# Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes<sup>†</sup>

By Philip Oreopoulos\*

Thousands of randomly manipulated resumes were sent in response to online job postings in Toronto to investigate why immigrants, allowed in based on skill, struggle in the labor market. The study finds substantial discrimination across a variety of occupations towards applicants with foreign experience or those with Indian, Pakistani, Chinese, and Greek names compared with English names. Listing language fluency, multinational firm experience, education from highly selective schools, or active extracurricular activities had no diminishing effect. Recruiters justify this behavior based on language skill concerns but fail to fully account for offsetting features when listed. (JEL J15, J24, J61)

Recent immigrants to Canada struggle in the labor market. Their unemployment rates compared to similarly aged non-immigrants are almost twice as high (Table 1 shows this for immigrants arriving between 2001 and 2005 using the 2006 Canadian Census). Median wages of recent immigrant workers are also 36 percent lower compared to native-born workers. Previous research finds little evidence for expecting that this wage gap will significantly narrow with host-country experience. While the immigrant-native wage gap used to disappear (and sometimes even reversed sign) after 10 to 15 years for immigrants arriving prior to the 1970s, wages of immigrants arriving in the 1990s are still about 25 percent lower than wages of non-immigrants even after 2005 (Marc Frenette and René Morissette 2005).

Recent immigrants to other countries, such as the United States, also experience similar labor market disadvantages (Darren Lubotsky 2007), but what is particularly noteworthy in the Canadian case is the fact that immigration policy focuses on attracting immigrants with superior levels of education, experience, and industry demand to offset an anticipated skilled labor force shortage and encourage

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	Unemployment rate (1)	Mean earnings for positive earners in labor force (2)	Median earnings for positive earners in labor force (3)
Non-immigrants	0.059	39,841	33,000
Recent immigrants (0–4 years)	0.104	27,462	21,000
Ratio (Non-immig/immig)	0.57	1.45	1.57
Estimated ratio, conditional on age, schooling, and city	0.54	2.20	1.94
Sample size	127,149	119,275	119,275

TABLE 1—UNEMPLOYMENT AND EARNINGS DIFFERENCES BETWEEN RECENT IMMIGRANTS AND NATIVES AGED 25-39 FROM THE 2006 CENSUS

Notes: The sample in column 1 includes all individuals from the 2006 Public-Use Canadian Census, aged 25–39, in the labor force, and either recorded as a non-immigrant, or a recent immigrant (arrived within the last 5 years). The sample in columns 2 and 3 is restricted further to individuals with positive earnings. All amounts are in 2005 Canadian dollars. The estimated ratio is computed by first regressing unemployment status or log earnings on immigrant status, plus fixed effects for age, highest degree, and city of residence. The unemployment rate and mean earnings is imputed using the immigrant coefficient from the regression, relative to the actual value for non-immigrants, and the ratio of this is reported in the table. For column 3, quantile regregression around the median is used instead of ordinary least squares.

economic growth. More than half of today's immigrants enter Canada under a point system, which rates applicants based on their highest degree, language ability, age, whether they have work experience at occupations deemed "in demand," whether they already have a job offer, have worked or studied in Canada previously, and have cash at hand. Virtually every immigrant who enters Canada under the point system now has at least an undergraduate degree. The overall percentage of recent immigrants with an undergraduate degree is about 60 percent, compared to 20 percent for Canadian born of similar age (Statistics Canada 2008). Conditioning on highest degree completed, therefore, causes the relative wage gap between recent immigrants and non-immigrants to *increase*, from 36 percent lower wages for immigrants to 48 percent (Table 1).

Canada has the largest per-capita immigration rate in the world (Benjamin Dolin and Margaret Young 2004). Policymakers are concerned about the lack of immigrant assimilation because it suggests that recent immigrants are not integrating into the high-skilled labor market, despite efforts to attract immigrants who will. This raises questions about the role immigration plays in providing Canada with a source of highly skilled individuals to boost economic growth. It also has important implications for the use of government transfer programs, such as social assistance and child tax benefits, as well as for income tax revenues. A number of other countries such as the United Kingdom, Spain, and Germany are also considering or in the process of bringing in a point system as part of a plan to shift their immigration policies more towards a skill-based focus. The international competition to attract

<sup>&</sup>lt;sup>1</sup> See Charles M. Beach, Alan G. Green, and Christopher Worswick (2007), Heather Antecol, Peter Kuhn, and Stephen J. Trejo (2006) or George J. Borjas (1993) for more details about the Canadian point system (more formally called Federal Skilled Status Category). Language ability is evaluated based on an applicant's International English Language Test System (IELTS) score, or by submitting a written explanation detailing training in and usage of English language. If an immigration officer believes that the written explanation is inadequate, he or she may require that the applicant take the IELTS instead.

skilled immigrants is increasing and more attention is being devoted to a point system approach to evaluate the desirable characteristics of prospective immigrants. While the United States has traditionally emphasized the role of family reunification in its immigration policy, some debate has come about over the possible adoption of a point system. As a result, it is also worthwhile to investigate, from the perspective of other countries, why Canada's point system does not appear to be having its desired effect.

The usual suspects to explain the gap include the possibility that employers do not value foreign education as much as they value Canadian education. The point system treats any degree from any institution the same. Foreign experience may also be treated as inferior to Canadian experience, since less is known about the foreign employer and tasks involved. Other possibilities are that cultural and language differences have grown as the proportion of applications from Europe has decreased and the proportion from Asia and the Pacific Coast has increased. The point system also places no role on an applicant's understanding of social etiquette. Concerns about language proficiency may remain.

This paper presents results from an audit study to investigate why Canadian immigrants arriving under the point system struggle in the labor market.<sup>2</sup> Thousands of resumes were submitted online in response to job postings across multiple occupations in the Greater Toronto Area after randomly varying characteristics on the resume to uncover what affects employers' decisions on whether to contact an applicant. The resumes were constructed to plausibly represent recent immigrants under the point system from the three largest countries of origin (i.e., China, India, and Pakistan) and Britain, as well as non-immigrants with and without ethnic sounding names (including Greek names). In addition to names, I randomized where applicants received their undergraduate degree, whether their job experience was gained in Toronto or Mumbai (or another foreign city), whether their job experience was from well-recognized multinational firms or large firms, or not, whether they listed being fluent in multiple languages (including French), whether they had additional education credentials, whether the credentials were accredited by a Canadian agency, whether resumes with foreign education or experience listed Canadian references or indicated permanent residency status, and whether they listed active extracurricular activities.

A related study by Marianne Bertrand and Sendhil Mullainathan (2004) found that resumes sent to blue-collar jobs in Boston and Chicago, with white-sounding names, generated callbacks about 50 percent more often than the same resumes sent with black-sounding names.<sup>3</sup> Whereas that study focused on callback differences





<sup>&</sup>lt;sup>2</sup>Previous studies have attempted to explain the immigrant-native wage gap using a Blinder-Oaxaca-type decomposition methodology (Abdurrahman Aydemir and Mikal Skuterud 2005; Frenette Morissette 2005; David A. Green and Christopher Worswick 2010; Joseph Schaafsma and Arthur Sweetman 2001; Robert J. Lalonde and Robert H. Topel 1992; Anna Ferrer and W. Craig Riddell 2008). The general consensus view from this work appears to be that the immigrant-native wage gap in Canada exists mostly because of lower returns to foreign experience, especially among immigrants from Asia and the Pacific (I also find this). This approach, however, does not offer details about what underlies these relationships, and whether indicating more specific skills or listing different kinds of job experience would alter the relationship.

<sup>&</sup>lt;sup>3</sup>See P. A. Riach and J. Rich (2002) for a review of the audit study literature. Resume audits have the advantage over ones with actors in that they provide more control over the information employers use to make a decision. Although these types of studies only measure the interview selection stage of the hiring process, they allow for larger samples to be collected, and thus more degrees of freedom to examine interactions and sub-groups. A

between white and black names, this one examines differences generated by manipulating a wider set of resume characteristics to disentangle the many possible factors explaining why natives perform better than recent immigrants in the labor force, even among those with Bachelor degrees. I also explore more closely what mechanisms might underlie applicant discrimination using predictions generated by alternative models of discrimination, and complement the audit study methodology with a qualitative one that involves discussing results directly with recruiters and human resource managers.

