarkable in light of the fact that human capital characteristics of the applicants are found to have no effect on the probability of callback. That is, there is no enough years of experience or enough years of education that can compensate for the ethnic differential in callbacks. Try as they may, non-Georgian applicants will not be able to match the callback rate of their Georgian counterparts.

The striking result here is not only the significant and stable preferential treatment of Georgians overall, but the fact that once the employer knows the ethnicity of the applicant he or she does not look further at the applicants' qualifications and background—these have no effect whatsoever on the probability of being called back.[13] Put simply, the single most important variable in hiring decisions in Georgia is ethnicity.

B. Results from Observational Data

To evaluate the representativeness of our experimental sample—and thus the external validity of our results, as well as to test the implication of using observational data in estimation, we pooled the Integrated Household Surveys of Georgia (collected and maintained by GEO-STAT: the statistical office of Georgia) of two years: 2009 and 2010. We then restricted the sample to Georgians, Azeri, and Armenians, aged 23-32, with higher education, to match the selection criteria in our experiment.[14]

Table 6 shows the summary statistics of the demographic variables which are the counterparts of the variables

[13] We also estimated similar models with job applicants' characteristics as controls, separately for Georgians and non-Georgians (tables not shown but available upon request). According to these results the coefficients of resume characteristics are not statistically different between Georgians and non-Georgians. Also, the firm being domestic having a positive effect (only once significant) is related to the issue of workers' competition for jobs at multinational corporations (see Asali et al. 2016, for a discussion).

[14] We analyze the household survey data from all regions, not only Tbilisi. The sample size of observations from Tbilisi only is too small to warrant precise estimation of the complementary log-log model; notwithstanding, the summary statistics of the subsample of Tbilisi are very similar to those from the general sample.

devised in our experiment. Comparing the averages of each of these variables from the national data (Table 6) with the averages of the equivalent variables from our study (Table 4), we observe that the averages almost completely coincide with each other, lending support to the representativeness of our sample, as well as to the external validity of the analysis results based on these data.

[TABLE 6]

While it is impossible to replicate the analysis using data from the readily available household surveys, because there is no data about job search activities—in particular, no data about "callbacks" after job applications, it is still possible to carry out a closely related exercise. Namely, we carry out similar analysis using the household data, but replacing the dependent variable of "callbacks" with the actual variable of being "employed," defined as a worker with positive income from hired work. Table 7 reports the results from this analysis.

[TABLE 7]

As is expected from observational data, the causal effects of the different variables would be biased unless one controls for all potential, relevant variables. Hence, column (1) of the table, where we calculate the marginal effects from a complementary log-log model of employment against female, Georgian, and Armenian, without controlling for any additional variable, indeed reports a huge estimate of favoritism towards Georgians (about 30% more likely to be employed than Azeri); it also reports a large estimate of favoritism towards Armenians as opposed to Azeri (26.5%), and these effects are highly statistically significant.

Controlling for some demographic variables, like age and experience, as shown in column (2), does not ameliorate the bias—it still reports a large and significant favoritism factor for Georgians and Armenians, similar to column (1). Controlling for occupational and industrial affiliation, however, pulls the estimates to the ballpark of the experimental estimates both qualitatively and quantitatively. In particular, Georgians are shown to enjoy a higher probability of being employed (11.4%) than Azeri, and Armenians are equally employable to Azeri, and experience no favoritism.

These findings match what we found for callbacks in our experimental study, although the effect for Georgians is slightly exaggerated. Not only findings from the two exercises (using experimental data as opposed to using observational survey data) support each other, but their similarity is reassuring, as it invalidates the claims about observational data being futile for causal inference. If used correctly, observational data can still help us learn about and answer important questions, even if not perfectly precisely.

C. Macroeconomic trends and discrimination

Unlike other similar studies, our experiment has a longitudinal virtue: rather than being a one-shot experiment, it is an exercise that spans twelve months. This fact can be used to study the relationship between the overall healthiness of the economy, measured by unemployment, and the extent of discrimination in hiring as measured in this study.

To do that, we estimate the difference in the probability of a callback between Georgians and non-Georgians, controlling for the applicants' characteristics—similar to the coefficient of Georgian in column (2) of Table 5—separately for each month in the study period. This is our measure of discrimination in hiring; call it ΔP=Pr(callback|X,G)-Pr(callback|X,NG). We then estimate the following equation:

$$\Delta P_t = \alpha + \beta U_{t-1} + \gamma_1 t + \gamma_2 t^2 + e_t$$

where ΔP_t is the coefficient of the Georgian dummy estimated from a linear probability model of callbacks against a Georgian dummy and a set of applicant characteristics (like age, experience, and education), in month t, where $t = 3/2009, \dots, 2/2010$; and U_{t-1} is the unemployment rate in the previous month. Quadratic time trend is added to control for variables that change with time and affect both the unemployment rate and hiring differentials.

