WORKING PAPER Nº IDB-WP-01610

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Wladimir Zanoni
Raissa Fabregas

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Cataloging-in-Publication data provided by the

Inter-American Development Bank

Felipe Herrera Library

Zanoni López, Wladimir, 1975 -

The migrant penalty in Latin America: experimental evidence from job recruiters / Wladimir Zanoni, Raissa Fabregas.

p. cm. — (IDB Working Paper Series; 1610)

Includes bibliographical references.

1. Foreign workers-Ecuador-Mathematical models. 2. Labor market-Ecuador-Mathematical models. 3. Labor supply-Ecuador-Mathematical models. 4. Wages-Ecuador-Mathematical models. I. Fabregas, Raissa. II. Inter-American Development Bank. Country Department Andean Group. III. Title. IV. Series.

IDB-WP-1610

JEL CODES: J71, J61, C93, O15

KEY WORDS: Migrant, Labor Market, Wage

http://www.iadb.org

Rea_can@iadb.org

The Migrant Penalty in Latin America: Experimental Evidence from Job Recruiters

Wladimir Zanoni and Raissa Fabregas*

October 28, 2024

Abstract

We conducted an artifactual field experiment with human resource recruiters in Ecuador to investigate the extent to which migrants are penalized in the formal labor market. Human resource recruiters were hired to evaluate pairs of job candidates competing for jobs. The candidate profiles were comparable in observables, except that one was randomly assigned to be a Venezuelan migrant. Recruiters assessed job fitness, proposed salaries for each candidate, and made hiring recommendations. We find robust evidence of a penalty against migrants across all dimensions. Venezuelans are penalized despite being from a population that shares cultural, historical, and linguistic characteristics with natives and has, on average, higher levels of education. We do not find evidence that recruiters' demographic characteristics, experience, cognitive scores, or personality traits correlate with a preference for natives. Instead, there is suggestive evidence that jobs requiring a greater degree of local knowledge or public interface carry a higher migrant penalty.

*Fabregas: LBJ School of Public Affairs, University of Texas at Austin. Email: rfabregas@utexas.edu; Zanoni: Interamerican Development Bank. Email: wladimirz@iadb.org. We thank the partner organization Grupo-FARO for their support with this project and seminar participants at the Colegio de Mexico and the LBJ school for helpful comments. Jorge Paredes-Murillo provided excellent research assistance.

1 Introduction

Out of the 184 million migrants worldwide, 43% have settled in low- and middle-income countries (LMICs), which also host nearly 74% of the world's refugees (World Bank, 2023). For many of these host countries, the social and economic integration of immigrants has become a critical item on their policy agendas, with discrimination and xenophobia often cited as major obstacles to migrant assimilation (UNHCR, 2019; World Bank, 2020a).

A substantial experimental literature, mostly relying on correspondence and audit studies, has documented that migrants to high-income countries are discriminated against in the labor, rental, and retail markets (see Bertrand and Duflo (2017) and Lippens et al. (2023) for summaries).[1] Surprisingly, there is much less evidence about the existence and magnitude of these penalties in LMICs. On the one hand, weaker legal institutions and greater market frictions in LMICs could imply even less favorable outcomes for migrants. On the other hand, the skill complementarity between natives and migrants in LMICs could differ significantly from patterns observed in more developed countries. For example, if migrants have higher levels of education than the native population, employers may hold more positive perceptions about their productivity. Additionally, given that a significant portion of migration in LMICs originates from neighboring countries, closer cultural, linguistic, and social ties often exist, potentially mitigating any differences in these characteristics as sources of preference for natives.

This paper uses an artifactual field experiment to investigate the extent to which immigrant status affects job offers, offered salaries, and perceptions of candidates' suitability for different formal sector jobs. Experienced Human Resource Recruiters (HRRs) were hired to evaluate job candidate profiles in a setup that simulated realistic conditions of remote work. HRRs had to assess pairs of candidates for various high- and low-skilled positions typical of the Ecuadorian labor market. HRRs were informed that each candidate pair had already been pre-selected for the position, and their task was to evaluate each profile, rate their suitability for the job, propose salaries for each, and make a hiring recommendation. The profiles presented were

[1] In standard correspondence callback studies researchers send fictitious resumes to real job openings, experimentally varying a characteristic of interest (e.g. race or gender). Researchers then measure whether each fictitious applicant receives a callback from employers.

constructed to be comparable in observable characteristics that predict on-the-job productivity, such as education levels and years of experience. However, in some cases, one profile was randomly assigned to be that of a Venezuelan migrant.[2] This experimental setup enables us to explore how migrant status influences HRRs' decisions while holding other candidate characteristics constant.

The focus on Venezuelan migrants is deliberate. Since 2015, Venezuela has witnessed the departure of over 7.7 million individuals, with most of them settling in other Latin American countries. This migration flow constitutes the region's largest displacement and ranks as the world's second-largest (IDB, 2023). Such significant and rapid migration flows can provoke anti-migrant sentiments among host populations (Hangartner et al., 2019; Ajzenman et al., 2023), yet how employers and recruiters respond to these arrivals remains less understood. Particularly, Venezuelan migrants often possess higher educational levels compared to native populations in neighboring countries, including Ecuador. Additionally, Venezuelans and Ecuadorians share historical, cultural, and racial similarities, with Venezuelans in Ecuador less likely than Ecuadorians to identify as a racial minority, a factor associated with worse labor market outcomes due to discrimination (Arceo-Gomez and Campos-Vazquez, 2014). Moreover, the common use of Spanish in both countries mitigates concerns about language competency influencing preferences for natives (Oreopoulos, 2011). However, while these shared characteristics may facilitate migrant integration, observational estimates from a nationally representative household survey in Ecuador indicate a wage gap of at least 14% between Ecuadorians and Venezuelans in the formal sector, controlling for relevant demographic factors. The drivers of these disparities—whether stemming from employer preferences, migrant behavior, or other unobservable factors—remain unclear.

In the experiment, if there were no preferences for natives, we would expect each candidate profile to be chosen approximately 50% of the time. However, we find that native candidates' profiles were selected for the positions 59% of the time, while Venezuelan candidates' profiles

[2]Because the objective of this exercise was to determine the potential penalties that migrants face in the labor market, candidate profiles were built to resemble those of Venezuelan migrants in the Ecuadorian population. Therefore, Venezuelan profiles had at least some education or experience in their home country. HRRs' perceptions of the quality or relevance of this foreign education and experience could contribute to the migrant penalty. This approach contrasts with other research focused solely on disentangling the impact of national or ethnic origin on labor market outcomes.

were chosen 41% of the time, on average. Converting these percentages to a 'relative callback rate' to align with the broader correspondence literature, we estimate a callback ratio of 1.4.[3] This magnitude is in line with results from existing callback experimental studies on migration to high-income countries, which typically report relative callback rates ranging from 1.1 to 2.5 for positions that are predominantly low-skilled and entry-level (Bertrand and Duflo, 2017). Additionally, HRRs perceived Venezuelan candidates to be 0.22 standard deviations less suitable for the jobs and proposed salary offers for them that were approximately 3% lower. This not only provides evidence of a penalty in salary offers but also suggests that the possibility of offering differential compensation does not fully offset the preference for natives.