## I. Theories of Job-Applicant Discrimination

As a descriptive exercise, audit studies help quantify the magnitude to which characteristics, such as experience, schooling, and extracurricular experience, influence reactions of prospective employers. An advantage of using resumes instead of actors seeking employment is that the investigator knows exactly what information employers have when making a decision to contact an applicant back.

Audit studies can also help reveal or rule out statistical discrimination, which arises when employers use observable characteristics as signals for inferring unknown information (Edmund S. Phelps 1972). For example, with limited time and budget, employers may make marginal decisions on whom to interview or telephone by using resume name or country of education/experience to predict an applicant's language skills.<sup>4</sup>

Since productivity expectations under this model are determined conditional on other information, listing additional resume characteristics that correlate with unlisted skills reduces uncertainty and the need to infer. Applicants with ethnic sounding names who have only Canadian experience and education, for example, are most likely Canadian born and should generate fewer language skill concerns than applicants with foreign experience or education. If employers are statistically discriminating, the callback gap between foreign educated or foreign named resumes and native resumes should fall by adding information related to unobservable skill. I also explore how the callback rate changes when changing a Canadian experienced and educated resume with an English name to a Greek name, to increase the likelihood that the applicant is Canadian born and to minimize language and communication concerns. Another prediction of the statistical discrimination model is that the callback rate gap between foreign named or foreign educated resumes and native resumes should be larger in cases where jobs applied to require more of the skills being inferred from the name or immigrant status. For example, the callback rate gap for Computer Programmer jobs, which require less language skills to perform well, should be smaller than that for Sales jobs.

typical search model predicts lower wage progression from slower arrival rates of job offers (Alan Manning 2000). Additional discrimination may arise after the interview selection stage.

<sup>&</sup>lt;sup>4</sup>Another model of statistical discrimination focuses on productivity variance. Even if abilities between two groups are, on average, the same, risk averse employers will prefer the group with lower ability variance, all else equal (Dennis J. Aigner and Glen G. Cain 1977). My qualitative research finds no evidence of this behavior. Many recruiters interviewed mentioned lower expectations of language ability for immigrants but no one expressed a concern about more uncertainty for whether an applicant's language skill was exceptionally good or bad.

Applications that are matched across a wide set of characteristics and sent to jobs that mostly require skills that can easily be noted on a resume should generate similar callback responses under the models of statistical discrimination mentioned above. If racial or ethnic differences remain, taste based theories of employer discrimination may be at play. Employers may prefer hiring individuals from particular groups, independent of productivity. Another explanation for remaining callback differences may be through unconscious mistakes generated by unconditional biases or stereotypes. A number of researchers suggest that the setting by which employers sort through resumes make it more likely that name discrimination is unintentional (Damian Stanley, Elizabeth Phelps, and Mahzarin Banaji 2008; Dolly Chugh 2004). Social psychologists differentiate between explicit attitudes, which describe one's expressed views, and implicit attitudes, which are unconscious mental associations between a target (such as immigrants) and a given attribute (such as poor communication skills). Implicit discrimination may operate subconsciously, and cause people to make decisions in ways contrary to their own conscious and deliberative views (Kate A. Ranganath, Colin Tucker Smith, and Brian A. Nosek 2008).

Several modern theories of prejudice align with this model. Christian Crandall and Amy Eshleman (2003), for example, describe how employers may believe that they are rejecting an applicant out of language skill concerns when in fact it is their implicit biases that are driving the decision. An applicant's name or country of origin may trigger particular stereotypes that cause employers to overweight these concerns and underweight the offsetting factors on the resume. While recruiters may consciously attempt to avoid discrimination and missing out on the best hire, subconscious beliefs and attitudes may influence assessments and decisions none-theless. Pressure to avoid bad hires exacerbates these effects, as does the need to review resumes quickly. Employers may erroneously use unconditional productivity expectations to determine whether to call back an applicant rather than conditioning on other characteristics on the resume.

Implicit discrimination can also arise from thinking in categories. Roland Fryer and Matthew Jackson (2008) and Mullainathan (2002) note that types of experiences that are less frequent in the population are more coarsely categorized and more often lumped together. As a result, decision makers make less accurate predictions when confronted with such objects. This can result in discrimination against minority groups even when there is no malevolent taste for discrimination. Employers who are less accustomed to seeing foreign named or foreign educated applicants with adequate language skills are more likely to lump all foreign named and foreign educated applicants into one category even if there are other listed characteristics that offset the concerns about language skills. This leads to a more general pattern of rejection for these applicants regardless of what other skills are listed.

To explore further why callback differences exist after listing many other attributes on the resume, I complement the audit study by asking recruiters why others might discriminate in a manner to generate my empirical results, and whether this behavior is likely intentional or not. I then relate responses back to the findings and draw conclusions.

## II. Research Design

Thousands of randomly created resumes were sent by email in response to job postings across multiple occupations in the Greater Toronto Area between April and November 2008. An additional set of resumes was sent across Toronto, and Montreal between February and September 2009 in order to improve precision and consider effects from adding other attributes.<sup>5</sup> The resumes were designed to plausibly represent typical immigrants who arrived recently under the Canadian point system from China, India, and Pakistan (the current top three source countries) and Britain, as well as non-immigrants with and without ethnic-sounding names (including Greek names). They were constructed after consulting actual resumes of recent immigrants and online submissions. The sample of jobs I applied to represent all jobs posted during these periods that accepted applications via direct e-mail and generally required three to seven years of experience and an undergraduate degree. Positions that specifically required at least a graduate degree, North American experience, or certification were ignored.

With few exceptions, four resumes were sent to each employer over a two- to three-day period in random order. The first represented an applicant with an English sounding name, Canadian undergraduate education, and Canadian experience (Type 0). The second resume had instead a foreign sounding name (Chinese, Indian, Pakistani, or Greek), but still listed Canadian undergraduate education and Canadian experience (Type 1). The third resume included a foreign sounding name (Chinese, Indian, or Pakistani), corresponding foreign undergraduate degree, and Canadian experience (Type 2). The fourth included a foreign sounding name, foreign education, and some foreign experience (Type 3) or all foreign experience (Type 4).8 I also randomized applicants' alma mater, whether the applicant listed being fluent in multiple languages (including French), whether they had additional Canadian education credentials, and whether their job experience was from well recognized multinational firms or large firms, or not. To address concerns whether employers shy away from resumes with foreign credentials because of additional costs in contacting references or concerns about legal working status, I also randomize a subset of resumes with foreign experience to list Canadian references (with a local telephone number) and explicitly list permanent residency status.

The English-sounding names on Type 0 resumes were picked randomly from a list of the most popular Anglophone surnames in Canada (Smith, Martin, Brown,

<sup>&</sup>lt;sup>5</sup>Montreal was included during follow-up data collection to address questions about the results' generalizability (for English job postings). I include the Montreal sample (18 percent of my total sample) in this paper because, while the point estimate for the effect of listing a Greek versus English name in Toronto  $(-0.02, \text{s.e.}\ 0.021)$  is similar to that for Montreal (-0.05, s.e. 0.035), only the combined sample allows us to statistically reject a null effect at the 5 percent level. All other findings are similar when the samples are combined or not.

<sup>&</sup>lt;sup>6</sup>Chinese and South Asians make up more than 50 percent of all immigrants with a bachelor's degree in Toronto in the 2006 Census. According to the 2006 Census, 45 percent of all individuals in the Greater Toronto Area are immigrants (Danielle Zietsma 2007).

<sup>&</sup>lt;sup>7</sup>A human resource director at a job placement organization in Bangladesh provided very helpful advice and a comprehensive set of anonymized resumes of individuals who qualified under the point system to immigrate to Canada. I also consulted resumes posted on www.workopolis.com and www.jobbank.ca.

<sup>&</sup>lt;sup>8</sup>Resume sets with more than one applicant with foreign experience or education from the same country were excluded.

