Do firms redline workers?
A controlled experiment in Bogotá

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Abstract

This paper explores whether firms redline workers using a controlled experiment in Bogota. Firms may redline workers for two main reasons. First, employers might be reluctant to hire individuals living far away because long commutes may affect the productivity of workers. Second, firms might have discriminatory preferences relative to the reputation of the place of residence of their potential employee. In our experimental design we aim to explore to what extent labor market, measured as access to employment, discriminates against places of residence as the result of these mechanisms. Moreover, we aim to explore which of the two channels drive the empirical results. We use a correspondence test by responding to job advertisements posted by firms in newspapers. We send three identical fictitious résumés to every single job offer posted on the main job vacancy web pages. The only difference between the résumés being the residential address of the job applicant. Two of them are located at the same commuting time (and geographic distance) but one is located in a low crime neighborhood while the other is located in a high crime area. The third résumé corresponds to an individual located in a low crime neighborhood at a higher distance. Results suggest that firms do redline low-skilled females in Bogota.

Keywords: discrimination, productivity, employment experiment, neighborhood, spatial mismatch, high and low crime neighborhoods.

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Introduction

Labor market discrimination has been widely studied using several methods, measuring various outcomes with different populations. In developing as well as developed countries, the minority population struggle more to obtain a well paid job. Lately, experimental methods have been used to try to solve the weaknesses that remain in that data-based studies, such as unobserved variation that may bias the results. In economics as well as in other areas, lab and field experiments such as audit and correspondence test studies have been implemented in order to test differences in hiring, access to employment and wages, and the motivations that drive those differences, in controlled environments.

This study tests whether employers in Bogota discriminate against job applicant's as a result of reputation of the neighborhood where the applicant resides. The design uses a 'correspondence test', involving sending out multiple applications to real job ads for non-professional vacancies in the local labor market of Bogota. Everything in the resumes of applicants is the same, varying only the residential address of the applicant. Some papers (Petit et al. [2011], Tunstall et al. [2014] and Bunel et al. [2016]) have assessed residential discrimination using a similar approach in the analysis, however the population used and the source of variation are different, leading to different conclusions. Our design allows us to test if residential discrimination is explained by two hypotheses: reputation of the neighborhood of residence and productivity losses. The former implies that an employee would discriminate against individuals that reside in high crime places, while the later implies that an employer would discriminate against individuals that live farther away from work. In both cases, we analyze discrimination from the employer's perspective.

Using a correspondence test methodology, we compare access to employment of individuals who are similar in all respects except for the location of their residence. We vary the place of residence by classifying neighborhoods in Bogota in high and low crime geographical places, using homicide rates. Then we identified real addresses in those neighborhoods and select a list of addresses to be used in our experiment. We have three treatments: An applicant that lives in a low crime neighborhood at distance x from the job vacancy, an applicant that lives in a high crime neighborhood at distance x from the job vacancy, and an applicant that lives in a low crime neighborhood at a distance y of the job vacancy (where $y > x$). Our measure of distance considers the commute time (using public transportation) that takes to an applicant, from each treatment neighborhood, to arrive at the workplace on Mondays at 7 am. We construct six female and six male profiles with very similar attributes (in terms of education, age, labor market experience) except for the residential address. Every week, we send via certified mail three identical fictitious résumés to every non-professional job offer posted on the main job vacancy web pages in Bogota that include a physical address. We rotate the profiles that are used in each treatment and measure access to employment as whether or not the applicant receives a callback for an interview. We record the exact date and time at which the employer calls back a particular applicant.

Using a linear probability model, we estimate the probability of being called back for an interview of applicants with similar attributes except for their residential address. In other words, we estimate the probability of being called for an interview if the applicant resides in a high crime, or in a low crime neighborhood but at a longer distance, in comparison to living in a low crime neighborhood close to the workplace. Preliminary results show that, for the whole sample, firms do not redline workers in Bogota. However, once we estimate the model for males and females separately, there is evidence of residential discrimination when we explore the presence of heterogeneous effects. In particular, a strong localized reputation treatment effect, that implies that firms located in high crime neighborgoods are more likely to discriminate against job applicants that reside also in high crime areas. This result is driven by women, however. Employers from high crime areas call back females that live in high crime areas 9.1 percentage points less than those that live in low crime rates, and 12.1 percentage points less for those women that live far away from the workplace. We do not find evidence of either productivity nor reputation for males.

Related Literature

The spatial mismatch hypothesis proposes that minorities have poor outcomes in the labor market because they are geographically disconnected job opportunities [Kain, 1968].Under this scenario, labor outcomes depend not only on the individual characteristics of the unemployed (e.g, age, education, experience), but also on the geographic location of the place of residence [Dujardin et al., 2008]. Several papers have tested the spatial mismatch hypothesis and have shown that poor job accessibility worsens labor market outcomes. This literature has mostly taken the point of view from the labor supply. Very few studies consider an analysis from the labor demand. We focus mainly on the labor demand channel, but it is useful to give a short description of the labor supply explanations.

Four mechanisms have been put forward to explain the spatial mismatch hypothesis from the point of view of workers. First, if workers reside far away from jobs they might increase their reservation wage and if the offered wage does not compensate for this extra cost it will be more likely to not accept the job and to remain unemployed [Brueckner and Zenou, 2003]. According to Hellerstein et al. [2008], this is true for individuals whose travel costs represent a high percentage of their incomes as low-skilled workers, those who work part-time or who are seeking employment in occupations whose expected returns are low. Second, distance might increase search costs and job seekers facing higher cost may restrict their horizon of search to places close to their place of residence [Gobillon et al., 2007]. Third, there might be a loss in search efficiency due to information frictions because workers living far from employment centers have less information about vacancies than those who live nearby [Gobillon et al., 2007, Wasmer and Zenou, 2006]. Finally, workers living away from job centers have little incentive to find a job. Smith and Zenou [2003] and Aslund et al. [2010] claim that the distance to the employment centers can be damaging because it involves a low intensity of search.

From the point of view of the firms, the urban economic literature states that employers might be less likely to hire workers residing far away from jobs for two main reasons: productivity losses and residential discrimination. The remainder of this section describes these two potential mechanisms in detail.

There are a few studies that explore the productivity hypothesis. Zenou [2002] developed an efficiency wage model in which firms determine their spatial efficiency wage and a geographical red line beyond which they do not recruit workers. This is because workers involuntarily provide less work effort due to larger commutes. The intuition of his model is the following: workers can either shirk and produce zero effort or not shirk and produce a strictly positive effort level. However, as effort depends on the distance between jobs and the location of workers, even if they decide not to shirk, they provide a lower effort level if they live far away from work. Firms anticipate this behavior and draw a red line beyond which they do not recruit workers.

In addition, Ross and Zenou [2008] show that if shirking and leisure time are substitutes in the worker's utility function, one may expect a positive effect of commuting on shirking. In equilibrium, residing far away from jobs affects the trade off between job effort and the frequency of unemployment spells by reducing the time available for leisure. Furthermore, they demonstrate that wages positively vary across commutes, because firms want to minimize shirking by setting wages conditional on the length of the commute. Their model implies the existence of a relationship between expected commutes and either unemployment and/or wages. They tested empirically this idea using the Public Use Microdata sample of 2000 U.S Decennial Census. Results suggest that longer commutes imply higher levels of unemployment and higher wages for workers who tend to be in occupations that face higher levels of supervision.