As part of the hiring process, HRRs provided sociodemographic information and completed a set of questionnaires commonly used in recruitment to assess cognitive abilities and personality traits. This allows us to correlate these characteristics with HRRs decisions, a feature not viable in correspondence studies. Existing work has associated job recruiters' years of experience and discriminatory practices in observational data (Gutfleisch and Samuel, 2022), and the psychology literature has linked traits such as agreeableness and openness with self-reported levels of prejudice (Sibley and Duckitt, 2008; Crawford and Brandt, 2019) and negative attitudes toward immigrants (Gallego and Pardos-Prado, 2014). However, we find little evidence that the age, experience, personality traits, levels of self-esteem, or cognitive scores of HRRs correlate with their hiring preferences or salary offers. In contrast, there is suggestive evidence that job characteristics affect the preference for natives. For instance, we observe a higher migrant penalty in low-skilled positions and in roles that require a higher degree of local knowledge.

This paper makes three contributions to the existing literature. First, it provides experimental estimates of the migrant penalty in a labor market outside high-income or OECD countries.[4] While callback experiments focusing on the role of ethnicity and gender have been imple-

[3]This ratio is computed by dividing the proportion of positive callbacks in the native group by that in the immigrant group, akin to a risk ratio or discrimination ratio (Lippens et al., 2023).

[4]Of the several studies that have experimentally found lower callback rates for people of foreign origin (first or second generation), the vast majority focus on the role that being from an ethnic minority or LMIC origin plays in high-income countries such as Italy (Busetta et al., 2018), Germany (Kaas and Manger, 2012), the Netherlands (Andriessen et al., 2012), Canada (Oreopoulos, 2011; Dechief et al., 2012), Australia (Booth et al., 2012), the United States (Pager et al., 2009), Switzerland (Fibbi et al., 2006), and Norway (Midtbøen, 2013).

mented in LMICs (Galarza and Yamada, 2017; Arceo-Gomez and Campos-Vazquez, 2014), there is little experimental work concerning the magnitude of the migrant penalty in these contexts. An exception is an experiment by Loiacono and Vargas (2019), who experimentally vary refugee status in vignettes presented to Ugandan employers, who show a preference for Ugandan natives, and Abarcar (2015) who show evidence of penalties to return migrants in the Philippines. Our study also identifies a substantial preference for native workers, despite the shared language and the higher average education level of Venezuelans in the population.

Second, this study, along with a series of companion papers focusing on different markets or populations (Zanoni et al., 2023; Zanoni, Acevedo, Zane, and Hernandez, Zanoni et al.; Hernández et al., 2023), adopts an alternative approach to that of correspondence studies to examine penalties against minorities. This approach allows to experimentally investigate outcomes typically unavailable in callback studies, such as effects on salary offers. Moreover, while the estimated callback rate from this methodology is not necessarily comparable to that from a traditional correspondence study, this alternative approach mitigates some ethical and practical considerations associated with conventional correspondence experiments (Bertrand and Duflo, 2017; Zschirnt, 2019). One significant difference is that HRRs are directly compensated for their participation, addressing the concern of wasting their time or resources. Additionally, this setup eliminates the risk of reinforcing stereotypes when there is no follow-up response from applicants after a callback. To counter any perception of artificiality, the experiment was carefully structured around a real job task. HRRs applied for the position and completed tasks remotely from home using an online platform that mirrored industry standards for this type of work. To formally examine the external validity of our field experiment, we rely on the SANS framework proposed by List (2020) and, through the paper, describe issues around selection, attrition, naturalness, and scalability.[5]

Finally, our study provides novel evidence on how the characteristics of HRRs influence a specific type of decision-making. Although personality traits and cognitive scores have been shown to predict job fit, earnings, and employment outcomes in the labor market (Groh et al.,

[5]'SANS' refers to an approach to assessing external validity. The idea is to better understand how differences between the empirical and target settings might affect the observed phenomena. This provides a structured way of discussing deviations that affect external validity.

2015; Almlund et al., 2011), we do not find evidence that these factors correlate with decisions in this particular context. Instead, the characteristics of the jobs and the potential match between candidates and positions seem to have greater explanatory power. While we consider these results as simply suggestive, they imply that interventions aimed at addressing HRRs' perceptions of the potential costs (real or perceived) associated with lower levels of local knowledge could be a promising approach for reducing the migrant penalty. Such interventions might prove more effective than those solely focusing on changing strategies for HRR recruitment or broad interventions targeting taste biases.

2 Background

2.1 Venezuelan Migrants in Ecuador

The exit of refugees and migrants from Venezuela is one of the most significant displacement crises in the world today. Between 2017 and 2024, over 7.7 million people have left the country, with 84% relocating to other countries in Latin America (UNHCR, 2024). Ecuador currently stands as the destination for the third-largest number of Venezuelan migrants in the region. Approximately 475,000 Venezuelan immigrants resided in Ecuador as of 2024 (UNHCR, 2024), accounting for 55% of all immigrants in the country (Jokisch, 2023). The arrival of Venezuelans since 2017 is the most significant immigration inflow that Ecuador has ever experienced (Herrera, 2022).

Migration policies in Ecuador regarding Venezuelans have evolved over the years. Prior to 2019, Venezuelans could enter Ecuador without a visa and were eligible for temporary residency and work authorization. However, since then the influx of migrants has increased substantially, which has resulted in a policy shift toward more restrictive measures regarding regularization and employment and an increase in the number of Venezuelans working in the informal sector (Herrera, 2022). Several experts have pointed out the economic benefits of integrating Venezuelans into the labor market, emphasizing the value of adding a more skilled workforce: Venezuelans are more educated than Ecuadorians and are more likely to have a tertiary education (Alvarez et al., 2022; Mejia-Mantilla et al., 2024).

Estimates of the impacts of Venezuelan migrants to Ecuador suggest limited overall effects on labor market participation or employment, with some displacement of women and workers with low levels of education (Olivieri et al., 2022). Yet, there is a widespread belief among Ecuadorians that this migration has had negative effects; in a perception survey, 73% of Ecuadorians perceived Venezuelan migrants as having a negative economic impact (World Bank, 2020b). At the same time, perceptions of discrimination against Venezuelans are prevalent: in a recent survey, 47% of Venezuelans in Ecuador reported experiencing at least some form of discrimination (International Organization for Migration, 2021).