Wilson, or Johnson), and matched randomly with one of four possible male names (Greg, John, Matthew, or Michael) or four possible female names (Alison, Carrie, Emily, or Jill) used previously by Bertrand and Mullainathan (2004). Resumes with foreign education or experience from Britain had the same names. Greek names were either Lukas Minsopoulos or Nicole Minsopoulos. The other resumes of Type 1 to 4 had names picked randomly among a list of 24 popular male and female names from China, India, and Pakistan. In some cases, I used names with Chinese last names and English first names picked from these same lists. Table 2A shows the number of resumes sent by name and type. Email addresses were set up for all 44 names using both gmail.com and yahoo.ca accounts. The total sample size is 12,910 resumes, sent in response to 3,225 job postings.

Work experiences were constructed from actual resumes accessible online. The descriptions were sufficiently altered to create distinct sets that would not be associated with actual people, but I also tried to maintain original overall content and form. Each resume listed the job title, job description, company name, and city location for an applicant's three most recent jobs covering four to six years, with the first job beginning in the same year as the applicant's undergraduate degree completion. The city listed was always the same (except for Type 3 resumes). 11 Experience sets were constructed for 20 different occupation categories, almost all the same ones used by the online job site workopolis.com. 12 Within each category, I created four different experience sets, whose job titles and corresponding job descriptions were randomly assigned to one of the four resumes sent to a single employer. 13 It is worth emphasizing that this randomization not only made years of experience the same across immigrant and non-immigrant resumes (on average), but it also made the description of this experience the same. In addition, company names were also independent of resume type for about half the sample. International companies were chosen wherever possible to keep the experience sets identical across immigrant and non-immigrant resumes except for location (for example ABC Inc., Toronto versus ABC Inc., Mumbai). In cases where no obvious international company was available, I picked closely related companies in size and industry. For the later sample of resumes constructed in 2009, firms were randomly assigned based on whether they might subjectively be considered large and prestigious and those not. Interestingly, the overall results using identical company names were similar as those using different names (I discuss this more below).

<sup>&</sup>lt;sup>9</sup>The common Canadian surname list comes from an article titled "Common Surnames," *CBC News*, July 26, 2007, accessed March 12, 2008, http://www.cbc.ca/news/background/name-change/common-surnames.html. The article mentions the list comes from infoUSA, "which claims to have put together a directory of every telephone listing in Canada."

<sup>&</sup>lt;sup>10</sup>Chinese names were picked from a most common names list on the website http://zhidao.baidu.com/question/41504421.html. The web page cited the National Citizen Identity Information Center of China as the source. Indian names were gathered from the web page http://hinduism.about.com/library/babynames/bl-babynames-index.htm, and with consultation with one of my research assistants with Indian heritage. I saved these web pages, which are available on request.

<sup>&</sup>lt;sup>11</sup>The city was either Mississauga, Toronto, Beijing, Shanghai, Guangzhu, New Delhi, Mumbai, Punjab, or London.

<sup>&</sup>lt;sup>12</sup>The categories were administrative, insurance, arts and media, biotech-pharmaceutical, marketing, ecommerce, production, education, retail, maintenance, programmer, civil engineering, electrical engineering, executive, finance, technology, human resources, computer, healthcare, and hospitality.

<sup>&</sup>lt;sup>13</sup>The main sites I used for this were workopolis.com and jobbank.ca.

Table 2A—Number of Resumes Sent by Resume Type and Ethnicity

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Notes: Cdn = Canadian, Educ = country where bachelor's degree obtained, and Exp = country where job experience obtained. Mixed experience corresponds to first two jobs listed on resume as being from a foreign country, and most recent (third) job listed from Canada.

Table 2B—Number of Callbacks Received by Resume Type and Ethnicity

Name ethnicity and sex English males Greg Johnson John Martin Matthew Wilson Michael Smith English females Alison Johnson Carrie Martin Emily Brown Jill Wilson Midian males Arjun Kumar Panav Singh Rahul Kaur Samir Sharma Johnson J	English name Cdn educ Cdn exp 0  47 48 50 29 66 82 38 69	Foreign name Cdn educ Cdn exp  1  13 10 15 14  19 13 16 20	Foreign name Foreign educ Cdn exp 2  3 5 2 3 5 6 8 2 13 15 10 7	Foreign name Foreign educ Mixed exp 3  2 3 5 4  5 6 6 3 3 7 6 9	Foreign nam Foreign educ Foreign exp  4  4 4 3 1  5 3 6 7  3 2 5 4
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ong Zhang hinese females		7	5	4	3
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			-	_	
ang Wang		11	5	5	2
lin Liu		19	9	11	10
a Li		9	11	8	2
iuying Zhang		16	6	7	5
hinese/English males					
llen Wang		7	0	3	1
ill Zhang		4	1	2	4
ric Wang		9	2	4	0
ck Li		0	1	1	1
mes Liu		4	1	2	1
hinese/English females					
my Wang		8	1	1	0
nnifer Li		3	3	1	0
ichelle Wang		12	4	2	2
Ionica Liu		9	2	1	0
ivian Zhang		5	2	1	2
reek males ukas Minsopoulos		18			
reek females					
ficole Minsopoulos		19			
otal		363	211	164	119

*Notes:* Cdn = Canadian, Educ = country where bachelor's degree obtained, and Exp = country where job experience obtained. Mixed experience corresponds to first two jobs listed on resume as being from a foreign country, and most recent (third) job listed from Canada.

Since virtually all immigrants that arrived recently under the point system had at least a bachelor's degree, all resumes generated in this study did so as well. A job posting's occupation category determined the set of degrees to randomly pick. For example, resumes generated for a position as a financial analyst had either a Bachelor of Arts in Economics or a Bachelor of Arts in Commerce while those for a software developer position had a bachelor's degree in computer science or one in computer engineering. Alma mater was picked randomly from a list of about four universities in the same country as the applicant's corresponding name and in the same proximity to the applicant's location of experience. About half of the universities were listed in the 2008 QS World University Rankings' Top 200.14 The other universities were less prestigious. Manipulation of this characteristic helps examine whether employers prefer applicants with degrees from Canada even in cases where, all else constant, other applicants have foreign degrees from arguably the most selective schools in China, India, or Pakistan. It is interesting to note that under the point system, an applicant receives the same number of points for a bachelor's degree, regardless of where he or she received it.

To assess whether additional Canadian educational credentials may offset lower callback rates from having foreign experience or foreign schooling, 20 percent of resumes, except those of Type 4, were randomly assigned Canadian master's degrees. 15 Master's degrees were occupation specific and completed during the same three year period as the applicant's most recent (Canadian) experience, so that it looked like the applicant was enrolled part-time while working full-time.

We also explore the role of accreditation by assigning some resumes with foreign education certificates by the fictitious "Canada International Skills Certification Board." Joerg Dietz et al. (2009) find that such certification reduces discrimination found by undergraduate students in judging whether to follow-up with applicants from South Africa with white or African names. One concern with this earlier work is that students were specifically asked to focus on the quality of the resume, potentially priming subjects to focus on productivity stereotypes. Our field setting considers a more real world environment.

Language skills and extracurricular activities were also manipulated to help explore whether language or cultural concerns underlie callback differences. I randomly selected 20 percent of resumes in Toronto to list fluency in multiple languages and 60 percent of resumes in Montreal. Resumes with English or Greek sounding names listed fluency in English and French. The other resumes listed fluency in English, French, and the applicant's mother tongue (Mandarin, Cantonese, Hindi, or Punjabi), depending on the applicant's ethnic name origin. In addition, 60 percent of resumes listed active extracurricular activities. One of three possible sets was chosen listing characteristics such as volunteer initiative (e.g., Big Brother/Sister, Habitat for Humanity), social interests (e.g., competitive squash player, classical pianist) and proactive work skills (e.g., excellent common sense, judgment, and

<sup>&</sup>lt;sup>14</sup>See www.topuniversities.com.

<sup>&</sup>lt;sup>15</sup>I note in the results section below that callback differences between Type 4 and other type resumes are about the same whether master's degrees are listed on the other type resumes or not.