Van Ommeren and Gutiérrez-i Puigarnau [2011] employ absenteeism as a direct measure of shirking (or productivity losses) and explore the effect of commuting distance on productivity. They describe two mechanisms behind this relationship. First, an involuntary relationship between worker's productivity and commuting. They argue that workers with long commutes are more likely to fall ill due to increase in fatigue than workers with short commutes. In other words, involuntary absenteeism is a positive function of the length of the commute. Second, a voluntary relationship between worker's productivity and commuting. The intuition is as follows: the worker's utility derived from a job depends on the length of the commute, because worker's net wage and leisure time are reduced when monetary commuting costs and time increase. Then, workers who have longer commutes might be considered to have lower "cost" of absence as they save on commuting cost by not attending work. They also tested empirically the effects of commuting on absenteeism using ten waves of the 1999-2008 German Socio-Economic Panel survey. Their results indicate that in the hypothetical cases that all workers in the economy have a negligible commute, absenteeism would be about 15 to 20 per cent lower.

The second hypotesis that explain why employers may redline workers is due to labor market discrimination. An employers seeking to fill a vacancy may be reluctant to hire an individual that resides in a disadvantaged neighborhood for many reasons: stereotypes, signaling (statistical discrimination) and taste or preferences.

This topic has been widely studied in economics literature (see two complete reviews by Neumark [2016] and Bertrand and Duflo [2016]). Most studies have tested the hypothesis of labor market discrimination in the field by exploring the existence of racial and gender discrimination[Bertrand and Mullainathan, 2004, Pager, 2007, Duguet et al., 2010]. Most of the literature focus on discrimination against groups of population by analyzing wage gaps, and a few use measures of hiring. Another types of discrimination, tested in the field, analyze physical attractiveness [Hamermesh, 2011] and criminal background [Finlay, 2009]. In both cases, discrimination could be statistical because these characteristics of workers may reflect lower productivity to employers.

However, few studies asses the question whether employers discriminate against the place of residence of workers. Tunstall et al. [2014] study discrimination in the UK labor market as a result of reputation of the neighborhood of residence of job applicants. Using a correspondence test analysis, the study found no statistically significant difference in how employees treated job applicants from poor reputation neighborhoods, suggesting no stigma effects in hiring. The identification consisted in sending 2001 applications of individuals living in different neighborhoods (classified as poor or deprived using indices of Multiple Deprivation) to 667 real job vacancies to test whether employers discriminated against neighborhood of residence of low-skilled applicants in three local labor markets in England and Wales.

Distance, skill mismatch or spatial mismatch was not considered in their analysis. They measured and compared employment rates between neighborhoods within labor markets, focusing on stigma or poor neighborhood reputation and found no differences in hiring. The study of Bunel et al. [2016] analyzes the degree of employment discrimination against young people in the Ile-de-France region according to their place of residence. Using also a correspondence test, the experimental design considers several spatial scales in order to measure the effect of the reputation of the geographic unit (i.e. administrative department or county, the town or municipality, and local neighborhoods) on access to employment. The variation of the neighborhoods comes from difference sin socio-economic status. The authors use two occupations within the restaurant/catering industry with a skill dimension. Specifically, use 498 job offers of waiters and cooks, adding two skills of qualification. The results show that living in a good address increases the likelihood of being called back for a job interview by three times.

Although some studies have used correspondence test analysis to test the reputation effect on labor discrimination, there is no consensus about the potential effect of neighborhood on access to employment. Our study differs from those in two ways: First, our design allows us to control for distance or commuting time from the workplace to the place of residence of the job applicant. This means that we have two vacancies that are at the same distance (in commuting time) but one corresponds to an applicant that resides in a high crime/disadvantaged neighborhood, while the other lives in a low/advantaged neighborhood. Second, we use information for all non-professional vacancies that are posted weekly in the main newspapers of Bogota.

Experimental Design

In this paper we want to test the extent to which access to employment varies to changes in the place of residence of their potential employees. To accomplish this, we compare access to employment of individuals who are similar in all respects except for the location of their residence. Our experiment consist of sending three identical fictitious résumés to every single job offer posted on the main job vacancy web pages. The only difference between the resumes being the residential address of the job applicant. The résumé identified as $CV1$ corresponds to an individual located in a low crime neighborhood at distance x from the job vacancy, the résumé in $CV2$ is of an individual located in a high crime neighborhood at distance x of the same vacancy, and the résumé in $CV3$ corresponds to an individual located in a low crime neighborhood at distance y of the job vacancy (where $y > x$).

We collect weekly job ads posted on two of the main job offers web pages in Bogota. We select all non-professional job offers that have an address in the job posting in order to be able to send a printed triplet of résumés with the characteristics explained above. Also, we constructed profiles of individuals that rotate every week from each comparison group (i.e. CV1 CV2, CV3) to obtain balance across individual's characteristics. Every profile have similar applicants' attributes (e.g., sex, age, city of birth), and the same human capital (e.g. non-professional candidates, additional specific education, experience), a name and a photo. Therefore, three apparently identical résumés are sent simultaneously to each vacancy every week in an envelope via certified mail. Our measure of access to employment is the discrete and observable event of whether or not the applicant receives a callback for an interview. This research involves comparing the apparent chances of hiring three candidates for which the only difference is their place of residence. We describe the experimental design in more detail in the following sections.

Neighborhoods

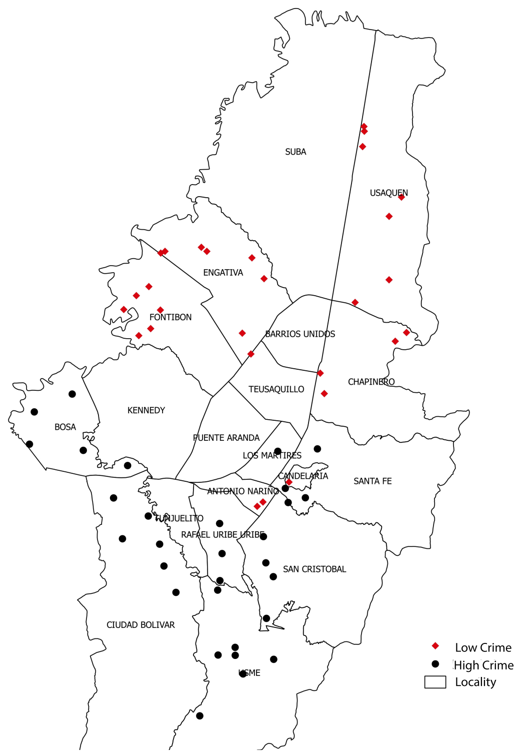
Bogota is a city of 350 km^2, 8 million inhabitants and a density of 205.7 people per hectare. The city is divided into 19 localities and among these are grouped 112 Zonal Planning Units (ZPU) and almost 200 neighborhoods.[1] The place of residence of the three fictitious candidates is selected in order to measure two potential channels of labor discrimination: the effect of reputation and the effect of distance on productivity. To measure the effect of reputation we choose places that are plausibly discriminated against based on their homicide rate. We select seven localities with homicide rate higher than 20 homicides per 100 thousand inhabitants during the last four years as plausibly discriminated localities (i.e. Santafé, San Cristobal, Usme, Bosa, Los Martires, Rafael Uribe Uribe, and Ciudad Bolivar). On the other hand, localities with homicide rate lower than 20 homicides per 100 thousand inhabitants were considered as non-discriminated localities (i.e., Usaquen, Chapinero, Fontibon, Engativa, Antonio Nariño, and Candelaria). Six localities were left out of the analysis because their residents did not have the attributes of the study (i.e., Teusaquillo, Barrios Unidos, and Puente Aranda) or because they have an heterogeneous population that may confound and compromise identification (i.e., Tunjuelito, Kennedy, and Suba). Within each locality, we randomly selected geographical units (UPZs) with the characteristics of the population of the study (nonprofessional inhabitants that live in Socio Economic Strata 1 and 2). Figure presents the spatial distribution of the low and high crime rates Localities.