It is worth emphasizing that statistical inference form this estimation is limited, given the small sample (we have only twelve observations to run this regression); also due to the fact that ΔP is itself estimated rather than given. This estimation provides at best a suggestive correlational interpretation rather than a decisive causal one. That said, the result of this estimation is $\hat{\beta} = 1.92$ ($R^2 = .56$).

This result simply means that unemployment is positively correlated with ethnic discrimination in hiring. The increase in unemployment reduces the number of callbacks (employers are more reluctant to hire new staff) but more so for non-Georgians. A 1% increase in (absolute) unemployment increases the ethnic gap in the probability of callback by 0.02. (Given an average differential in the probability of callback of 0.058 and an average unemployment rate of 16.2%, this implies an elasticity of discrimination with respect to unemployment of 0.5.)

IV. Conclusions

This paper is the first using an experimental design similar to that devised by Bertrand and Mullainathan (2004) to document the existence and the extent of ethnic-based discrimination in the Former Soviet Union. Our analysis provides robust evidence about the discriminatory treatment that non-ethnic-Georgian job searchers face in the hiring process. This may well explain their observed lower employment rate in the labor market. We find that Georgians are twice more likely to receive a callback for their job application than a non-Georgian applicant. Whereas a Georgian applicant needs to send 7 applicants to receive one callback, a non-Georgian applicant needs to send out 16 applications.

Gender does not play a clear role in the issue of discrimination in hiring in Georgia. Also, while the inter-ethnic difference in callback rates is strikingly large, there is no evidence for intra-ethnic callback differentials—Georgian citizens of Azeri or Armenian ethnic background are treated similarly.

The single most important variable that employers consider in hiring is ethnicity. Apparently, they decide whether or not to hire the applicant only based on his or her ethnicity. Since the applicants' credentials do not matter for the hiring decision, we conclude that statistical discrimination models (due to asymmetric information) and taste-based discrimination models (due to employers' preferences) are equally likely explanations for the source and causes of discrimination. We finally note that differentials in callbacks, and thus discrimination, tend to increase during economic busts.

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TABLES:

Table 1: Distribution of Job Posts, Sent Resumes, and Callbacks, by Month.

Month	3/2009	4/09	5/09	6/09	7/09	8/09	9/09	10/09	11/09	12/09	1/10	2/10	Total
Posted Vacancies	221	201	204	209	228	211	230	295	261	205	239	241	2745
Sent resumes	340	164	228	180	244	216	220	168	148	56	48	188	2200
Callbacks	33	17	38	21	22	10	17	24	11	2	6	15	216
Callbacks per sent resumes (%)	9.71	10.37	16.67	11.7	9.0	4.6	7.7	14.3	7.4	3.6	12.5	7.9	9.8

Notes: The number of posted vacancies per month is taken from the job advertisements web sites www.jobs.ge and www.hr.com.ge. Originally we sent 2208 job applications/resumes, and received 220 callbacks. However, in our analysis we only used jobs/ads for which a full set of applications was sent: that is, 4 applications; for male-Georgian, for female-Georgian, male-non-Georgian, and female non-Georgian; where non-Georgian can be Armenian or Azeri.

Table 2: Mean Callback Rates by Ethnicity

	Georgian	Armenian	Azeri	% Difference GE-NGE (p-value)	% Difference AM-AZ (p-value)
All	13.36	6.19	6.34	7.09	-.15
	[1100]	[485]	[615]	(0.000)	(0.916)
Old (age>26)	11.38	4.8	3.63	7.45	1.17
	[536]	[125]	[358]	(0.000)	(0.563)
Experienced (exp.>3)	11.82	6.19	8.21	4.82	-2.02
	[660]	[485]	[329]	(0.001)	(0.267)
High Education	11.78	4.17	4.67	7.23	-0.5
	[484]	[120]	[364]	(0.000)	(0.818)
Female	13.64	7.36	7.84	6.00	-0.48
	[550]	[231]	[319]	(0.001)	(0.835)
Male	13.09	5.12	4.73	8.18	0.39
	[550]	[254]	[296]	(0.000)	(0.834)

Notes: Percent of callbacks from the total applications within the cell group. In square brackets are the total numbers of sent resumes within the cell group. The fourth column shows the difference in callback rates between Georgians and non-Georgians, with the p-value of the test of equality in callbacks between Georgians and non-Georgians within the row group. The fifth column shows the difference in callback rates between Armenian and Azeri applicants within the row group, with the p-value of the test of equality of callbacks between these two groups.