TABLE 3—Proportion of Resumes Sent with Particular Characteristics by Resume Type

	Resume type sent					
•		0	1	2	3	4
		English name	Foreign name	Foreign name	Foreign name	Foreign name
		Cdn educ	Cdn educ	Foreign educ	Foreign educ	Foreign educ
	Full sample	Cdn exp	Cdn exp	Cdn exp	Mixed exp	Foreign exp
Characteristics of resume	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.51	0.51	0.51	0.50	0.50	0.52
Top 200 world ranking university	0.54	0.59	0.64	0.46	0.45	0.45
Extra curricular activities listed	0.60	0.60	0.61	0.60	0.59	0.61
Fluent in French and other languages	0.25	0.25	0.26	0.24	0.24	0.23
Canadian master's degree	0.17	0.20	0.20	0.21	0.20	0.00
Multinational firm work experience	0.25	0.28	0.23	0.24	0.26	0.26
High quality work experience	0.31	0.33	0.31	0.30	0.30	0.31
List Canadian references	0.03	0.00	0.00	0.00	0.09	0.08
Accreditation of foreign education	0.04	0.00	0.00	0.08	0.07	0.07
Permanent resident indicated	0.04	0.00	0.00	0.10	0.07	0.06
Name ethnicity						
English-Canadian	0.23	1.00	0.00	0.00	0.00	0.00
English-British	0.07	0.00	0.00	0.15	0.13	0.15
Indian	0.26	0.00	0.32	0.36	0.35	0.33
Pakistani	0.07	0.00	0.13	0.07	0.07	0.09
Chinese	0.22	0.00	0.28	0.29	0.31	0.28
Chinese with English first name	0.11	0.00	0.17	0.13	0.12	0.14
Greek	0.03	0.00	0.10	0.00	0.00	0.00

*Notes*: Cdn = Canadian, Educ = country where bachelor's degree obtained, and Exp = country where job experience obtained. Mixed experience corresponds to first two jobs listed on resume as being from foreign country, and most recent (third) job listed from Canada.Top 200 World Ranking University according to the 2008 QS World Rankings (http://www.topuniversities.com/).

decision-making abilities). Table 3 shows average frequencies of these and other characteristics on the resumes sent for each type.

Clearly resumes had to look different when sending to the same employer, so I also randomized each applicant's cover letter (i.e., a short, general message sent as a part of the e-mail text), and the e-mail subject line and the resume file name (resumes were saved as pdf files unless word documents were specifically requested). I randomized each resume's layout, residential address and telephone number (all possibilities were within Toronto or Montreal. Each applicant listed three previous jobs, with earlier years of experience being over two, three, or four years for each particular job, and with the most recent job always being listed as starting from the year the bachelor's degree was obtained. I randomized each applicant's e-mail address (e.g., s.shreya6@gmail.com or shreya.sharma48@yahoo.ca) and resume profile, which was listed near the top of the resume. Profiles mentioned general and specific skills, such as "highly motivated" and "fast learner." Some bullet points were occupationally specific (e.g., "six years experience in customer service and sales environment"). Within each occupation, profiles were selected randomly from five sets. On average, all resumes are the same across description of job experience, years of schooling, style of resume, and cover e-mail.

A program by Johana N. Lahey and Ryan A. Beasley (2009) was used to randomly select the characteristic codes of each resume. Microsoft Office was then used to transform these choices into text and mail merge them into actual resume templates. Some resume sets were dropped to avoid repeating names sent to the same employer. Research assistants developed a program to make the data collection process more menu-driven. When a job posting was identified for the study (from an Internet site), a research assistant would open a dialog window prompting for the job's corresponding occupation. Phone numbers or e-mail addresses on the post were used to check that someone had not applied to this employer previously. A second window allowed the user to enter the job title, the job posting's source, the company name, contact information, and whether additional certificates needed to be added to the resume. The program then updated the data collection spreadsheet and created four resumes that could be edited for cosmetic quality (to ensure they fit cleanly on one or two pages). The output also included instructions for what cover letter, subject line, and file name to use. The resumes were saved as pdf files and e-mailed from the addresses of the corresponding names to the employer over a twoto three-day period in random order. Any applications whose corresponding e-mail bounced, indicating it was never received, were dropped from the sample.

Multiple telephone numbers and two e-mail accounts for each name were set up to collect employer responses. Employers who telephoned an applicant received the same automatically generated message mentioning the number dialed and a request to leave a message. Messages and e-mails were recorded and redirected to a single e-mail address. Responses were classified as callbacks, if the employer requested an applicant to contact them (not just for clarification). Responses were classified as requests for interviews, if one was specifically mentioned. Employers that contacted an applicant twice were contacted themselves during off-hours by e-mail or phonemessage and told that the applicant had accepted another position and was no longer looking for employment.

I also recorded measures of language and social skills associated with each job using the Occupational Information Network (O\*NET). The purpose was to examine whether callback differences across resume types differ by the extent to which jobs require language or social skills. For each job title, I recorded the O\*NET's corresponding skill measure for speaking, writing and, social perceptiveness. 16 Each variable ranges from possible values of 0 to 100. I created a summary variable by adding the three values for each job and using this measure to sort occupations into deciles.

With random assignment, simple comparisons of callback rates can identify relative effects of the different resume characteristics. One exception is that small changes were made to the probability distribution of resume characteristics over the two-year period of data collection. Applicants with Chinese last names but English first names, for example, were added in September 2008. Pakistani names were removed in February 2009, after finding similar results compared to applicants with Chinese or Indian names. Greek names were also randomly added in February 2009, as were permanent residency status, Canadian references, accreditation signals, and

<sup>&</sup>lt;sup>16</sup>Occupations were matched to these skill measures using O\*NET's website, http://online.onetcenter.org/.

refined sets of experience to better distinguish by firm size and prestige. To account for these changes, I include in the regression an indicator variable for whether the resume was sent between April and August 2008, September and November 2008, and February and September 2009. The findings are similar when allowing for separate period trends by resume type, ethnicity, and city, but are somewhat less precise. More specifically, I estimate regressions using versions of the following linear probability model:

(1) 
$$y_{ijt} = \delta_0 + \delta_1 Resume\_Type_{ijt} + \delta_2 \mathbf{X}_{ijt} + \delta_3 [Resume\_Type_{ijt} \times \mathbf{X}_{ijt}] + v_t + e_{iit}.$$

Where  $y_{ijt}$  is an indicator variable for whether resume i sent to job posing j in period t generated a call back,  $Resume\_Type_{ijt}$  is an indicator variable for resume type, with the indicator for Type 0 being omitted.  $\mathbf{X}_{ijt}$  is a vector of other resume characteristics. Equation (1) allows for interactions between resume type and other characteristics. This allows me to estimate, for example, whether callback differences between resumes with English and Chinese sounding names become smaller, when additional language skills or educational credentials are listed. Standard errors are corrected for possible heteroskedasticity by job.

#### III. Results

Table 4 shows the main results. The sample excludes foreign resumes with listed accreditation, local references, or permanent resident status for comparability with resumes featuring Canadian experience and education (I examine the impact of adding these characteristics in the next table). Row 1 shows the estimated baseline callback rate of about 16.0 percent for Type 0 resumes with English-sounding names, Canadian experience, and Canadian education in period 1 (April to August 2008).<sup>17</sup> Changing only the name to one with Indian origin lowers the callback rate by 4.5 percentage points, to 11.5 percent (s.e. = 1.2 percentage points), and changing it to one with Pakistani or Chinese origin lowers it slightly more, to 11.0 percent and 11.3 percent, respectively. Overall, resumes with English sounding names are 39 percent more likely to receive callbacks than resumes with Indian, Pakistani, or Chinese names (column 7). For comparison, Bertrand and Mullainathan (2004) find that resumes with similar English sounding names are 50 percent more likely to receive callbacks than resumes with African-American sounding names sent to employers in Boston and Chicago (4 percent versus 8 percent, respectively). Interestingly, switching applicants' names from English to Greek origins generates lower callback rates by 4.0 percentage points. The callback rate gap between English and Greek names is about the same as it is between English and other ethnic names and significant at the 5 percent level.