[1] Zonal Planning Units were defined in 2003 to identify homogeneous areas that corresponded to an intermediate geographic level between the town and the district. In other words, the area of a ZPU is less of the localities, which in turn group several neighborhoods. Zonal planning units have an important role in this analysis since the database used for the empirical analysis is representative at this level.

Figure 1: High and Low Crime Localities

Within these 16 geographical units, we selected 59 actual addresses located in different neighborhoods using the Bogota Mobility Survey 2011 (EMB), which surveyed more than 16,000 households and 40,333 individuals. It is representative at the ZPU level. The survey collects information of household characteristics (including real address), attributes of household members, commuting times and transportation. We followed a two step procedure to finally select the 59 actual addresses. First, we selected, from the entire sample, only those individuals who live in strata 1 and 2 (the poorest neighborhoods in Bogota) and whose maximum level of education was technical education. We end up with 4,328 individuals residing in 45 ZPUs (i.e., 15 in low crime areas and 29 in high crime areas). Second, we randomly picked two real addresses from each low crime ZPUs and one real address for each high crime ZPU. Figure 2 shows the spatial distribution of the 59 addresses considered in our sample, 30 located in high crime areas and 29 located in low crime areas.

Figure 2: Actual Addresses Location



The following table compares demographic attributes of high and low crime areas from our sample. The results confirm that high crime areas are, on average, more violent, have lower occupation rate and a slightly higher unemployment rate. Additionally, the residents of high crime areas are, on average, poorer, more likely to live in stratum one and two and are less educated. The third column in Table 1 shows the mean difference of such attributes if we compare low and high crime ZPUs. We do find large differences between these two type of neighborhood which are statistically significant.

Table 1: Descriptive Statistics Neighborhoods Attributes

Attribute	Non-Discriminated	Discriminated	Difference	SE
	(1)	(2)	(2-1)	SE
Homicide Rate	8.55	31.78	23.22***	(.12)
Ocupation Rate	.61	.58	−.02***	(.00)
Unemployment Rate	.05	.07	.03***	(.00)
Poverty Rate	.26	. 55	.29***	(.00)
Stratum 1	.00	.33	.32***	(.00)
Stratum 2	.22	.47	.25***	(.01)
Stratum 3	.45	.20	−.25***	(.01)
Stratum 4	.19	.01	−.19***	(.00)
Stratum 5	.05	.00	−.05***	(.00)
Stratum 6	.09	.00	−.09***	(.00)
Primary	.20	.35	.14***	(.01)
Secondary	.34	.47	.12***	(.01)
Technical	.09	.07	−.01***	(.00)
Higher or more	.37	.11	−.25***	(.01)
N	11120	11207		

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

Candidates

We construct a set of six males and six females profiles whose individual characteristics, name and photo remain fixed and rotate across comparison groups. We send three identical applications in terms of individual's attributes to the same job offer every week. The only difference is the place of residence of the applicant. The following table presents the fixed attributes of the constructed profiles:

Table 2: Candidates' Attributes

Females					
No	Name	Surname	Age	Photo	Format
1	Diana Beatriz	Gonzalez Acosta	36	3	3
2	Sandra Carolina	Perez Torres	37	1	1
3	Martha Cecilia	Molina Moreno	35	2	2
4	Maria Isabel	Gonzalez Acosta	36	3	3
5	Luz Andrea	Perez Torres	37	1	1
6	Ana María	Molina Moreno	35	2	2
Males					
No	Name	Surname	Age	Photo	Format
1	Jose Luis	Chaves Flores	36	3	3
2	John Andres	Gonzalez Molina	37	1	1
3	Cristian David	Torres Moreno	35	2	2
4	Juan Carlos	Chaves Flores	36	3	3
5	Jorge Eduardo	Gonzalez Molina	37	1	1
6	Jesus Francisco	Torres Moreno	35	2	2

These names are among the most common names in Colombia and are not related to minorities. We choose the set of females or males depending on the genre that the vacancy requires. During one week we send resumes using the profiles one to three and the following week we use the profiles four to six of each gender. This strategy facilitates call-back identification whenever employers take more than a week to call.

Although each week individuals are similar in their attributes, they have some elements of differentiation. For example, the age among applicants may differ in one year. We included photographs of the candidates on their written application. The format of the resumes also varies in terms of font style, font size, layout of the page and order of the information provided (see their format on Appendix A1). To avoid having this attributes confounding the employer's selection for a particular candidate for characteristics other than the place of residence, we developed a simple system of rotation of the candidates every week. Table 3 illustrates the rotation system for eight weeks. For example, if we look at Diana Beatriz: the first week she appears in résumé 1, then in week three her profile moves to résumé 3, two weeks after she jumps to résumé 2, and on week seven she starts again in résumé 1. This loop continues during the entire experiment. Recall that the only difference is the place of residence.

Table 3: Candidates' Attributes

Females			
Week	Resume 1	Resume 2	Resume 3
1	Diana Beatriz	Sandra Carolina	Martha Cecilia
2	Maria Isabel	Luz Andrea	Ana Maria
3	Sandra Carolina	Martha Cecilia	Diana Beatriz
4	Luz Andrea	Ana Maria	Maria Isabel
5	Martha Cecilia	Diana Beatriz	Sandra Carolina
6	Ana Maria	Maria Isabel	Luz Andrea
7	Diana Beatriz	Sandra Carolina	Martha Cecilia
8	Maria Isabel	Luz Andrea	Ana Maria
Males			
Week	Resume 1	Resume 2	Resume 3
1	Jose Luis	John Andres	Cristian David
2	Juan Carlos	Jorge Eduardo	Jesus Francisco
3	John Andres	Cristian David	Jose Luis
4	Jorge Eduardo	Jesus Francisco	Juan Carlos
5	Cristian David	Jose Luis	John Andres
6	Jesus Francisco	Juan Carlos	Jorge Eduardo
7	Jose Luis	John Andres	Cristian David
8	Juan Carlos	Jorge Eduardo	Jesus Francisco

Besides the attributes described in Table 2, all candidates display their education level, job experience, personal and job references in the résumé, maintaining the format that corresponds to every profile. These characteristics have slight differences across the three applicants for every vacancy to avoid mistrust from the potential employers, but are statistically identical when we compare aggregated characteristics across comparison groups. This variation allows us to measure the true effect of the place of residence on access to employment. Although profiles were designed ex-ante, we adjusted the résumé of every candidate according to the requirements and description of the vacancy, in order to make them attractive enough to the employer.