2.2 Observational Estimates of Labor Market Differences by Country of Origin

We use data from the 2022 Ecuadorian National Household Survey to analyze the profiles of Venezuelan migrants in Ecuador. Table 1 presents socio-demographic characteristics comparing natives with individuals born in Venezuela, all aged 18–65. Columns (1) and (2) display means for the overall sample, columns (3) and (4) focus on those working for a salary, and columns (5) and (6) further narrow down to those in the formal sector.[6] Despite Venezuelans being more likely to be employed, which aligns with their status as economic migrants, we find similar patterns across these samples: Venezuelans in Ecuador appear to have higher educational attainment than natives and are more likely to self-identify as white or mestizo rather than Black or Indigenous. They are typically more likely to be younger and unmarried, with a reasonably balanced gender distribution. However, they also report a lower monthly income and hourly wages.[7]

To more formally explore earning differences by country of origin, Appendix Table A1 presents two sets of analyses. First, simple regressions of the logarithm of reported labor wages on an indicator variable denoting Venezuelan origin, controlling for other observable characteristics. Second, a Oaxaca-Blinder decomposition of this wage differential. In both cases we hold constant age and age squared, gender, years of education, province of residence,

[6] To classify individuals in the formal sector, we adhere to the standard definition in Ecuador of working in establishments with a tax ID number or registro único del contribuyente (RUC).

[7] Due to survey data limitations, the wage variable is constructed by dividing monthly income reported in December 2022 with the number of hours worked in the previous week multiplied by 4. While imperfect, we take this as a rough measure of earnings adjusted for the number of hours worked.

years of experience in the current occupation, and race/ethnicity. Column (1) shows results for all salaried workers, and column (2) re-analyzes the data just for those salaried in the formal sector. In general, we find a negative and statistically significant coefficient for Venezuelans. Row one in column (2) shows that Venezuelans earn 14% lower wages even among those in the formal sector, controlling for other determinants of productivity. As expected looking at the decomposition, most of the wage gap cannot be explained by endowments (row 3), rather it must be by other unobserved factors (row 4). The extent to which demand-side preferences from employers and recruiters might drive these gaps is something we investigate in the following sections.

3 Experimental Design

The experiment was implemented in 2022 in partnership with Grupo FARO, an Ecuadorian nongovernmental organization (NGO) with expertise in job search and training program initiatives.[8] The experiment was structured to appear as a plausible regular consulting opportunity for remote work, in which the HHRs were recruited to assist a multinational company in selecting and recommending candidates for various positions in Quito.

3.1 HRR Recruitment and their Characteristics

HRRs were recruited by Grupo FARO using two methods: advertisements posted on LinkedIn and respondent-driven sampling (RDS) referrals. RDS starts with a small group of individuals ('seeds'), who are then incentivized to refer other individuals with a specific profile. This is a common approach to sample populations who are difficult to reach (Crawford et al., 2018; Gile, 2011).[9] The HRR position was advertised as a temporary work assignment. Hired HRRs

[8]The organization conducts research, advocacy, and capacity-building activities. Grupo FARO supported various aspects of the project, for example, by providing guidance and assistance with data collection, designing job candidate profiles to mimic what would be standard in the Ecuadorian labor market, and handling the recruitment of the HRRs.

[9]As part of the RDS, each participant was asked to refer four additional HRRs. Referred individuals received an invitation to complete the task. If, after two days, the invited HRR had not responded, a second reminder email was sent. As long as they completed the task, an additional $5 US was paid for every additional HRR referred.

were compensated competitively based on local labor market rates.[10]

Following the referral or applications, HRRs were invited to register on an online platform. As part of the registration process, they provided information about their demographics, education, and work experience, mirroring what is typically required in any other job application and selection process. Additionally, they were asked to complete cognitive and non-cognitive assessments, commonly used to recruit job candidates. These included the Wonderlic Intelligence Quotient (IQ) test, the Rosenberg self-esteem scale, and the OCEAN-based personality test, which evaluates openness, conscientiousness, extroversion, agreeableness, and neuroticism (details can be found in Appendix B). To further ensure their suitability for the role, HRR candidates were also asked knowledge questions about local labor market laws and recruitment processes in Ecuador.

After completing the registration process, those who answered most of the knowledge questions correctly were emailed instructions to continue the process and access the online platform, where they would perform the candidate selection tasks.

A total of 836 HRRs showed interest in starting the application process, and of them, 391 completed at least one trial of the migrant experiment (38% were recruited from LinkedIn, and 62% recruited through RDS). Appendix Table A2 describes the characteristics of participating HRRs by the sampling method used to hire them.[11]

3.2 Data and Experimental Design

The experiment was carried out using an online platform designed to mirror a professional interface for candidate recruitment. HRRs were presented with job vacancies through the platform and had to evaluate pairs of candidates for each position. HRRs were told that the candidates had been pre-selected for each position, and their role was to assess their fit and propose a salary for each. While this preliminary vetting might influence how candidates were

[10] HRRs recruited through RDS were paid a lump-sum of US$20 after completing the exercise. Those recruited through LinkedIn were paid approximately US$30. The Ecuadorian minimum wage at the time was approximately US$2.5 per hour. The average assignment took less than an hour, so their compensation was eight times the minimum wage.

[11] Of the RDS recruits, 453 opened the platform, 244 completed the task, 75 registered but did not start the task, and 3 start but did not finish the task. Of the LinkedIn recruits, 321 opened the platform, 150 completed the task, 27 registered but did not start, and 3 started but did not finish.

perceived, potentially reducing the observable extent of penalties against migrants, portraying the candidates as pre-selected helped ensure that unequal treatment of migrants by HRRs did not stem from perceived differences in legal status in the country.

The jobs included low-skill (call center operator, maintenance technician, warehouseman, cleaning operator, and sales agent) and high-skill positions (accountant, software developer, computer engineer, project manager, and production supervisor in manufacturing). HRRs could click on each vacancy tab, and the platform would display the description of the position and show information about the objectives, tasks performed in the job, and the technical knowledge or training required by the position.

The platform would then show the candidates' profiles. Each job had two potential candidates, and for each, the platform showed the name and contact information of both side by side. Under each candidate, HRRs could click on four different tabs: personal information, education, experience, and additional information (see Appendix Figure A1 for an example).[12]

Each HRR was presented with ten randomly ordered job positions (which we denote trials). For all of them, the characteristics of applicants were designed to be similar in observables, however for three out of these ten trials, Venezuelan nationality and background was randomly assigned to one of the candidates. The nationality information was displayed under the personal tab, and profiles of Venezuelan candidates also indicated that they had previous education and/or work experience in their home country. However, all migrant profiles specified that the candidates had recent work experience in Ecuador. In that sense, our estimates capture not only national origin but also other characteristics of migrants and more closely represent the penalty that Venezuelans would face in the formal labor market. The remaining six trials randomized other personal characteristics, while one trial served as a placebo where no systematic differences were introduced between candidates.[13] In this article, we focus on the trials related to migrant status and exclude other trials from the analysis.

[12]The following was shown for each tab: (1) contact information (name, area of residence, telephone, and email), (2) personal information (date of birth, gender, nationality, area of residence, and whether the candidate belongs to a minority group), (3) educational background, (4) work experience, and (5) additional information.