<sup>&</sup>lt;sup>17</sup>Reflecting deteriorating economic conditions, callback rates fall, on average, 1.4 and 1.5 percentage points for the two subsequent periods September to November 2008 and February to September 2009, respectively. As mentioned earlier, findings are similar when allowing for separate time trends by resume and ethnic type, but are slightly less precise.

	Са	Callback rate for Type 0 resumes with English name, Canadian experience, and Canadian education						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Type 0 English name Cdn educ Cdn exp	0.160	0.158	0.154	0.158	0.158	0.158	0.157	

Callback rates and relative differences by ethnic origin and experience/education location

(Difference compared to Type 0) [Standard error of difference] {Callback ratio: Type 0/Type}

	{Canback ratio. Type 0/ Type}							
	Indian	Pakistani	Chinese	Chinese with English first name	English- British	Greek	Indian/ Pakistani/ Chinese	
Type 1 Foreign name Cdn educ Cdn exp	0.115 (-0.045) [0.012]*** {1.39}	0.110 (-0.050) [0.016]*** {1.44}	0.113 (-0.041) [0.013]*** {1.40}	0.125 (-0.033) * [0.014]** {1.26}	NA	0.118 (-0.040) [0.019]** {1.34}	0.113 (-0.044) [0.009]*** {1.39}	
Type 2 Foreign name Foreign educ Cdn exp	0.115 (-0.045) [0.015]*** {1.39}	$0.140 \\ (-0.018) \\ [0.027] \\ \{1.13\}$	0.097 (-0.057) [0.015]*** {1.59}		0.129 (-0.029) [0.019] {1.22}	NA	0.110 (-0.047) [0.011]*** {1.43}	
Type 3 Foreign name Foreign educ Mixed exp	0.075 (-0.085) [0.013]*** {2.13}	0.078 (-0.080) [0.020]*** {2.05}	0.101 (-0.053) [0.016]*** {1.58}	0.098 (-0.060) [0.020]*** {1.61}	0.157 (-0.001) [0.023] {1.01}	NA	$\begin{array}{c} 0.085 \\ (-0.072) \\ [0.010] *** \\ \{1.85\} \end{array}$	
Type 4 Foreign name Foreign educ Foreign exp	0.062 (-0.098) [0.013]*** {2.58}	0.052 (-0.106) [0.015]*** {3.04}	0.059 (-0.095) [0.014]*** {2.61}	$ \begin{array}{c} 0.141 \\ (-0.017) \\ \hline [0.021] \\ \{1.12\} \end{array} $	$0.141 \\ (-0.017) \\ [0.021] \\ \{1.12\}$	NA	0.059 (-0.098) [0.009]*** {2.71}	

Notes: Cdn = Canadian, Educ = country where bachelor's degree obtained, and Exp = country where job experience obtained. Mixed experience corresponds to first two jobs listed on resume as being from a foreign country, and most recent (third) job listed is from Canada. The table shows coefficient estimates from regressing call back status on resume type and two time indicators for when the sampling distribution of resumes changed (i.e., adding Pakistani and Greek names) with robust standard errors. Each column shows separate regression results after selecting on the sample of Type 0 resumes and Types 1-4 resumes with the indicated ethnic backgrounds. The first row indicates the call back rate estimate for Type 0 resumes during the first period of data collection.

The callback rate among Type 1 resumes with English first names and Chinese last names in column 4 (e.g., Allen and Michelle Wang) is 12.5 percent, which is significantly different from the callback rate among those with first and last English names (e.g., John and Carrie Martin), but not significantly different from the callback rate among those with first and last Chinese names (e.g., Lei and Na Li). Many secondgeneration Chinese adopt and use an English sounding name to make pronunciation easier for non-Chinese and to signal North American assimilation. Interestingly, this adoption does not improve one's chances for a callback.

There does not appear to be a large difference in callback rates between Type 1 and Type 2 resumes, which systematically differ only by whether they list a bachelor's

<sup>\*\*\*</sup>Significant at the 1 percent level.

<sup>\*\*</sup>Significant at the 5 percent level.

<sup>\*</sup>Significant at the 10 percent level.

degree from a Canadian university (Type 1) or a foreign university (Type 2). Both sets of resumes do not include Canadian names and foreign experience. Thus, conditional on listing four to six years of Canadian experience, employers do not seem to care whether an applicant's education is from a foreign institution or not, when deciding whether to contact the applicant for an interview.

In contrast, switching from job experience acquired in Canada to job experience acquired from a foreign country seems to matter a lot. Types 2, 3, and 4 resumes all list foreign names and foreign degrees. The experience descriptions are also identical, but Type 4 resumes list previous job experience with companies located in foreign cities, and Type 3 resumes list foreign cities for two of the three previous jobs (the most recent job is listed as being in Toronto). The callback rate for resumes that list almost all job experience from India, China, or Pakistan drops 2.5 percentage points compared to resumes with all Canadian experience (from 11.0 percent to 8.5 percent), as shown in column 7. Callback rates drop 5.1 percentage points for resumes listing only foreign job experience. Interestingly, the resumes that list only British experience do not generate any significant fall in callback rates compared to Type 0 Canadian resumes (14.1 percent compared to 15.8 percent, as reported in column 5).

For the remaining results, Types 2, 3, and 4 resumes exclude applicants with British experience and education, in order to focus on comparisons with the three largest immigrant groups from China, India, and Pakistan, and all resumes exclude applicants with Greek or English-Chinese names.

If remaining concerns about language or other traits not directly observed explain the callback rate gaps discussed above, adding additional information related to these concerns should help reduce the gap. Table 5 shows whether this pattern occurs when conditioning on whether the applicant is female, graduated from a top 200 world ranked university (according to the 2008 QS University World Rankings), listed active social extracurricular activities (e.g., volunteer work, competitive sports, travel), fluency in French, English, and a mother tongue (applicable for Indian and Chinese named resumes), graduated with a occupation related Canadian master's degree, with job experience from large, prestigious-national firms or with Multinational firms with establishments in all three countries, listed a reference with a Canadian phone number, listed education accredited by the Canada International Skill Certification Board (resume Types 2, 3, and 4 resumes only), or listed legal permanent residency status (Types 2, 3, and 4 resumes only). The first panel shows the callback rate between Type 0 resumes and other types with and without these dummy variable controls. The results clearly indicate that conditioning on these

<sup>&</sup>lt;sup>18</sup> Type 4 resumes also differ from other types in that they list no Canadian master's degrees because the resumes would look strange with master's degrees acquired in Canada during a period the individual was working outside of Canada. Dropping the 20 percent of Type 0 and Type 4 resumes with master's degrees makes no difference to these results.

<sup>&</sup>lt;sup>19</sup>Type 3 and Type 4 resumes list foreign experience, but in about half the sample company names and job descriptions are identical with those in Type 2 resumes (with Canadian experience). For example, some resumes list experience with ABC Inc., Toronto, while others list experience with ABC Inc., Mumbai. The results using resumes with the same company names are similar to those using samples whose company names are different (but whose job descriptions are identical). More specifically, the callback rates for Types 3 and 4 resumes listing experience with international companies (that could instead be used for resumes with Canadian experience) are 0.071 and 0.068, respectively. The callback rates for Types 3 and 4 resumes listing local foreign company names are 0.099 and 0.040, respectively.