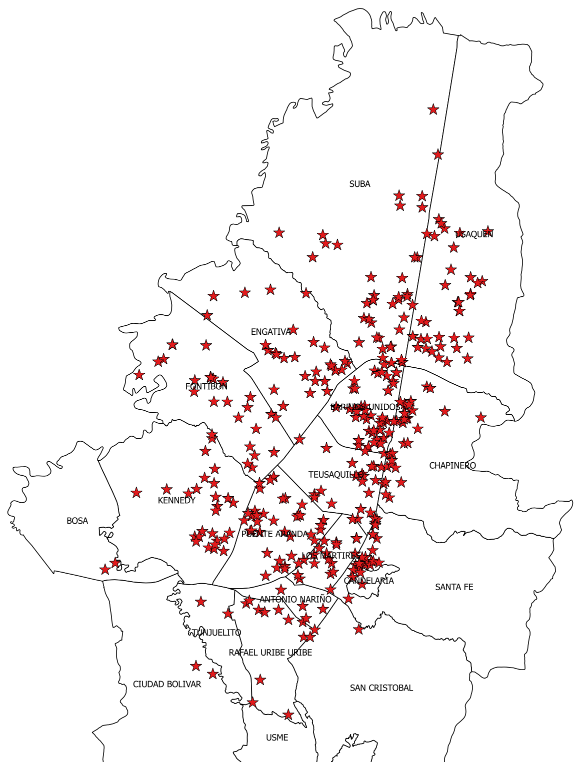
Vacancies

Every week we collect newspaper job ads from the two most widely read and circulated newspapers (i.e. El Tiempo and ADN). This process is done through a web-scrapping procedure and manual verification. We select job ads that have the following characteristics: i. do not require college degree, ii. have an address, and iii. the application does not require the applicant to deliver the résumé in person. We get, on average, 30 job ads that meet these requirements every week.

For each job ad we create three fictitious résumés with different residential addresses. Resume 1 ($CV1$) is located in a low crime area at a distance x from the vacancy, resume 2 ($CV2$) is located at the same distance x but in a high crime area, and resume 3 ($CV3$) is located at distance y from the job vacancy (where $y > x$) in a low crime area. The estimated commuting duration to the vacancy is at least 2.5 times larger that the duration between the vacancy and the other two résumés. Figure shows an example of the places of residence that correspond to a triplet sent to a vacancy.

To select the addresses we follow a simple procedure every week. First, we randomly select an address from our sample of 30 low crime locations and assign it to CV1. Then we calculate the duration, in real time, between the place of residence and the vacancy via the Google Maps Distance Matrix. Let's call this duration $D1_i$ where i represents each vacancy of every week. Then, we calculate the duration, in real time, between each of the 30 high crime areas and one particular vacancy, and assign it to CV2. Let's call each estimated duration $D2_{ij}$ where i represents each vacancy and j represents each of the 30

Figure 3: Vacancies Location



discriminated addresses. We then select the address for each vacancy following this rule:

$$D2_i = \text{arg min}_j \left|\left| D1_i - D2_{ij} \right|\right|$$

Although $D1_i$ and $D2_i$ are not exactly the same, every week we test and make sure that this difference is not statistically significant. Finally, we calculate the duration, in real time, between each of the 30 low crime areas and one that particular vacancy and assign it to CV3. Let's $D3_{ik}$ denote the duration between each vacancy i and every one of the 30 low crime areas k. We then select the address for each vacancy with this criteria:

$$D3_i = \text{arg max}_k \left|\left| D3_{ik} - D1_i \right|\right| \geqslant 1.25$$

In other words, we select the address for applicant of CV3 to be at least 25 percent as large as the duration of the address from CV1. We repeat this procedure during 30 weeks, corresponding to 720 vacancies and 2,160 résumés sent.

Sending the résumés

Once we identify the vacancies for our study, we adjust the profiles of the three applicants to be sent to the specified addresses. All résumés are sent via certified mail. We hired a courier company to deliver the résumés every Monday after we create and print the résumés. The job postings are usually posted within 4-5 days prior to the selection and we aim to deliver the résumés 1 to 4 days after the date of the posting. We have the exact date and time at which the envelopes are delivered.

The Empirical Strategy

With the experimental design, we test to what extent labor market, measured as access to employment, discriminates against place of residence as a result of two potential channels: reputation of the neighborhood of residence and productivity losses. We measure access to employment by recording a call-back of an applicant from a potential employer.

To test our hypothesis we estimate a linear probability model, in which the probability of receiving a callback is a linear function of our treatments and some control variables:

$$Pr(Y_i|CV2, CV3, X) = G(\beta_1 + \beta_2 CV2_i + \beta_3 CV3_i + X_i\delta)$$

Where Y_i is a binary variable equal to one when the résumé i receives a callback and zero otherwise, $CV2_i$ indicates that the résumé is located in a high crime area and $CV3_i$ indicates that the résumé is located in a low crime area but farther away, and finally we control for a different set of covariates X_i such as the duration of a commute between the place of residence and the locality of the vacancy, gender, job experience, and economic sector of the vacancy.[2] If $\hat{\beta}_2$ is negative and statistically significant, it means that potential employers are less likely to hire individuals living in high crime neighborhoods than individuals living in low crime neighborhoods, which might indicate discrimination against these neighborhoods. Also, if $\hat{\beta}_3$ is negative and statistically significant, it indicates that potential employers are less likely to hire individuals living farther away as a result of productivity losses. Positive or non significant coefficients would indicate that firms do not redline workers in their hiring process.

This regression framework is commonly used in correspondence test analyses. A somewhat more complex form would allow for interactions between the type of résumé (i.e., CV2 and CV3) and other relevant variables in the equation. We use interaction between the type of résumé (treatment) and duration of the commute (and distance), if the applicant is hig school graduate, if the vacancy is located in a high crime neighborhoos, and a binary variable of services (for vacancies that require a one on one interaction with clients). This specification would indicate whether firms evaluate different the geographic locations by résumé type and hence would shed additional light on the mechanism through by which firms redline workers.

Finally, we repeat the analysis for males and females separately to explore the specificities of each market.

[2] We control for these variables not only to improve precision but also to explore how these variables are related to the probability of call-back.

Data

We use information from non-professional vacancies that are posted in two of the main newspapers from Bogota each week. We collected 493 vacancies with addresses in different economic sectors for men and women during 25 weeks. We observe a large number of job adds for men in occupations such as car drivers, delivery, commercial actrivities and carpentry. For women, the most common occupations in our sample are hair stylist and manicurist, sewing, cooks or waitress for restaurants and sellers.

We use a set of locality characteristics in order to identify the neighborhoods and addresses of potential applicants from the EMB 2011. Table 1 above describes the averages of those characteristics for low and high crime neighborhoods. The selection of ZPUs ensures that the addresses of each treatment group are statistically as well as observationally different.

In order to check for balance, we compare applicants attributes across treatment groups. Table 4 shows also the mean distance in kilometers and average duration of a trip from actual addresses used in each treatment and the location of the vacancy. We observe an average distance of 12 Kms and duration of 0.74 hours of a trip from the vacancies and place of residence of applicants from CV1 and CV2. No statistical differences are found, suggesting that any difference in the measure of access to employment among these two treatment groups can be attributed to discrimination in the labor market. However, if we compare the distance (measured in kms) and duration of a trip across CV1 and CV3 and CV2 and CV3 we observe statistical differences suggesting that applicants assigned to CV3 reside farther away from those in CV1 and CV2. Other attributes such gender, age, labor market experience, format of the resume used and photos of applicants are balanced across treatment groups. There are difference in format, and in photo 1 and photo 3 because during some weeks we receive more vacancies than others; therefore, our sample is not fully balanced. We control for these variables in our regression to reduce confounding effects.