[13]Two sub-experiments evaluated discrimination by lesbian and gay self-identification and gender, respectively. That work documents a negative penalty for gays and a positive penalty for lesbians (Zanoni et al., 2024), and preference towards women candidates (Zanoni et al., 2024). In this article, we exclude the gay/lesbian and gender trials.

Appendix Table A3 presents the balance of candidate attributes by nationality. As expected, on average, candidates were equivalent in terms of age, qualifications, experience, and educational attainment.

Once HRRs had reviewed the profiles, the platform prompted them to propose salary offers for each candidate (whether chosen or not) in US dollars (the currency of Ecuador), score candidates according to their perceived potential fit for the job (on a scale of 1 to 10), and select the better candidate for the specific job vacancy.

Overall, 316 HRRs evaluated 3 pairs of native/Venezuelan candidates, 68 HRRs evaluated 2 pairs, and 7 HRRs evaluated 1 pair, producing an analytic sample comprising 2,182 observations.

3.3 Empirical strategy

To estimate the Venezuelan migrant penalty, we run equations of the form:

$$Y_{i_{tr}} = \beta_0 + \beta_1 X_{it} + \beta_k Z_{it} + \epsilon_{i_{tr}} \tag{1}$$

where $Y_{i_{tr}}$ represents the dependent variable for candidate i, in trial t, for HRR r. The variable X_{i_t} has the value of one if the candidate being evaluated is Venezuelan. Z_{it} is a vector of controls that might include trial fixed effects, a dummy variable indicating the HRR was recruited via RDS, and controls for characteristics of the candidate profiles, such as age, gender, education level, years of experience, and number of previous jobs. We also show specifications controlling for HRR-trial fixed effects. We report heteroskedasticity-robust standard errors clustered at the HRR level.

We focus on three dependent variables. The first is an indicator variable with a value of one if the candidate is selected as the HRR's primary choice for the job, and a value of zero otherwise. The second is a 'fit for the job' score, which indicates the HRR's assessment of the job candidate's suitability for the position and is constructed by standardizing the raw score (subtracting the sample mean and dividing it by its standard deviation). Finally, we use the logarithm of the monthly salary that HRRs propose as most appropriate for each candidate.

Finally, we also estimate effect heterogeneity by running fully interacted models with characteristics of HRRs and job positions (Feigenberg et al., 2023).

4 Results

4.1 Main Results

Time and Profiles Engagement. We start by examining the amount of time HRRs spent on the recruiting platform. Panel A of Appendix Table A4 displays the proportion of times HRRs opened each tab. Panel B shows the total amount of time that HRRs spent reviewing the tabs for the migration experiment candidates, conditional on having opened them. We show averages for the entire sample and by recruitment method.

The vast majority of HRRs opened most of the candidate tabs, with the experience tabs being opened, on average, 95% of the time. Candidate nationality was presented on the personal information tab, though HRRs might also have inferred nationality by a candidate's having had education or labor experience in Venezuela.

HRRs spent, on average, close to 6.7 minutes reviewing the applications related to the migrant trial, and this amount of time is reasonably similar regardless of the method used to recruit them (Panel B). Again, the experience tab received most of the attention, followed by the education and additional information tabs.

Does migrant status affect how much time HRRs spend reviewing a candidate? One might hypothesize, for instance, that if HRRs strongly prefer natives, they may spend less time reviewing migrant profiles as soon as they see Venezuela listed as the country of origin. However, we do not find statistically significant differences by nationality in the likelihood that HRRs opened the tabs (Panel A, Appendix Table A5) nor on the amount of time they spent on each tab, conditionally on opening (Panel B). Overall, it does not seem that HRRs spent a differential amount of time reviewing each candidate.

Effects on Candidate Selection and Salary Offers. Appendix Subfigures A3a-A3c show the distributions of the outcome variables by migrant status. Table 2 presents regression results of the main experimental effects. Panel A shows that candidates who were identified as Venezuelan were between 18 and 19 percentage points less likely to be selected for a position relative to their Ecuadorian counterparts. In other words, when we take the simple specification without additional controls (column 1), we see that while Ecuadorian profiles were selected 59% of the time, Venezuelan profiles were only selected 41% of the time, equivalent to a callback ratio of approximately 1.43. The difference is statistically significant, and the result is robust to including additional controls. These effects do not appear to result from a bimodal distribution of choices. Appendix Subfigure A3d shows the fraction of HRRs selecting the native profile in 0, 1, 2, or 3 of their trials. Overall, while over 20% of HRRs consistently chose the native candidate in all their trials, the vast majority (70%) selected the Venezuelan candidate at least once.

An advantage of working directly with HRRs is that we can elicit their beliefs and proposed salaries for all candidates. We find that HRRs recommend offering Venezuelan candidates a monthly salary that is 2 to 3 percent lower (Panel B) and perceive Venezuelans to be 0.23 standard deviations less likely to be a good fit for the job (Panel C). While the effect on salaries is relatively modest compared to the wage differences estimated in the observational data, it remains robust across specifications and is statistically significant. Moreover, the fact that HRRs offer lower salaries and perceive Venezuelans to be a worse fit for the job suggests that the preference to hire natives is not driven by a preconceived notion that Venezuelans have higher reservation wages or are overqualified for these jobs.

4.2 Robustness

We conduct a series of robustness checks of our main results. First, to assess the seriousness of HRRs' engagement, we examine predictors of salary offers. Candidates being considered for high-skilled jobs receive higher salary offers (Appendix Table A7, column 1), and candidates with more education and years of experience also receive higher salary offers (Appendix Table A7, column 2). This helps alleviate concerns about random or inattentive responses from HRRs. Second, each HRR participated in at least one placebo trial where no specific characteristic was tested. Analyzing data from these trials, we find no systematic preference for either candidate (Appendix Table A8). Third, as the placement of migrant trials was randomized among the ten trials completed by HRRs, we analyze whether HRRs changed their behavior depending on the position of each subsequent migrant trial (Appendix Figure A4). This could occur if HRRs adjusted their decisions if, over time, HRRs realized the nature of the experiment. However, the data does not support this interpretation: although coefficients are noisier due to smaller sample sizes by trial number, coefficients are consistently negative, and we cannot reject that the migrant effects are similar across trials, irrespective of the trial number.

4.3 Heterogeneity by HRR characteristics

This section explores whether HRR characteristics predict a preference for natives. If HRR characteristics are predictive of their decisions, it could imply that the recruitment processes of HRRs may play a role in reducing migrant penalties.

Demographic characteristics. We begin by examining whether choices are influenced by HRR socio-demographic characteristics. We find no evidence suggesting that the gender of HRRs or their years of experience significantly affect their decisions. The interaction coefficients are small and statistically insignificant (Appendix Table A9).