TABLE 5—ESTIMATED EFFECTS ON THE PROBABILITY OF CALLBACK FROM THE INCLUSION OF SPECIFIC RESUME CHARACTERISTICS

	Type 0	Type 1	Type 2	Type 3	Type 4
	English name	Foreign name	Foreign name	Foreign name	Foreign name
	Cdn educ	Cdn educ	Foreign educ	Foreign educ	Foreign educ
	Cdn exp	Cdn exp	Cdn exp	Mixed exp	Foreign exp
	(1)	(2)	(3)	(4)	(5)
Panel A. Callback rate differences w	rith and without	controls			
Callback rate (for Type 0) and unconditional callback difference between other resume types	0.157	-0.044 [0.009]***	-0.048 [0.010]***	-0.073 [0.009]***	-0.094 [0.009]***
Callback difference after conditioning on all resume characteristics		-0.044 [0.009]***	-0.049 [0.010]***	-0.074 [0.010]***	-0.096 [0.009]***
Panel B. Resume characteristic effect	cts on callback r	ate by type			
Resume characteristic female	0.049 [0.013]***	0.012 [0.012]	0.007 [0.015]	0.001 [0.014]	0.007 [0.012]
Top 200 world ranking university	-0.022 [0.014]	0.015 [0.013]	0.008 [0.016]	-0.018 [0.015]	-0.002 [0.014]
List extra curricular activities	-0.007 [0.013]	0.023 [0.012]*	0.003 [0.015]	0.006 [0.014]	0.001 [0.012]
Fluent in French and other languages	0.020 [0.015]	0.007 [0.014]	0.058 [0.019]***	-0.010 [0.015]	0.036 [0.016]**
Canadian master's degree	-0.003 [0.016]	0.006 [0.015]	-0.034 [0.017]**	0.019 [0.019]	NA
Multinational firm work experience	-0.020 [0.018]	0.010 [0.020]	0.027 [0.025]	-0.056 [0.021]***	0.028 [0.018]
High quality work experience	0.006 [0.016]	0.002 [0.015]	0.015 [0.020]	0.034 [0.019]*	-0.004 [0.016]
List Canadian references				-0.002 [0.023]	-0.006 [0.025]
Accreditation of foreign education			0.007 [0.024]	0.004 [0.025]	-0.014 [0.025]
Permanent resident indicated			-0.019 [0.024]	0.005 [0.025]	0.025 [0.027]
Sample size	3,026	2,631	1,618	1,501	1,408

Notes: Panel A reports call back rate differences by resume type, relative to Type 0, with and without including control variables for applicant gender, an indicator that the applicant obtained her bachelor's degree from a university ranked in the Top 200 according to the QS University World Rankings, and whether the resume listed extra curricular activities, fluency in multiple languages (including French), a Canadian master's degree, Canadian references, Canadian government accreditation of an applicant's foreign degree, and permanent resident status. Panel B reports coefficient results from regressing call back status on these characteristics. Robust standard errors are reported. Cdn = Canadian, Educ = country where bachelor's degree obtained, and Exp = country where job experience obtained. Mixed experience corresponds to first two jobs listed on resume as being from a foreign country, and most recent (third) job listed from Canada.

factors overall has virtually no impact on the callback rate by name, source country of education, or experience. In other words, taking into account whether resumes include or exclude this information has no role in the impact name, country of education, or experience, has on reducing the likelihood of a response.

<sup>\*\*\*</sup>Significant at the 1 percent level.

<sup>\*\*</sup>Significant at the 5 percent level.

<sup>\*</sup>Significant at the 10 percent level.

Panel B of Table 5 shows the estimated effect of listing each trait for each resume type separately. Under the model of statistical discrimination, the impact from listing language fluency for resumes from ethnically named applicants should be greater than that from English named applicants. The estimates show that listing this information improves the relative callback rate for Types 2 and 4 resumes, but not for Types 1 and 3 resumes. Type 2 resumes listing multiple language fluency improve the callback rate by 5.8 percentage points compared to a 2.0 percentage point improvement for Type 0 resumes. This relative improvement is enough to close most of the callback rate gap. I also find improvement in callback rates for Type 1 resumes from listing extracurricular activities (i.e., a 2.3 percentage point higher callback rate), but no improvement for other resume types.

The point estimates from listing a bachelor's degree from a higher ranked school are not statistically significant. Foreign applicants, in particular, with degrees from highly selective schools are no more likely to receive callbacks than applicants from schools far less known and less selective. The addition of a Canadian master's degree or experience from a large national or international firm has no significant positive effect on the callback rate.

The addition of Canadian references for resumes with all or some foreign experience to indicate to employers that they can contact someone in Canada, listing permanent residency status to indicate that an applicant is legally allowed to work in the country, or attaching accreditation to a foreign degree has no significant impact on raising callback rates among Types 2, 3, or 4 resumes with foreign education and/or experience. The point estimates are all close to zero.

Column 1 in Table 5 shows a substantial premium from listing a common female name compared to a male name for resumes with English last names only (Type 0). The callback rates for the Toronto and Montreal sample are estimated to be 4.9 percentage points higher for English named females compared to English named males. The premium arises for Type 0 resumes but not the other resume types. One explanation for this finding is that recruiters have difficulty spotting female applicants among resumes with Chinese-, Indian-, or Pakistaninamed applicants, but no such difficulty for English-named applicants. However, this hypothesis is inconsistent with results comparing English and Greek names. When examined separately, there are lower callback rates when applying as Nicole Minsopoulos compared to English-named females, but not when comparing Lukas Minsopoulos to other English-named males (results not shown in table). In addition, the female Indian names I use (i.e., Maya, Priyanka, Shreya, and Tara) seem straightforward to recognize even by English recruiters unfamiliar with these names, yet the callback rate gap among Indian named applicants compared to English named ones is larger than that for Chinese-named applicants. The cost to discern an applicant's gender, by phone call for example, is also not large. Another explanation for the female premium among Type 0 resumes is simply that recruiters prefer to interview English-named applicants, especially females.

Table 6 shows how callback rates differ after separating the sample by jobs applied that require above or below median language and social skills. The idea is to explore whether employers trying to hire in jobs that require more intensive

Language and social skill	Sample	Callback rate for English name Cdn educ	Callback diff. for foreign name  Cdn educ	
requirement decile	occupations	Cdn exp	Cdn exp	Ratio
(1)	(2)	(3)	(4)	(5)
1	Computer programmer Maintenance technician	0.127	-0.034 [0.020]*	1.4
2	Accountant Web developer	0.148	-0.050 [0.026]*	1.5
3	Bookeeper Systems administrator	0.128	-0.050 [0.018]***	1.6
4	Administrative assistant Office administrator	0.128	-0.059 [0.017]***	1.9
5	Electrical engineer Design assistant	0.122	-0.059 [0.022]***	1.9
6	Sales representative Quality analyst	0.157	-0.053 [0.018]***	1.5
7	Financial analyst Project manager	0.254	-0.056 [0.028]**	1.3
8	Account manager Receptionist	0.183	-0.041 [0.024]*	1.3
9	Human resources manager Collection officer	0.133	-0.029 [0.025]	1.3
10	Executive recruiter Community counselor	0.162	-0.067 [0.028]**	1.7

Table 6—Callback Rate Differences for Resumes Sent to Jobs with Different Language AND SOCIAL SKILL REQUIREMENTS

Notes: Job postings applied to were matched to speaking, writing, and social O\*NET defined occupational skill requirements (each with a 1-7 point continuous scale). All three measures were added to create an aggregate score, and used to separate the sample into deciles. Callback differences are estimated as in Table 4 Column 7. Cdn = Canadian, Educ = country where bachelor's degree obtained, and Exp = country where job experience obtained.

language or social skills are even less likely to interview immigrants out of concern that they have fewer of these skills than natives. I match each posting's job description with measures of speaking, writing, and social O\*NET defined occupational skill requirements and add these values together. I then run separate regressions for each decile to test for name differences between Type 0 resumes with English names, and Type 1 resumes with Chinese, Indian, or Pakistani names. The table shows general consistency across language and social skill deciles. Across a wide range of occupations ranging from computer programmer and web developer, in the lower decile categories of O\*NET language and social skills, to receptionist and project manager in higher decile categories, the ratio in callback rates between resumes with English names and ethnic sounding names remains about the same and statistically significant.

## IV. Discussing Results with Recruiters

After finding significant levels of name discrimination shown in Section III, even for Greek names and across a wide range of jobs, I e-mailed a random sample of

<sup>\*\*\*</sup>Significant at the 1 percent level.

<sup>\*\*</sup>Significant at the 5 percent level.

<sup>\*</sup>Significant at the 10 percent level.