Table 4: Mean Differences

	CV1	CV2	CV3	CV1 vs CV2	CV1 vs CV3
Distance (Km)	12.07	12.12	19.23	0.05	7.16***
	(6.22)	(5.96)	(5.39)	(0.39)	(0.37)
Duration (Hours)	0.74	0.73	1.06	-0.01	0.32***
	(0.30)	(0.27)	(0.25)	(0.02)	(0.02)
Male	0.52	0.52	0.52	0.00	0.00
	(0.50)	(0.50)	(0.50)	(0.03)	(0.03)
Age	35.89	35.71	35.86	-0.18*	-0.03
	(1.47)	(1.59)	(1.55)	(0.10)	(0.10)
Experience (years)	17.89	17.71	17.86	-0.18*	-0.03
	(1.47)	(1.59)	(1.55)	(0.10)	(0.10)
Format	1.89	2.04	2.07	0.15***	0.18***
	(0.82)	(0.78)	(0.85)	(0.05)	(0.05)
Photo 1	0.39	0.28	0.32	-0.11***	-0.07**
	(0.49)	(0.45)	(0.47)	(0.03)	(0.03)
Photo 2	0.32	0.39	0.28	0.07**	-0.04
	(0.47)	(0.49)	(0.45)	(0.03)	(0.03)
Photo 3	0.28	0.32	0.39	0.04	0.11***
	(0.45)	(0.47)	(0.49)	(0.03)	(0.03)
N	493	493	493	986	986

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

We also compare the outcome variables across treatment groups in Table 5. We find that 29 percent of vacancies reach back applicants that live in low crime neighborhoods, 27 percent call back individuals that live in high crime rates at the same distance and 27 percent call back individuals that reside in low crime rates but further away from the vacancies (see columns 1 to 3 of panel A). Columns 4 and 5 display the simple mean difference test between CV1 and CV2, and CV1 and CV3, respectively. These results show no statistical differences in call-backs between any treatment. Also, we report the order of the call-back. In most cases, the employer calls back all three applications. For that reason we decided to record the exact date and time of the call received for each treatment. On average, individuals in CV1 are called back first than individuals from CV2 and CV3. And this difference is statistically different from zero.

Table 5: Mean Differences Result Variables

	CV1	CV2	CV3	CV1 vs CV2	CV1 vs CV3
	(1) (2)	(3)	(4)	(5)	
	CV1	CV2	CV3	CV1 CV2	CV1 CV3
Callback	0.29	0.27	0.27	-0.02	-0.01
	(0.45)	(0.44)	(0.45)	(0.03)	(0.03)
Call Order 1st	0.47	0.44	0.41	-0.03	-0.05
	(0.50)	(0.50)	(0.49)	(0.06)	(0.06)
Call Order 2nd	0.30	0.33	0.40	0.03	0.10*
	(0.46)	(0.47)	(0.49)	(0.06)	(0.06)
Call Order 3rd	0.23	0.23	0.19	-0.00	-0.04
	(0.42)	(0.42)	(0.39)	(0.05)	(0.05)
Services	0.41	0.41	0.41	0.00	-0.00
	(0.49)	(0.49)	(0.49)	(0.03)	(0.03)
Attention	0.09	0.09	0.09	0.00	0.00
	(0.29)	(0.29)	(0.29)	(0.02)	(0.02)
N	493	493	493	986	986
MALE					
Callback	0.22	0.20	0.22	-0.02	0.00
	(0.41)	(0.40)	(0.41)	(0.04)	(0.04)
Call Order 1st	0.39	0.41	0.43	0.02	0.04
	(0.49)	(0.50)	(0.50)	(0.10)	(0.10)
Call Order 2nd	0.33	0.31	0.37	-0.03	0.04
	(0.48)	(0.47)	(0.49)	(0.09)	(0.09)
Call Order 3rd	0.28	0.29	0.20	0.01	-0.07
	(0.45)	(0.46)	(0.41)	(0.09)	(0.08)
Services	0.32	0.32	0.32	0.00	-0.00
	(0.47)	(0.47)	(0.47)	(0.04)	(0.04)
Attention	0.14	0.14	0.14	0.00	0.00
	(0.35)	(0.35)	(0.35)	(0.03)	(0.03)
N	258	258	258	516	516
FEMALE					
Callback	0.37	0.34	0.34	-0.02	-0.03
	(0.48)	(0.48)	(0.47)	(0.04)	(0.04)
Call Order 1st	0.52	0.46	0.40	-0.06	-0.12
	(0.50)	(0.50)	(0.49)	(0.08)	(0.08)
Call Order 2nd	0.28	0.34	0.42	0.06	0.14*
	(0.45)	(0.48)	(0.50)	(0.07)	(0.07)
Call Order 3rd	0.20	0.20	0.18	-0.00	-0.02
	(0.41)	(0.40)	(0.39)	(0.06)	(0.06)
Services	0.51	0.51	0.51	0.00	0.00
	(0.50)	(0.50)	(0.50)	(0.05)	(0.05)
Attention	0.03	0.03	0.03	0.00	0.00
	(0.18)	(0.18)	(0.18)	(0.02)	(0.02)
N	235	235	235	470	470

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

The second panel reports the call back rate and order of call backs of each treatment group for males. We observe that the frequency of call backs is much smaller than the full sample for all treatment groups, and are statistically similar. However, the order of the call received is different to the full sample case. In particular, employers call back applicants that reside in low crime neighborhoods first and more often in comparison with applicants residing in high crime and in farther areas. We also observe that employers call last those applicants that reside in high crime neighborhoods.

The last panel shows the numbers for women. We find that employers call back women more often, independent of the type of neighborhood where they live. And although they seem to call back women in low crime areas first, it is not statistically larger than the call back order of the other treatments.

Results

This section presents the results from the experimental exercise. The first column of Table 6 presents the results without controls, and columns 2 to 5 show the results under four different set of regressors. The first set includes the duration (measured in hours) that an applicant should take to cummute in public transportation between her place of residence and the vacancy, to determine the effect of the treatment while duration is held constant. The second set of regressors includes individual attributes of the applicants such as age and gender. The analysis involves sending résumés to low skilled occupations and technical occupations, and we control for it in the third specification by including a binary variable equal to one if the occupation requires only secondary education and zero for technical. Finally, we control for the location of the vacancy (whether it is located in a low or middle crime area) and a dummy variable if the occupation is in the service sector, that takes the value of one if the job requires in person interaction of the employee with clients.

The estimating sample contains all 1479 observations. The dependent variable is binary and measures whether the résumé or the applicant receives a callback. The results for the total sample confirm that the callback rate for CV1 is about 32 percent (when controlling for week fixed effects). Although CV2 and CV3 present, on average, a lower callback rate, in all specifications the estimates are small and not significantly different from zero. Table A.2, in the Appendix, presents the results when we control for distance between the candidate's place of residence and the vacancy instead of duration. Results remain unchanged. As an implication of our results, it appears that, for the entire sample, firms do not redline workers in Bogota.