Table 3: Distribution of Callbacks by Job Ad

Equal Treatment:	No callback	1G+1N	2G+2N
83.45	76.73	5.09	1.63
[459]	[422]	[28]	[9]
Georgian Favored (GF)	1G+0N	2G+0N	2G+1N
14.55	10.91	1.82	1.82
[80]	[60]	[10]	[10]
Non-Georgians Favored: (NGF)	1N+0G	2N+0G	2N+1G
2.0	1.64	0.18	0.18
[11]	[9]	[1]	[1]
H0: GF=NGF			
p-value=0.0000			
(z=10.23)			
Urban Institute net-discrimination:	12.55%		
ILO net discrimination:	53.91%		

Notes: G refers to Georgian, N refers to Non-Georgian. Main entries are the percentages of the respective cells from the total 550 job ads. 2N+1G refers to the percent of ads for which exactly 2 non-Georgian and 1 Georgian applicants received callbacks. The other cells are defined similarly. In brackets is the number of ads in each cell. Reported also is the test for the null hypothesis that employers who preferred Georgians and those who preferred non-Georgians have done so equally likely. The Urban institute definition of net discrimination is simply the difference between the cases where Georgians were favored and those where non-Georgians were favored, from the total ads (550). The ILO definition excludes the "no-callback cases" (422) altogether, so the difference is divided by a smaller subsample (here 550-422=128).

Table 4: Summary Statistics of Resume Characteristics

		Georgian		Non-Georgian	
	All	Male	Female	Male	Female
Female	0.5				
	(0.5)				
Age	26.60	26.82	26.09	26.96	26.51
	(2.01)	(1.92)	(2.35)	(1.61)	(1.97)
Old (age>26)	0.46	0.39	0.59	0.52	0.36
	(0.5)	(0.49)	(0.49)	(0.5)	(0.48)
Experience	4.56	4.78	4.17	4.68	4.63
	(2.24)	(2.16)	(2.23)	(2.12)	(2.39)
Experienced (exp.>3)	0.67	0.73	0.47	0.74	0.74
	(0.47)	(0.44)	(0.5)	(0.44)	(0.44)
Foreign Exp./Educ.	0.08	0.08	0.08	0.08	0.08
	(0.28)	(0.28)	(0.28)	(0.28)	(0.28)
BA	0.56	0.56	0.56	0.56	0.56
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)
MA or above	0.44	0.44	0.44	0.44	0.44
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)
MA or MBA	0.38	0.44	0.36	0.36	0.36
	(0.48)	(0.5)	(0.48)	(0.48)	(0.48)
MA & MBA, or PhD	0.06	0.00	0.08	0.08	0.08
	(0.24)	(0)	(0.28)	(0.28)	(0.28)
Sample size	2200	550	550	550	550

Notes: Reported are the means and standard deviations for the variables listed in the resumes, decomposed by gender and ethnicity of the applicants. The first column refers to the whole pooled sample of applicants.

Table 5: Complementary log-log regression with callback dummy as dependent variable

Callback	(1)	(2)	(3)	(4)
Female	0.015	-0.000	0.005	0.004
	[0.012]	[0.013]	[0.012]	[0.012]
Georgian ethnicity = 1	0.070***	0.057***	0.063***	0.062***
	[0.015]	[0.017]	[0.017]	[0.016]
Armenian ethnicity = 1	-0.002	-0.010	0.012	0.012
	[0.024]	[0.022]	[0.024]	[0.023]
Applicant Characteristics:				
Age		-0.008	-0.004	-0.006
		[0.006]	[0.006]	[0.006]
Experience		0.008	0.020	0.030
		[0.033]	[0.030]	[0.031]
Experience squared		-0.002	-0.003	-0.003
		[0.003]	[0.002]	[0.003]
Education (MA or MBA)		-0.029	-0.014	0.007
		[0.019]	[0.018]	[0.020]
Education (MA and MBA)		0.079	0.109	0.160
		[0.104]	[0.111]	[0.130]
Education (PhD)		-0.050	-0.025	-0.005
		[0.043]	[0.048]	[0.056]
Foreign experience or education		0.234	0.262	0.254
		[0.261]	[0.275]	[0.279]
Job Characteristics:				
Private			-0.001	-0.000
			[0.036]	[0.032]
Domestic			0.026*	0.020
			[0.015]	[0.016]
NGO			-0.011	-0.007
			[0.036]	[0.036]
Industry and Occupational Dummies	No	No	Yes	Yes
Job requirements	No	No	No	Yes
Observations	2,200	2,200	2,188	2,168

Notes: Each column represents a complementary log-log regression with the callback dummy as dependent variable. Reported are the marginal effects of the relevant variables on the probability of a callback for continuous variables and estimated discrete changes for the dummy variables. Job requirements controls include: required foreign language, required experience in years, dummies for minimum required education (BA, MA, etc...), dummies for technical skills (specific, generic), and dummies for other skills (specific, generic). Robust standard errors, clustered at the employment-ad level, are in brackets.