300 employers from the sample of resumes sent to gain perspective from the recruiters themselves about what they think drives the results. I offered \$25 amazon.ca gift certificates for responses to be used anonymously (and under guidance from University of Toronto's Ethics Review Board). I focused on the Chinese, Indian, and Pakistani name discrimination results for resumes with Canadian experience and education and asked whether recruiters thought that the observed behavior was due to remaining productivity concerns or something else. I also noted that listing active extracurricular activities, volunteer work, and fluency in multiple languages (including French) did not significantly affect the findings, and these differences were found for many different job types.

Only 29 responded. Virtually everyone that did, however, overwhelmingly said that employers often treat name, country of education or experience as a signal that an applicant may lack critical language skills for the job. When asked specifically about why otherwise identical resumes except for name would generate a different response, typical responses were:

The problem is the ability to communicate in English. Foreign sounding names may be overlooked due to a perception that their English language skills may be insufficient on the job site.

One reason for this to occur would be people's fear of strong accents not being understood by customers and/or co-workers.

Name suggests candidate is not fluent in English, is the candidate eligible to work in Canada, will the candidate need extensive time off to return home to visit family/friends, will the employer be required to provide additional time off in recognition of cultural holidays.

Some recruiters also pointed out that they often face more pressure to avoid bad hires than they are awarded for exceptional ones. Negative hiring experiences with workers of a specific ethnicity also created less openness to people from that ethnicity in the future:

The lesson and outcome of hiring someone who left the company angrily is to not hire anyone of the same ethnicity. The same politics work against all of us.

Some respondents also expressed difficulties evaluating the qualifications of someone with a non-English name:

A good recruiter will call everyone because there may be times that people aren't represented as you'd picture them from their resume. ... When you're calling someone with an English sounding name, you know what you're getting into. You know that you can call Bob Smith, and you can talk to him as quickly as you want to. It's less work because you know that his English will be fine. It also indicates that he's white looking. The brown guy who was born here is not less desirable in the workplace, but it takes something more to know for sure that he speaks English without an accent. We'd have to make a phone call and test the water.

### V. Conclusion

In this paper, I explore why immigrants who enter Canada based on skill fair so poorly in the labor market. The employed methodology involves sending mock resumes in response to thousands of job postings across a wide set of occupations and industries mostly around the Greater Toronto Area. Three main descriptive findings emerge. First, Canadian-born individuals with English-sounding names are much more likely to receive a callback for a job interview after sending their resumes than compared to foreign-born individuals, even among those with foreign degrees from highly selective schools, or among those with the same listed job experience but acquired outside of Canada. The results show that 15.7 percent of resumes sent with English-sounding names, Canadian education, and Canadian experience received a callback from an employer, compared to only 6.0 percent of resumes with foreign-sounding names from China, India, or Pakistan, and foreign experience and education. The callback gap lines up with overall unemployment differences. In 2006, for example, the national unemployment rate for immigrants was 11.5 percent, more than double the rate of 4.9 percent for the Canadian-born population (Statistics Canada 2007). Much of the unemployment difference may, therefore, be due to immigrants not even making it to the interview stage in the job application process.

Second, employers value Canadian experience far more than Canadian education when deciding to interview applicants with foreign backgrounds. Among resumes with foreign names and foreign education, the callback rate climbs from 6.0 percent to 8.5 percent by listing just one previous job with a company located *inside* Canada rather than outside. Listing all job experience with companies located inside Canada leads to the callback rate increasing further to 11.0 percent. These substantial increases are noteworthy especially in light of the fact that they also occur when only job location differs while keeping constant job descriptions and company names (e.g., ABC Inc., Toronto versus ABC Inc., Mumbai). Employers are much more interested in foreign-born applicants with more Canadian experience. If more of these immigrants are allowed to enter, or recent arrivals are provided with assistance to help them find initial work that matches their previous background, this may help to boost immigrants' wage trajectories.

While Canadian experience plays a crucial role in determining the likelihood of a callback, having a degree from a more prestigious foreign institution, or acquiring additional schooling in Canada does not appear to significantly impact the chances of a callback. Conditional on listing four to six years of Canadian experience on a resume, callback rates do not differ significantly by whether a resume lists a bachelor's degree from nearby Canadian university or lists one from a foreign university. I also find little effect from indicating an applicant graduated from a top-ranking school compared to a low-ranking school, even among resumes with degrees from Canadian institutions. This surprises me, since admission criteria varies widely by school. It may indicate employers do not pay close attention to education qualifications for resumes with several years of experience. I also find no effect from listing an additional Canadian master's degree. The recruiters, with whom I discussed these results, were not surprised. All recruiters said that education plays only a minor role

in deciding whether to call back for an interview once an applicant has accumulated four to six years of experience.

Third, employers discriminate substantially by name. Employer contact falls by 4.4 percentage points when switching from a Canadian resume with a common English name to one with a common Chinese, Indian, Pakistani, or even Greek name (15.7 percent to 11.3 percent, respectively). This difference is substantial, and almost as large as that found by Bertrand and Mullainathan (2004) using resumes in the United States with black- or white-sounding names.

When asked what explains these findings, recruiters who responded said overwhelmingly that employers often treat name as a signal that an applicant lacks critical language skills for the job. Some recruiters also pointed out that they often face more pressure to avoid bad hires than they are awarded for exceptional ones. This leads to risk aversion and exacerbates the impact from even small signals of lower expected productivity.

The empirical evidence, however, does not easily corroborate with the view that all the discrimination observed is statistically driven by concerns about language skills. The resumes sent were, on average, the same by description of job experience, years of schooling, style of resume, and cover e-mail. The statistical discrimination model predicts that adding information related to important characteristics not listed on the resume should reduce the degree of discrimination, yet I find little evidence of this. The listing of fluency in French, English, and mother tongue marginally increases callback rates for foreign educated and experienced applicants, but has no impact for foreign-named applicants. Listing prominently recognized firms, or large firms, also does not reduce the gap in callback rates. I find no obvious pattern between the English-named applicant premium and the degree of language skill required to perform successfully on the job.

An interesting (and unexpected) finding is that switching applicants' names from English to Greek origins generates lower callback rates. The callback rate gap between English and Greek names is about the same as it is between English and Chinese names, and significant at the 10 percent level. I believe employers likely view Greek-named applicants as Canadian born with little difference in English proficiency compared to the English applicant. A reinterpretation of the gap between English-named applicants and those with Indian, Pakistani, or Chinese names therefore is that recruiters place a premium on wanting to interview applicants with English names rather than a discount on Indian, Pakistani, or Chinese. Consistent with this conclusion, Nicolas Jacquemet and Constantine Yannelis (2011) find similar levels of discrimination in Chicago for applicants with African-American names and applicants with unknown ethnic origins compared to applicants with Anglo-Saxon names.

Surprisingly, no recruiters who responded explicitly acknowledged the possibility that information on the resume could offset or address their stated language concerns, despite efforts to point this possibility out. A majority of respondents seemed to assume an applicant with an Indian, Pakistani, or Chinese name implied an immigrant and justified the results based on language concerns. Those who expressed these concerns also failed to acknowledge that the cost to acquire more information about language skills is small. If employers are interested in a candidate but

concerned about the applicant's language skills, they could contact the applicant by telephone to determine whether an interview would be worthwhile.

Our contrasting quantitative and qualitative results, taken overall, are consistent with models such as Crandall and Eshleman (2003) of unintentional implicit discrimination, where employers justify name and immigrant discrimination based on language skill concerns, but incorrectly overemphasize these concerns without taking into account offsetting listed characteristics. There are two other audit studies that provide further evidence of implicit discrimination. Dan-Olof Rooth (2010) matches self-reported racial attitudes and implicit association test (IAT) scores of employers to callback outcomes from an audit study he carried out that looks at discrimination between resumes with common Swedish names and Arab-Muslim names. Those with more negative implicit association measures are less likely to callback Arab-Muslims, while self-reported measures of explicit association have little explanatory power. Bertrand, Chugh, and Mullainathan (2005) report similar results from a study involving picking qualified candidates from a set of resumes with White and African-American names and find a negative correlation between the number of African-American resumes selected by a given subject and that subject's IAT score. The stereotypes driving racial callback differences, however, are less focused on language ability than those likely driving the ethnic callback differences this paper finds. Bertrand, Chugh, and Mullainathan (2005) observe the correlation largest among those subjects that report feeling most rushed during the task.