Table 6: Callback Regression - Duration

	(1)	(2)	(3)	(4)	(5)
CV2	−.020	−.020	−.019	−.019	−.019
	(.016)	(.016)	(.016)	(.016)	(.016)
CV3	−.014	.007	−.000	−.000	.003
	(.015)	(.023)	(.023)	(.023)	(.023)
Duration (Hours)		−.064	−.050	−.050	−.061
		(.056)	(.055)	(.055)	(.055)
Constant	.316***	.368***	.825	.732	.720
	(.088)	(.099)	(.510)	(.522)	(.534)
F	2.15	2.06	2.85	2.79	2.64
R Squared	.0438	.0452	.069	.0704	.071
N	1479	1477	1477	1477	1477
Controls					
Week Dummy	✓	✓	✓	✓	✓
Individual Attributes			✓	✓	✓
Neighborhood Attributes				✓	✓
Vacancy Attributes					✓

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

Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement. For the entire set of controls refer to Table A1

There is evidence of a strong neighborhood reputation effect when the vacancy is localed in a high crime area (see Table 7 column (4)). When we interact the treatment variables (i.e., CV2 and C3) with a dummy variable that indicates if the vacancy is located in a low and medium crime neighborhood (takes the value of zero if the vacancy is located at high crime neighborhood), we find a negative effect of about 7 percentage points, which implies that potential employers discriminate against applicants that live in high crime neighborhoods if the vacancy is located in a high crime area also. We also find no evidence of a productivity effect since the coefficient associated to CV3 is not statistically significant. Moreover, there is no evidence of treatment effect heterogeneity for the other variables included in the analysis. We explore treatment effect heterogeneity by including interactions of the treatments and some relevant varibles (i.e, duration, distance, secondary education or high school graduates, and services which measures personal interaction with clients) and the coeffcients associated are not statistically significant.

Table 7: Callback Regression - Heterogenous Effects

	(1)	(2)	(3)	(4)	(5)
CV2	−.046	−.046	−.085	−.078**	−.007
	(.053)	(.041)	(.059)	(.036)	(.018)
CV3	.081	.045	−.045	−.056	−.010
	(.082)	(.076)	(.073)	(.036)	(.016)
Duration (Hours)	−.047				
	(.068)				
CV2*duration	.037				
	(.067)				
CV3*duration	−.077				
	(.086)				
Distance (Km)		−.003			
		(.003)			
CV2*distance		.002			
		(.003)			
CV3*distance		−.002			
		(.004)			
CV2*secondary			.069		
			(.061)		
CV3*secondary			.030		
			(.074)		
CV2*hrloc12				.072*	
				(.040)	
CV3*hrloc12				.049	
				(.040)	
CV2*services					−.031
					(.033)
CV3*services					−.016
					(.032)
Constant	.711	.716	.713	.715	.675
	(.534)	(.535)	(.531)	(.530)	(.528)
F	2.5	2.52	2.64	2.67	2.53
R Squared	.0717	.0715	.0702	.0707	.0702
N	1477	1477	1479	1479	1479

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

Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement.

Finally, we estimate the models for a subsample of males and females to explore potential treatment effects by gender. The results are depicted in Table 8. The first panel shows the estimated coefficients for males and the second panel presents the results for females. Consistent with the results for the whole sample, when there is no evidence that firms redline males nor females in the low-skilled labor market of Bogota.

Table 8: Callback Regression - Gender

	(1)	(2)	(3)	(4)	(5)
Male					
CV2	–.019	–.018	–.017	–.017	–.017
	(.018)	(.018)	(.019)	(.019)	(.019)
CV3	–.000	.004	.005	.005	.005
	(.010)	(.024)	(.022)	(.023)	(.023)
Duration (Hours)		–.011	–.015	–.015	–.015
		(.061)	(.061)	(.062)	(.062)
Constant	.217***	.226***	1.121	1.027	1.063
	(.033)	(.059)	(.965)	(.970)	(1.013)
F	.724	.417	.697	.79	.884
R Squared	.000502	.000489	.00569	.00698	.00751
N	774	772	772	772	772
Female					
	(1)	(2)	(3)	(4)	(5)
CV2	–.021	–.021	–.022	–.022	–.022
	(.022)	(.022)	(.022)	(.022)	(.022)
CV3	–.030	–.033	–.038	–.038	–.027
	(.018)	(.028)	(.027)	(.027)	(.029)
Duration (Hours)		.010	.007	.007	–.028
		(.082)	(.082)	(.083)	(.081)
Constant	.366***	.359***	.188	.141	.028
	(.036)	(.076)	(.547)	(.581)	(.663)
F	1.58	1.22	1.93	1.73	1.8
R Squared	.000691	.000719	.00248	.00293	.00813
N	705	705	705	705	705
Controls					
Week Dummy	✓	✓	✓	✓	✓
Individual Attributes			✓	✓	✓
Neighborhood Attributes				✓	✓
Vacancy Attributes					✓

*** p<0.01, ** p<0.05, * p<0.1
Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement.

However, when we explore the presence of heterogenous effects for females (see Table 9), there is evidence of a localized treatment effect: firms might be more likely to discriminate against women residing in high crime neighborhoods if the vacancy is located also in a high crime area. This implies that the heterogeneous effects found in the whole sample is driven by residential discrimination against females. There is also evidence of localized productivity effect sinces females receive on average 12 percentage points less callbacks if the vacancy is located in a high crime area. Similar to what we observed in the whole sample, the treatment effect is insignificant when we use other interactions.

The results of the experiment suggest that, in general, there is no residential discrimination in hiring in Bogota. However, when the job applicant is a woman, she is less likely to be called for an interview if she lives in a neighborhood with a criminal reputation or if she lives far away from the workplace, as a result of productivity losses.

Table 9: Heterogenous Effects Females

	1	2	3	4	5
CV2	−.088	−.112	−.133	−.091*	.013
	(.090)	(.070)	(.089)	(.053)	(.035)
CV3	.052	.041	−.077	−.121*	−.032
	(.136)	(.128)	(.109)	(.066)	(.038)
Duration (Hours)	−.107				
	(.115)				
CV2*duration	.092				
	(.120)				
CV3*duration	−.051				
	(.147)				
Distance (Km)		−.009*			
		(.005)			
CV2*distance		.008			
		(.005)			
CV3*distance		−.001			
		(.008)			
CV2*secondary			.119		
			(.093)		
CV3*secondary			.045		
			(.114)		
CV2*hrloc12				.085	
				(.062)	
CV3*hrloc12				.105	
				(.074)	
CV2*services					−.070
					(.054)
CV3*services					−.007
					(.059)
Constant	.528	.573*	.543	.543	.480
	(.338)	(.327)	(.332)	(.332)	(.325)
F	3.59	3.66	3.68	3.8	3.59
R Squared	.114	.117	.112	.112	.112
N	705	705	705	705	705

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

Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement. The difference between the coefficient of CV2 and CV3 is not significant different from zero.

Conclusion

This paper explores whether firms redline workers using a controlled experiment in Bogota. Firms may redline workers for two main reasons. First, employers might be reluctant to hire individuals living far away because long commutes may affect the productivity of workers. Second, firms might have discriminatory preferences relative to the reputation of the place of residence of their potential employee.

Our results suggest that the reputation of the place of residence can strongly influence the probability of obtaining a job for low-skilled females in Bogota. There is also weak evidence that firms redline low-skilled women living in high crime neighborhoods far from the location of the vacancy when the workplace is also in a high crime neighborhood. The evidence does not support any type of residential discrimination against men.