There is some suggestive evidence that having a professional degree in human resources may mitigate some of the migrant penalties. The interaction term is positive for all dependent variables, although only statistically significant for the perception of fitness for the job. This could potentially be attributed to HRRs having a better understanding of labor laws or hiring processes.[14]

Cognitive Skills and Personality Traits. Next, we explore whether cognitive skills, personality traits, and self-esteem affect preferences for natives. Appendix Figure A5 shows histograms of HRR scores for the different variables collected and their distribution, which is the variation that we exploit. Our sample appears to score low in neuroticism and cognitive ability but high

[14] Indeed, participating HRRs with an HR major show a significant 6 percentage point higher fraction of correct answers in knowledge tests.

in other traits such as extroversion, conscientiousness, and self-esteem.

Table 3 presents the results. Unlike existing literature that has linked these variables to job performance and labor market outcomes (Callen et al., 2015; Heckman et al., 2006; Borghans et al., 2008), we find little evidence that these factors play a significant role in HRRs' choice of candidate, perceptions of job suitability, or salary offers. All interaction terms are small and statistically insignificant. While we cannot conclude that these characteristics would not influence candidate selection in a population with greater variability in these traits, or that these traits are correctly measured through recruitment questionnaires, our results suggest that within the sample of recruited HRRs, they do not appear to play a predictive role.

4.4 Heterogeneity by job characteristics

Skills. Next, we investigate whether there is a higher migrant penalty in high-skilled positions. If HRRs think degrees from Ecuador are of higher quality than those from Venezuela, we might expect a stronger preference for natives in these roles. We find the opposite: the gap in selection between natives and migrants is halved for high-skill positions (statistically significant at the 10 percent level). We also estimate a smaller gap in perceptions of job fit and suggested salary offers for high-skilled jobs, although we cannot reject that these gaps are similar from those in low-skilled jobs (Table 4, Panel A).

Local Knowledge. HRRs might recognize location-specific human capital as a key source of productivity (Bazzi et al., 2016) or they might anticipate that customers prefer dealing with locals. To explore this, we further categorize jobs as requiring a higher degree of local knowledge and/or public interface.[15]

[15] To objectively classify jobs we match them to their closest descriptions in O*Net (https://www.onetonline.org). We use two variables that most closely approximate our concept of 'local knowledge'. First, the level of knowledge of law and government that the job requires (Knowledge of laws, legal codes, court procedures, precedents, government regulations, executive orders, agency rules, and the democratic political process). Second, the extent to which the job involves performing for or working directly with the public. We combine both level scores to create an equally weighted index and classify jobs as requiring a higher degree of 'local knowledge' if they score above the sample median. This includes both high- and low-skilled jobs. For instance, call center operators, accountants, and sales advisors are classified as requiring a higher degree of local knowledge, whereas cleaning personnel, software developers, or maintenance technicians are not. Note that for the jobs we have the scores tend to be correlated, so its difficult to disentangle which component is more important.

We observe a stronger preference for native candidates in jobs requiring high local knowledge. Migrants are 26 percentage points less likely to be selected for these roles, compared to a 10 percentage point disadvantage in jobs with low local knowledge requirements. HRRs perceive Venezuelan candidates as 0.32 standard deviations less suitable for high local knowledge jobs. Furthermore, the interaction term indicates that most of the wage penalty stems from these positions (Table 4, Panel B).

While we take this as suggestive evidence, given the limited variation in job types and the possibility that the classification of these jobs might capture other features that could influence HRR decisions, this result aligns with other literature indicating that employers punish candidates for having work experience abroad (Abarcar, 2015). We note two additional points. First, all Venezuelan profiles displayed labor experience in Ecuador, suggesting that the effect is not simply driven by the costs of adapting to a job in a new country for the first time. Second, there is still a negative and significant effect on the selection and perception of fitness for jobs that do not require this type of local knowledge, indicating that this dimension alone does not fully explain the penalty.

5 Discussion and Conclusion

There is general acknowledgment that Venezuelan migrants fare worse in various markets in their host countries, limiting their economic and social integration. However, the magnitude of this phenomenon, its occurrence in the more regulated formal labor market, and the extent to which it is driven by demand-side factors remain unclear. We contribute to these questions by providing experimental evidence of the migrant penalty faced by Venezuelans in the Ecuadorian labor market.

In an experiment with HRRs, we find that when presented with observationally similar job candidate profiles, they show a significant preference for natives. We also find that migrant candidates are less likely to be considered fit for the job, possibly because HRRs rationalize their choices or infer something about the candidate's experience or education. The effect on proposed salaries is negative and statistically significant, but smaller compared to the overall preference for native candidates.

The experimental design closely resembled real-world hiring tasks, which enhanced its perceived realism. The setup encouraged HRRs to follow their normal decision-making processes by presenting the evaluation process as genuine remote work. The use of realistic job postings— developed from actual labor market data and validated through extensive consultations with the partner organization— added to the authenticity. Additionally, the structured format of the experiment, with clear instructions and compensation, was meant to signal professionalism and improve HRRs' focus and engagement with the task.[16]

We do not find much evidence suggesting that HRR characteristics such as age, gender, IQ, or personality traits correlate with their choices of candidates. In contrast, the characteristics of the job seem to affect how candidates are evaluated. The preference for natives is particularly pronounced in positions that require more local knowledge. This might suggest that influencing the perception—whether real or perceived—of migrants' ability to perform well in jobs requiring more location-specific human capital or public-facing roles could help close these gaps. Better understanding the mechanisms driving these preferences appears to be a promising area for future research.

Overall, the large inflow of migrants worldwide and the challenge of equitably integrating them into labor markets will remain pressing issues for years to come, particularly in LMICs. Understanding how recruiters and employers evaluate them and finding ways to address the real or perceived costs of employing migrants is crucial for supporting their integration.

[16]We consider the SANS framework to assess external validity (List, 2020). Regarding selection, the sample is composed of HRRs recruited through two distinct methods. We believe these individuals are knowledgeable of their occupation and likely representative of others in the Ecuadorian labor market. Attrition within the experiment was low, although we note that some HRR candidates who initially displayed interest in the job did continue the process to participate. We aimed for a high degree of naturalness in the platform and setting, closely resembling a contract job for human resource recruiters. The jobs were chosen to be representative of those available in the Ecuadorian labor market, and the information presented about candidates followed local norms. One difference, however, was that HRRs were presented with only two candidate options for each position, something explained to them by mentioning that they had already gone through a vetting process. The setting was realistic, as many jobs today are remote, with people using their own computers and working from home. In terms of scaling, this seems less critical, though large-scale candidate recruitment for Venezuelans is common practice. Overall, we believe that our results likely have a high degree of external validity based on these criteria.