One direct policy recommendation that arises from concluding that implicit discrimination drives at least some of the results is that employers should consider masking names on applications before making initial interview decisions. Masking names is easily implemented for employers that collect applications online. Recruiters can also request that applicants list name and contact information on a separate page at the end of a resume that can then be ignored or removed during the initial interview selection process. It would not be difficult to explore this practice on a trial basis to determine whether such practice leads to better hiring or turns out to be onerous with little perceived benefit. As a related example, Claudia Goldin and Cecilia Rouse (2000) document how blind auditions procedures (e.g., auditioning behind a screen) fostered impartiality in hiring and increased the proportion of women in symphony orchestras. Another implication is to develop hiring policies that involve contacting marginal applicants to initially assess language abilities, when in doubt.

It should not be overlooked, however, that many recruiters are clearly concerned that immigrants may lack critical language skills for performing well on the job. These concerns appear to be based on real productivity worries. We cannot rule out that the stated reasons for discrimination belie underlying prejudice. Nevertheless, employers state they place high value on workers with strong communication skills and it may be worth considering additional ways to rank applicants under the point system higher for having these skills.



#### **REFERENCES**

- **Aigner, Dennis J., and Glen G. Cain.** 1977. "Statistical Theories of Discrimination in Labor Markets." *Industrial and Labor Relations Review*, 30(2): 175–87.
- Antecol, Heather, Peter Kuhn, and Stephen J. Trejo. 2006. "Assimilation via Prices or Quantities? Sources of Immigrant Earnings Growth in Australia, Canada, and the United States." *Journal of Human Resources*, 41(4): 821–40.
- **Aydemir, Abdurrahman, and Mikal Skuterud.** 2005. "Explaining the Deteriorating Entry Earnings of Canada's Immigrant Cohorts, 1966–2000." *Canadian Journal of Economics*, 38(2): 641–71.
- **Beach, Charles M., Alan G. Green, and Christopher Worswick.** 2007. "Impacts of the Point System and Immigration Policy Levers on Skill Characteristics of Canadian Immigrants." *Research in Labor Economics*, 27: 349–401.
- Bertrand, Marianne, Dolly Chugh, and Sendhil Mullainathan. 2005. "Implicit Discrimination." *American Economic Review*, 95(2): 94–98.
- **Bertrand, Marianne, and Sendhil Mullainathan.** 2004. "Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review*, 94(4): 991–1013.
- Borjas, George J. 1993. "Immigration Policy, National Origin, and Immigrant Skills: A Comparison of Canada and the United States." In Small Differences That Matter: Labor Markets and Income Maintenance in Canada and the United States, ed. David Card and Richard B. Freeman, 21–43. Chicago: University of Chicago Press.
- Chugh, Dolly. 2004. "Societal and Managerial Implications of Implicit Social Cognition: Why Milliseconds Matter." *Social Justice Research*, 17(2): 203–22.
- **Crandall, Christian S., and Amy Eshleman.** 2003. "A Justification-Suppression Model of the Expression and Experience of Prejudice." *Psychological Bulletin*, 129(3): 414–46.
- Dietz, Joerg, Victoria M. Esses, Chetan Joshi, and Caroline Bennett-AbuAyyash. 2009. "The Evaluation of Immigrants' Credentials: The Roles of Accreditation, Immigrant Race, and Evaluator Biases." Canadian Labour Market and Skills Researcher Network (CLSRN) Working Paper 18.
- **Dolin, Benjamin, and Margaret Young.** 2004. "Canada's Immigration Program." Parliamentary Information and Research Service Background Paper BP-190E.
- **Ferrer, Ana, and W. Craig Riddell.** 2008. "Education, Credentials, and Immigrant Earnings." *Canadian Journal of Economics*, 41(1): 186–216.
- Frenette, Marc, and René Morissette. 2005. "Will They Ever Converge? Earnings of Immigrant and Canadian-born Workers over the Last Two Decades." *International Migration Review*, 39(1), 228–57.
- **Fryer, Roland, and Matthew O. Jackson.** 2008. "A Categorical Model of Cognition and Biased Decision Making." *B.E. Journal of Theoretical Economics: Contributions to Theoretical Economics*, 8(1): Article 6.
- **Goldin, Claudia, and Cecilia Rouse.** 2000. "Orchestrating Impartiality: The Impact of 'Blind' Auditions on Female Musicians." *American Economic Review*, 90(4): 715–41.
- Green, David A., and Christopher Worswick. 2010. "Entry Earnings of Immigrant Men in Canada: The Roles of Labour Market Entry Effects and Returns to Foreign Experience." In *Canadian Immigration: Economic Evidence for a Dynamic Policy Environment*, ed. Ted McDonald, Elizabeth Ruddick, Arthur Sweetman and Christopher Worswick, 77–110. Montreal and Kingston: McGill-Queen's University Press.
- **Jacquemet, Nicolas, and Constantine Yannelis.** 2011. "Indiscriminate Discrimination: A Correspondence Test for Ethnic Homophily in the Chicago Labor Market." Unpublished.
- Lahey, Joanna N., and Ryan A. Beasley. 2009. "Computerizing Audit Studies." *Journal of Economic Behavior and Organization*, 70(3): 508–14.
- LaLonde, Robert J., and Robert H. Topel. 1992. "The Assimilation of Immigrants in the U.S. Labor Market." In *Immigration and the Work Force: Economic Consequences for the United States and Source Areas.*, ed. George J. Borjas and Richard B. Freeman, 67–92. Chicago: University of Chicago Press.
- **Lubotsky, Darren.** 2007. "Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings." *Journal of Political Economy*, 115(5): 820–67.
- Manning, Alan. 2000. "Movin' On Up: Interpreting the Earnings-Experience Profile." *Bulletin of Economic Research*, 52(4): 261–95.
- Mullainathan, Sendhil. 2002. "A Memory-Based Model of Bounded Rationality." *Quarterly Journal of Economics*, 117(3): 735–74.
- **Oreopoulos, Philip.** 2011. "Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes: Dataset." *American Economic Journal: Economic Policy*. http://www.aeaweb.org/articles.php?doi=10.1257/pol.3.4.148.

- Phelps, Edmund S. 1972. "The Statistical Theory of Racism and Sexism." American Economic Review, 62(4): 659-61.
- Ranganath, Kate A., Colin Tucker Smith, and Brian A. Nosek. 2008. "Distinguishing Automatic and Controlled Components of Attitudes from Direct and Indirect Measurement Methods." Journal of Experimental and Social Psychology, 44(2): 386–96.
- Riach, P. A., and J. Rich. 2002. "Field Experiments of Discrimination in the Market Place." Economic Journal, 112(483): F480-518.
- Rooth, Dan-Olof. 2010. "Automatic Associations and Discrimination in Hiring: Real World Evidence." Labour Economics, 17(3): 523-34.
- Schaafsma, Joseph, and Arthur Sweetman. 2001. "Immigrant Earnings: Age at Immigration Matters." Canadian Journal of Economics, 34(4): 1066–99.
- Stanley, Damian, Elizabeth Phelps, and Mahzarin Banaji. 2008. "The Neutral Basis of Implicit Attitudes." Current Directions in Psychological Science, 17(2): 164–70.
- Statistics Canada. 2008. Earnings and Incomes of Canadians Over the Past Quarter Century, 2006 Census. Catalogue no. 97-563-X. Ottawa, May.
- Statistics Canada. Census of Canada. 2006. Public Use Microdata File of Individuals [computer file]. Ottawa, Ont.: Statistics Canada [producer]; Statistics Canada. Data Liberation Initiative [distributor], 2010-03-04. (STC cat. 95M0028XVB).
- Zietsma, Danielle. 2007. "The Canadian Immigrant Labour Market in 2006: First Results from Canada's Labour Force Survey." Labour Statistics Division, Statistics Canada Research Paper, Catalogue no. 71-606-XIE2007001.

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