The experiment responds only to job advertisements posted by firms in newspapers. These firms are unlikely to represent a random sample of all firms in the labor market. For that reason, there is a threat of external validity maybe because only less discriminatory firms use newspapers, which could understate the likelihood of discrimination in the labor market. However, we have a large range of low-skilled occupations in our sample.

Finally, the spatial structure of a city plays an important role in the females' returns to employment through the behavior of employers. In other words, employers use the address as a screening criteria in the case of women. Therefore, policy recommendations aimed to reduce the consequences of the spatial mismatch in the labor market largely depend on the mechanism that is causing the discriminatiry behavior. Despite the small effects found in our estimations, we recommend to promote practices to reduce the risk of discriminatory employment decisions against high crime areas in the cities.

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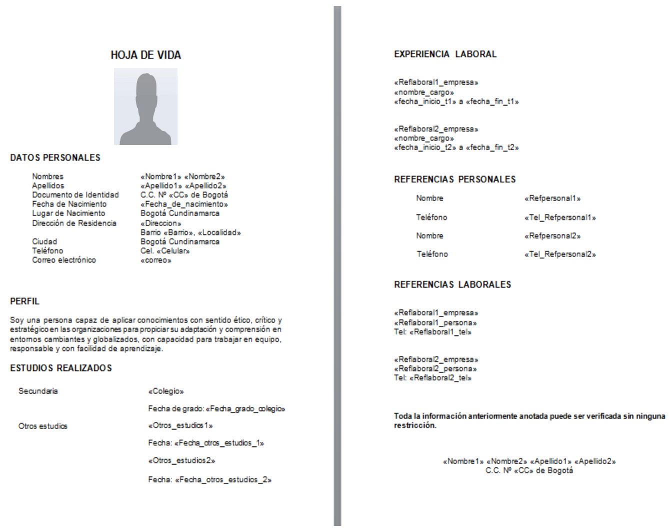
Appendix

A1. Formats

Figure A.1: Format 1



HOJA DE VIDA

DATOS PERSONALES

Nombres	«Nombre1» «Nombre2»
Apellidos	«Apellido1» «Apellido2»
Documento de Identidad	C.C. Nº «CC» de Bogotá
Fecha de Nacimiento	«Fecha_de_nacimiento»
Lugar de Nacimiento	Bogotá Cundinamarca
Dirección de Residencia	«Direccion»
	Barrio «Barrio», «Localidad»
Ciudad	Bogotá Cundinamarca
Teléfono	Cel. «Celular»
Correo electrónico	«correo»

PERFIL

Soy una persona capaz de aplicar conocimientos con sentido ético, crítico y estratégico en las organizaciones para propiciar su adaptación y comprensión en entornos cambiantes y globalizados, con capacidad para trabajar en equipo, responsable y con facilidad de aprendizaje.

ESTUDIOS REALIZADOS

Secundaria	«Colegio»
	Fecha de grado: «Fecha_grado_colegio»
Otros estudios	«Otros_estudios1»
	Fecha: «Fecha_otros_estudios_1»
	«Otros_estudios2»
	Fecha: «Fecha_otros_estudios_2»

EXPERIENCIA LABORAL

«Reflaboral1_empresa»
«nombre_cargo»
«fecha_inicio_t1» a «fecha_fin_t1»

«Reflaboral2_empresa»
«nombre_cargo»
«fecha_inicio_t2» a «fecha_fin_t2»

REFERENCIAS PERSONALES

Nombre	«Refpersonal1»
Teléfono	«Tel_Refpersonal1»
Nombre	«Refpersonal2»
Teléfono	«Tel_Refpersonal2»

REFERENCIAS LABORALES

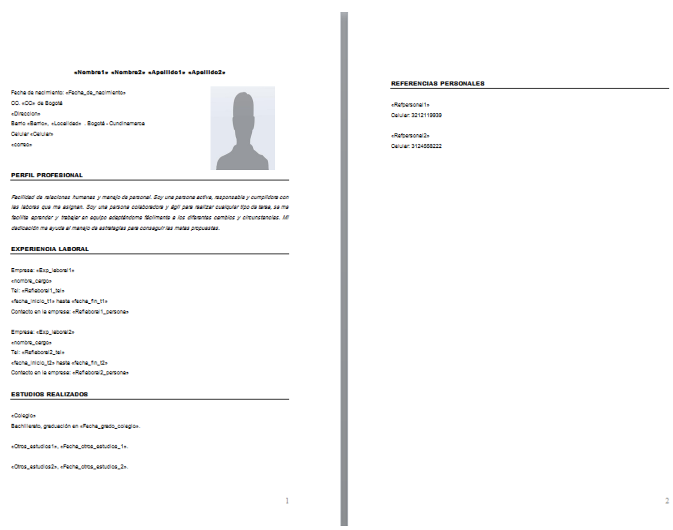
«Reflaboral1_empresa»
«Reflaboral1_persona»
Tel: «Reflaboral1_tel»

«Reflaboral2_empresa»
«Reflaboral2_persona»
Tel: «Reflaboral2_tel»

Toda la información anteriormente anotada puede ser verificada sin ninguna restricción.

«Nombre1» «Nombre2» «Apellido1» «Apellido2»
C.C. Nº «CC» de Bogotá

Figure A.2: Format 1



«Nombre1» «Nombre2» «Apellido1» «Apellido2»

Fecha de nacimiento: «Fecha_de_nacimiento»
CC. «CC» de Bogotá
«Direccion»
Barrio «Barrio», «Localidad» . Bogotá - Cundinamarca
Celular «Celular»
«correo»

PERFIL PROFESIONAL

Facilidad de relaciones humanas y manejo de personal. Soy una persona activa, responsable y cumplidora con las labores que me asignen. Soy una persona colaboradora y ágil para realizar cualquier tipo de tarea, se me facilita aprender y trabajar en equipo adaptándome fácilmente a los diferentes cambios y circunstancias. Mi dedicación me ayuda al manejo de estrategias para conseguir las metas propuestas.

EXPERIENCIA LABORAL

Empresa: «Exp_laboral1»
«nombre_cargo»
Tel: «Reflaboral1_tel»
«fecha_inicio_t1» hasta «fecha_fin_t1»
Contacto en la empresa: «Reflaboral1_persona»

Empresa: «Exp_laboral2»
«nombre_cargo»
Tel: «Reflaboral2_tel»
«fecha_inicio_t2» hasta «fecha_fin_t2»
Contacto en la empresa: «Reflaboral2_persona»

ESTUDIOS REALIZADOS

«Colegio»
Bachillerato, graduación en «Fecha_grado_colegio».

«Otros_estudios1», «Fecha_otros_estudios_1».

«Otros_estudios2», «Fecha_otros_estudios_2».