6 Figures & Tables

Table 1: Demographic characteristics of Native and Venezuelan Adults in Ecuador

	All		Salaried		Salaried & Formal Sector	
	Natives	Venezuelan	Natives	Venezuelan	Natives	Venezuelan
	(1)	(2)	(3)	(4)	(5)	(6)
Age	38.52	33.39	37.01	32.59	35.58	31.50
	(13.57)	(10.28)	(11.89)	(9.60)	(11.52)	(9.18)
Male	0.47	0.46	0.64	0.59	0.61	0.60
	(0.50)	(0.50)	(0.48)	(0.49)	(0.49)	(0.49)
Married	0.32	0.15	0.29	0.13	0.26	0.12
	(0.46)	(0.35)	(0.46)	(0.34)	(0.44)	(0.33)
Minority	0.15	0.03	0.11	0.03	0.07	0.03
	(0.35)	(0.18)	(0.32)	(0.18)	(0.25)	(0.16)
Years of Education	10.50	12.67	11.35	12.78	12.14	12.65
	(4.40)	(3.15)	(4.34)	(3.15)	(3.65)	(2.98)
Worked last week	0.67	0.74	0.92	0.93	0.98	0.99
	(0.47)	(0.44)	(0.27)	(0.26)	(0.15)	(0.08)
Weekly hours worked	25.17	31.64	36.41	41.08	39.66	45.50
	(20.55)	(22.27)	(15.05)	(16.91)	(12.68)	(11.98)
Monthly Income	459.48	397.22	555.70	427.61	499.49	429.14
	(443.21)	(312.85)	(457.42)	(306.88)	(350.11)	(257.50)
Log(wage)	1.26	1.14	1.39	1.17	1.35	1.17
	(0.57)	(0.46)	(0.51)	(0.44)	(0.44)	(0.39)
Salaried	0.39	0.50	1.00	1.00	1.00	1.00
	(0.49)	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	212,396	3,189	83,334	1,662	22,913	880

Notes: Data are from the ENEMDU (2022). The table shows mean outcomes for adults aged 18–65 residing in Ecuador. Columns (1) and (2) show means for the entire sample, columns (3) and (4) restrict to those working for a salary (including government workers, employees and laborers, and excludes those self-employed, employers, house workers on non-paid employees). Columns (5) and (6) further restrict the sample to those working for a formal establishment, defined as establishments with a tax ID number or RUC. *Minority* has the value of one if the respondent self-reports as indigenous, Afro-descendant, or Black. The variable *Worked Last Week* has the value of one if the respondent worked at least one hour the previous week. The variable *Monthly Income* is reported in US dollars and corresponds to the labor salary the respondent received in December of 2022. *Log(wage)* was constructed taking the logarithm of the *Monthly Income* variable divided by the number of hours the respondent worked during the previous week multiplied by four (which might not correspond to the number of hours worked in that specific month) and adding one to deal with zeros. All summary statistics use sample weights.

Table 2: Effects of Venezuelan Origin on Selection, Salary Offers, and Perception of Job Fit

	(1)	(2)	(3)	(4)
Panel A. Selected for the job:				
Venezuelan	-0.18***	-0.19***	-0.19***	-0.18***
	(0.03)	(0.03)	(0.03)	(0.03)
Mean Native	0.59	0.59	0.59	0.59
Observations	2182	2182	2182	2182
Panel B. Log of salary:				
Venezuelan	-0.03***	-0.02***	-0.02**	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Mean Native	6.71	6.71	6.71	6.71
Observations	2180	2180	2180	2180
Panel C. Fit for the job:				
Venezuelan	-0.23***	-0.23***	-0.23***	-0.23***
	(0.04)	(0.04)	(0.04)	(0.04)
Mean Native	0.08	0.08	0.08	0.08
Observations	2182	2182	2182	2182
Candidates' characteristics	NO	YES	YES	NO
Recruitment method dummy	NO	YES	NO	NO
Position skill level dummy	NO	YES	YES	NO
HRRs' FE	NO	NO	YES	NO
Trial Number FE	NO	NO	YES	NO
Trial-HRR FE	NO	NO	NO	YES

Note: In Panel A, the dependent variable is a dummy variable indicating whether the candidate was selected for the position ('Selected for the job'). In Panel B, the dependent variable is the natural logarithm of the salary proposed for the candidates. In Panel C, he dependent variable represents the HRR rating of the candidate's fitness for the job, standardized to have a mean of zero and a standard deviation of one in the sample. Each column controls for different characteristics. *Candidates' characteristics* include: their age, gender, education, number of previous jobs, and years of experience. Robust standard errors are clustered at the HRR level and are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 3: Heterogeneity by HRR test results

	(1) Selected	(2) Fit for job	(3) Log(salary)
Panel A. Big 5			
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Agreeableness	0.01	0.02	0.00
	(0.03)	(0.04)	(0.01)
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Openness	0.01	0.02	0.01
	(0.03)	(0.04)	(0.01)
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Extroversion	0.01	0.03	-0.00
	(0.03)	(0.04)	(0.01)
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Neuroticism	-0.01	0.01	-0.00
	(0.03)	(0.04)	(0.01)
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Conscientiousness	0.03	0.05	0.01
	(0.03)	(0.04)	(0.01)
Panel B. Cognitive ability			
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Wonderlic test	0.03	0.06	0.00
	(0.03)	(0.03)	(0.01)
Panel C. Self-esteem			
Venezuelan	-0.18***	-0.23***	-0.03***
	(0.03)	(0.04)	(0.01)
Venezuelan × Rosenberg test	-0.00	0.02	-0.00
	(0.03)	(0.04)	(0.01)

Note: The values in the table are OLS coefficients that identify the mean difference in the outcomes associated with candidates who belong to a minority and those who do not. In horizontal Panel A, the dependent variables are dummy variables indicating whether the candidate was selected ('called back') for the position. In Panel B, the dependent variable is the natural logarithm of the wage proposed for the candidates. In Panel C, the dependent variable represents the candidate's fit for the job, measured on a scale of 1 to 10. Regressions control for recruitment method fixed effects and trial number fixed effects. Standard errors clustered at the HRR level and robust are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4: Heterogeneity by job characteristics

	(1) Selected for job	(2) Fit for job	(3) Log(salary)
Panel A. High-skilled jobs			
Venezuelan	-0.25***	-0.28***	-0.03**
	(0.05)	(0.06)	(0.01)
Venezuelan $\times$ High skill	0.13*	0.11	0.01
	(0.07)	(0.08)	(0.02)
Panel B. Job requires local knowledge			
Venezuelan	-0.10*	-0.12*	-0.01
	(0.05)	(0.06)	(0.01)
Venezuelan $\times$ Local Knowledge	-0.16**	-0.21**	-0.04**
	(0.07)	(0.08)	(0.02)

Note: The dependent variables are dummy variables indicating whether the candidate was selected for the position ('selected for job'), a standardized measure of the perception of whether the candidate is fit for the job, and the natural logarithm of the proposed salary. The regressions show a heterogeneity analysis by whether the position is classified as high-skilled or by whether it requires a higher degree of local knowledge (see text for details). Regressions control for HRR fixed effects and trial number fixed effects. Standard errors clustered at the recruiter level and robust are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