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

Table 6: Summary Statistics of workers from the Integrated Household Survey National Data (2009-10)

		Georgian		Non-Georgian	
	All	Male	Female	Male	Female
Female	0.53				
	(0.5)				
Age	27.36	27.47	27.27	27.25	27.22
	(2.86)	(2.89)	(2.87)	(2.32)	(2.7)
Old (>26)	0.57	0.59	0.56	0.65	0.58
	(0.49)	(0.49)	(0.5)	(0.48)	(0.5)
Experience	4.77	4.86	4.72	4.35	4.57
	(2.93)	(2.94)	(2.95)	(2.23)	(2.89)
Experienced (>3)	0.62	0.63	0.61	0.66	0.61
	(0.49)	(0.48)	(0.49)	(0.48)	(0.49)
Foreign Exper/Educ	0.09	0.08	0.09	0.14	0.07
	(0.28)	(0.27)	(0.29)	(0.34)	(0.25)
BA	0.16	0.16	0.18	0.05	0.10
	(0.37)	(0.36)	(0.38)	(0.21)	(0.3)
MA or above	0.84	0.84	0.82	0.95	0.90
	(0.37)	(0.36)	(0.38)	(0.21)	(0.3)
Sample size	8345	3739	4231	195	180

Notes: Reported are the means and the standard deviations (in parentheses) of the respective characteristics in the relevant cells. Calculations from the Integrated Household Survey of Georgia (2009-10), the National Statistics Office of Georgia. To be most comparable to our experimental sample, the household survey samples were restricted to: Georgians, Azeri, and Armenians (excluding other minority groups); workers aged 23 to 32; those with higher education (above high school). Experience is defined as $age - 5 - b$, where b is 9, 12, 14, 16, 18, 20 for the education groups gymnasium, college, bachelor, master's, and doctor's. Old is a dummy variable for workers aged 27 or older, and experienced is a dummy variable for workers with 4 or more years of experience.

Table 7: Complementary log-log regression with "employed" as dependent variable, Household Survey Data

Employed	(1)	(2)	(3)
Female	-0.016	-0.015	0.000
	[0.010]	[0.010]	[0.015]
Georgian	0.299***	0.303***	0.114***
	[0.040]	[0.040]	[0.048]
Armenian	0.265***	0.265***	0.032
	[0.032]	[0.032]	[0.044]
Age		-0.012	-0.058
		[0.016]	[0.047]
Experience		0.022	0.061
		[0.017]	[0.049]
Experience squared		-0.001*	-0.001
		[0.001]	[0.001]
Worker controls	No	Yes	Yes
Industry and Occupational Dummies	No	No	Yes
Observations	8345	8345	4085

Notes: "Employed" is defined as worker with positive income from hired work. Regressions use data from the Integrated Household Survey of Georgia for the years 2009 and 2010 (GeoStat: the National Statistics Office of Georgia). The household survey samples were restricted to: Georgians, Azeri, and Armenians (excluding other minority groups); workers aged 23 to 32; those with higher education (above high school). Reported are the marginal effects (or the discrete changes) for the respective variables. Other variables include the type of diploma the worker got, foreign experience, and one digit occupational and industry fixed effects. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1: A sample of estimates of "ethnic disadvantage" in the literature

Study	Country	Disadvantaged group(s)	Disadvantage size
Arceo-Gomez and Campos-Vazquez (2014)	Mexico	Indigenous	18%
Bertrand and Mullainathan (2004)	United States	Black	50%
Carlsson and Rooth (2007)	Sweden	Middle-Eastern men	53%
Kaas and Manger (2012)	Germany	Turkish men	49%
Maurer-Fazio (2012)	China	Mongolian women	37%
		Ughur women	75%
		Tibetan women	123%

Source: respective authors' calculations

Note: disadvantage size is meant as the percentage increase in the number of applications to be sent by the disadvantaged group in order to obtain the same number of callbacks as the non-disadvantaged group.