1

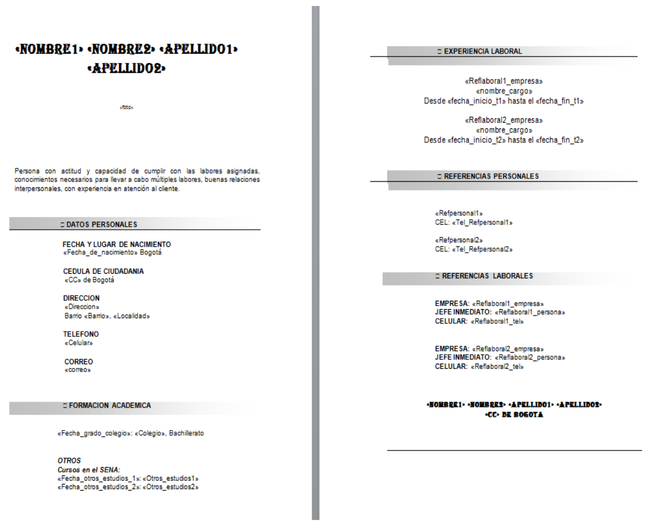
REFERENCIAS PERSONALES

«Refpersonal1»
Celular: 3212119939

«Refpersonal2»
Celular: 3124558222

2

Figure A.3: Format 1



«NOMBRE1» «NOMBRE2» «APELLIDO1» «APELLIDO2»

«foto»

Persona con actitud y capacidad de cumplir con las labores asignadas, conocimientos necesarios para llevar a cabo múltiples labores, buenas relaciones interpersonales, con experiencia en atención al cliente.

DATOS PERSONALES

FECHA Y LUGAR DE NACIMIENTO
«Fecha_de_nacimiento» Bogotá

CEDULA DE CIUDADANIA
«CC» de Bogotá

DIRECCION
«Direccion»
Barrio «Barrio», «Localidad»

TELEFONO
«Celular»

CORREO
«correo»

FORMACION ACADEMICA

«Fecha_grado_colegio»: «Colegio», Bachillerato

OTROS
Cursos en el SENA:
«Fecha_otros_estudios_1»: «Otros_estudios1»
«Fecha_otros_estudios_2»: «Otros_estudios2»

EXPERIENCIA LABORAL

«Reflaboral1_empresa»
«nombre_cargo»
Desde «fecha_inicio_t1» hasta el «fecha_fin_t1»

«Reflaboral2_empresa»
«nombre_cargo»
Desde «fecha_inicio_t2» hasta el «fecha_fin_t2»

REFERENCIAS PERSONALES

«Refpersonal1»
CEL: «Tel_Refpersonal1»

«Refpersonal2»
CEL: «Tel_Refpersonal2»

REFERENCIAS LABORALES

EMPRESA: «Reflaboral1_empresa»
JEFE INMEDIATO: «Reflaboral1_persona»
CELULAR: «Reflaboral1_tel»

EMPRESA: «Reflaboral2_empresa»
JEFE INMEDIATO: «Reflaboral2_persona»
CELULAR: «Reflaboral2_tel»

«NOMBRE1» «NOMBRE2» «APELLIDO1» «APELLIDO2»
«CC» DE BOGOTA

A2. Results

Table A.1: Callback Regression - Duration

	(1)	(2)	(3)	(4)	(5)
CV2	−.020	−.020	−.019	−.019	−.019
	(.016)	(.016)	(.016)	(.016)	(.016)
CV3	−.014	.007	−.000	−.000	.003
	(.015)	(.023)	(.023)	(.023)	(.023)
Duration (Hours)		−.064	−.050	−.050	−.061
		(.056)	(.055)	(.055)	(.055)
Male			−.136***	−.139***	−.138***
			(.036)	(.036)	(.036)
Age			−.011	−.010	−.010
			(.014)	(.014)	(.014)
Photo 2			−.036	−.035	−.036
			(.032)	(.032)	(.032)
Photo 3			.003	.004	.004
			(.021)	(.021)	(.021)
Secondary				.079	.077
				(.077)	(.078)
Low Med Crime Vac					.030
					(.043)
Services					.000
					(.038)
Constant	.316***	.368***	.825	.732	.720
	(.088)	(.099)	(.510)	(.522)	(.534)
F	2.15	2.06	2.85	2.79	2.64
R Squared	.0438	.0452	.069	.0704	.071
N	1479	1477	1477	1477	1477

*** p<0.01, ** p<0.05, * p<0.1
Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement.

Table A.2: Callback Regression - Distance

	(1)	(2)	(3)	(4)	(5)
CV2	−.020	−.019	−.019	−.019	−.019
	(.016)	(.016)	(.016)	(.016)	(.016)
CV3	−.014	.008	.002	.002	.005
	(.015)	(.024)	(.024)	(.024)	(.023)
Distance (Km)		−.003	−.003	−.003	−.003
		(.003)	(.003)	(.003)	(.003)
Male			−.136***	−.139***	−.138***
			(.036)	(.036)	(.036)
Age			−.011	−.010	−.010
			(.014)	(.014)	(.014)
Photo 2			−.036	−.035	−.035
			(.032)	(.032)	(.032)
Photo 3			.004	.004	.004
			(.021)	(.021)	(.021)
Secondary				.080	.079
				(.077)	(.078)
Low Med Crime Vac					.027
					(.043)
Services					.001
					(.038)
Constant	.316***	.361***	.820	.726	.710
	(.088)	(.096)	(.510)	(.522)	(.534)
F	2.15	2.07	2.86	2.8	2.65
R Squared	.0438	.0452	.0691	.0705	.071
N	1479	1477	1477	1477	1477

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

Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement.

Table A.3: Heterogenous Effects- Male

	1	2	3	4	5
CV2	.002	.001	.001	−.066	−.022
	(.061)	(.046)	(.005)	(.048)	(.018)
CV3	.056	.025	.003	.000	.005
	(.093)	(.084)	(.006)	(.031)	(.010)
Duration (Hours)	.011				
	(.080)				
CV2*duration	−.026				
	(.074)				
CV3*duration	−.055				
	(.096)				
Distance (Km)		.001			
		(.004)			
CV2*distance		−.002			
		(.003)			
CV3*distance		−.002			
		(.005)			
CV2*secondary			−.020		
			(.019)		
CV3*secondary			−.004		
			(.013)		
CV2*hrloc12				.059	
				(.051)	
CV3*hrloc12				−.001	
				(.033)	
CV2*services					.011
					(.041)
CV3*services					−.015
					(.028)
Constant	1.010	1.006	1.007	1.032	1.015
	(1.005)	(1.005)	(.999)	(.999)	(.999)
F	2.8	2.8	2.9	2.9	2.91
R Squared	.126	.126	.126	.127	.127
N	772	772	774	774	774

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

Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement

Table A.4: Heterogenous Effects Females

	1	2	3	4	5
CV2	–.088	–.112	–.133	–.091*	.013
	(.090)	(.070)	(.089)	(.053)	(.035)
CV3	.052	.041	–.077	–.121*	–.032
	(.136)	(.128)	(.109)	(.066)	(.038)
Duration (Hours)	–.107				
	(.115)				
CV2*duration	.092				
	(.120)				
CV3*duration	–.051				
	(.147)				
Distance (Km)		–.009*			
		(.005)			
CV2*distance		.008			
		(.005)			
CV3*distance		–.001			
		(.008)			
CV2*secondary			.119		
			(.093)		
CV3*secondary			.045		
			(.114)		
CV2*hrloc12				.085	
				(.062)	
CV3*hrloc12				.105	
				(.074)	
CV2*services					–.070
					(.054)
CV3*services					–.007
					(.059)
Constant	.528	.573*	.543	.543	.480
	(.338)	(.327)	(.332)	(.332)	(.325)
F	3.59	3.66	3.68	3.8	3.59
R Squared	.114	.117	.112	.112	.112
N	705	705	705	705	705

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

Notes: Standard errors are in parentheses and clustered at the level of job vacancy advertisement.