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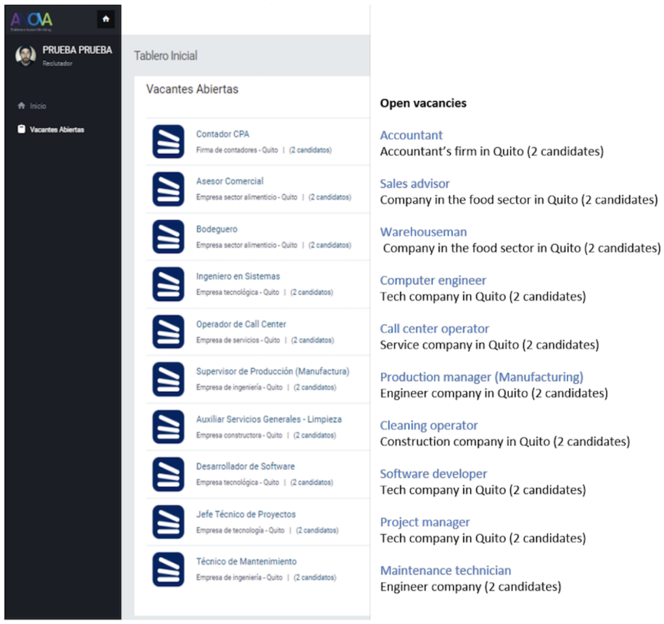
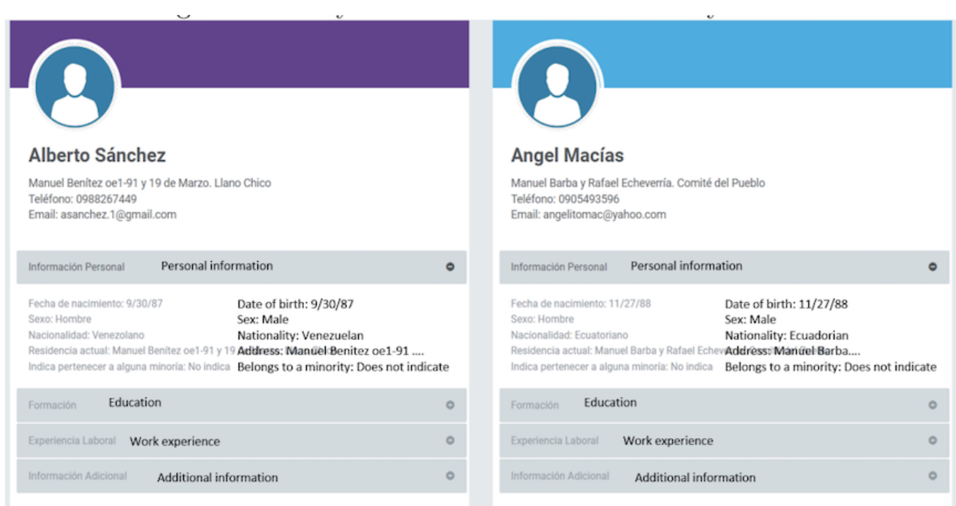
A Appendix: Additional Figures and Tables

Figure A1: Vacancies and candidate profiles

(a) Job vacancies

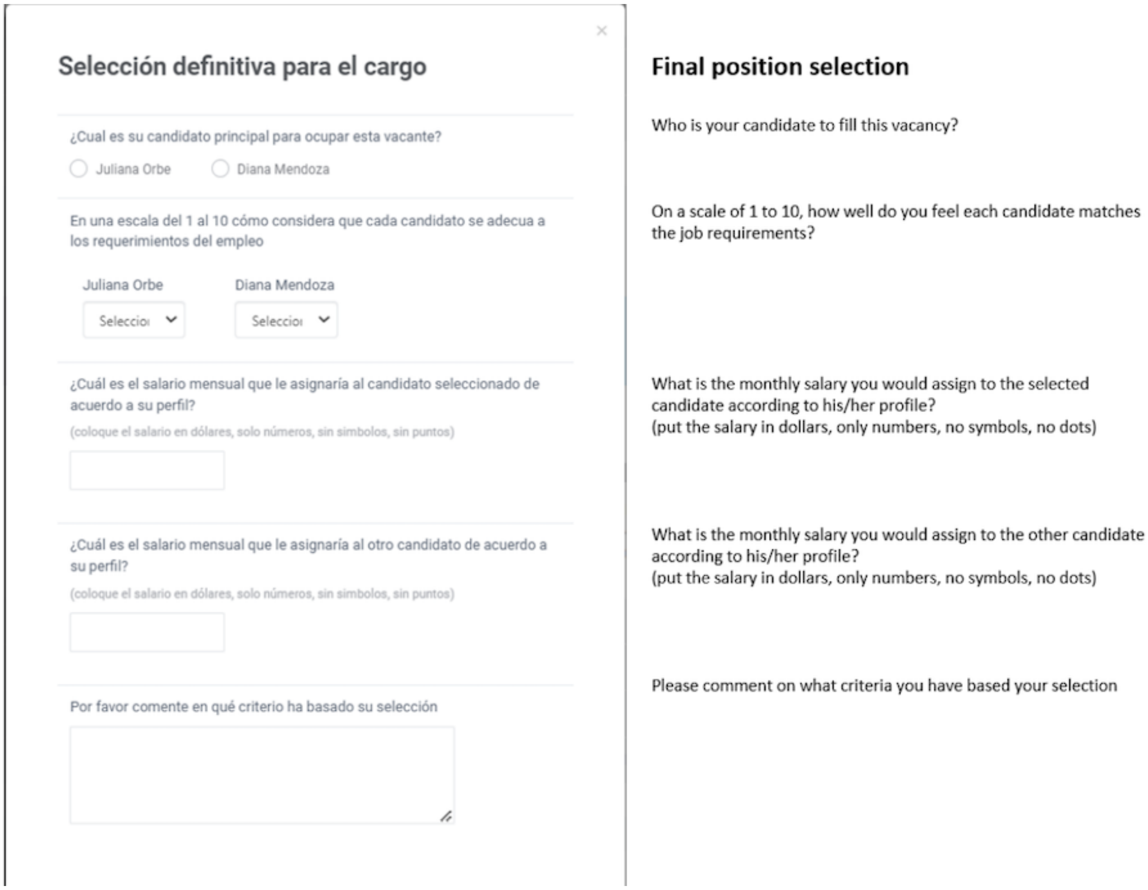


(b) Candidate profiles



Note: The figures show the platform's appearance and what HRRs could see (we present an English translation of the tabs on the right-hand side). Panel (a) shows the screen with all job vacancies, and Panel (b) shows the appearance of the candidate profiles. In this example, the personal information tab is open (HRRs had to click on it to open it). Information about nationality was presented on this tab.

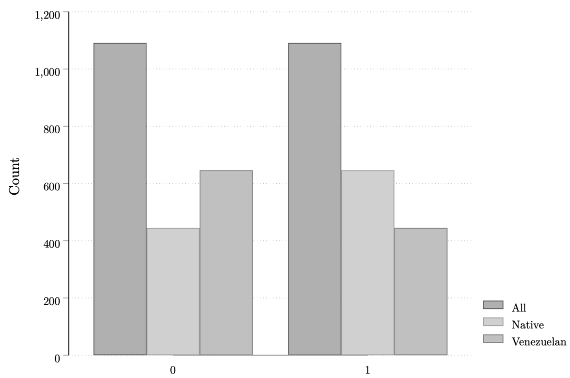
Figure A2: Outcome measurement



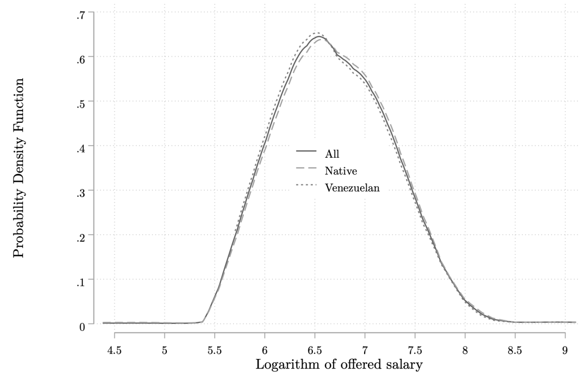
Note: The figure shows the screen on the platform where HRRs could report their evaluations once they had seen both candidate profiles (we present an English translation on the right-hand side).

Figure A3: Distributions of outcome variables

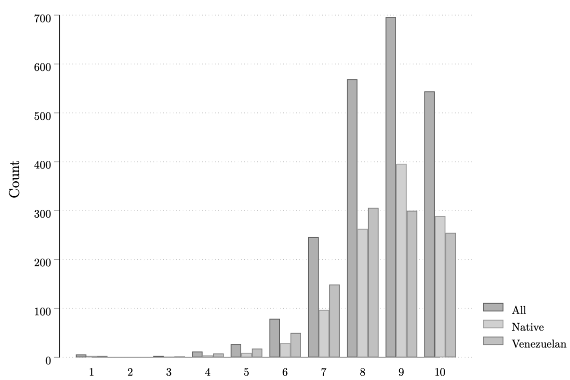
(a) Candidate Selection



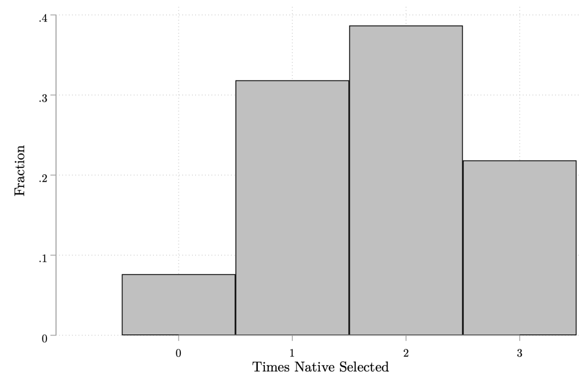
(b) Log of salary



(c) Fit for the job

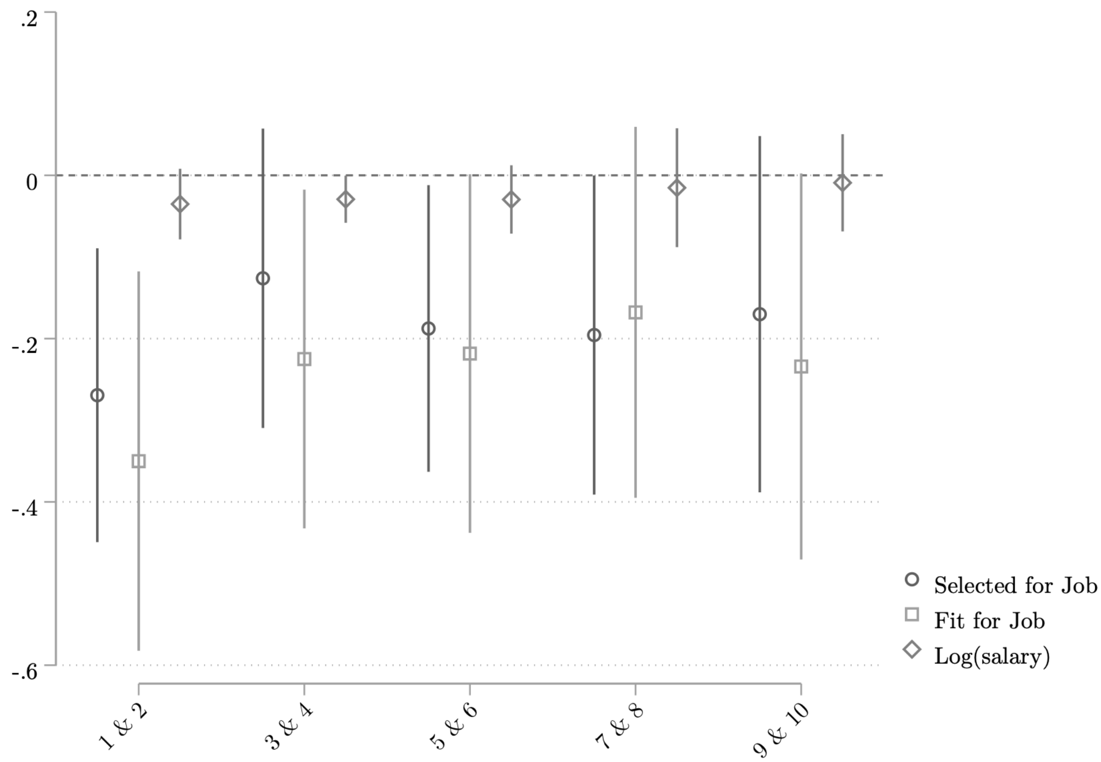


(d) Fraction of times natives selected (out of 3 trials)



Note: Subfigure (a) shows a histogram of selected profiles by Venezuelan or native status. Subfigure (b) shows a probability distribution function for the logarithm of the proposed salary by immigrant status, and Subfigure (c) shows a histogram of the raw scores on the fit-for-the-job scale (from 1 to 10) by Venezuelan or native status. Subfigure (d) shows the fraction of HRRs that choose the native profile in 0, 1, 2 or 3 of their trials.

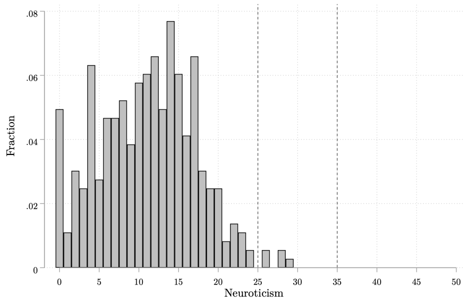
Figure A4: Effects by Trial Number



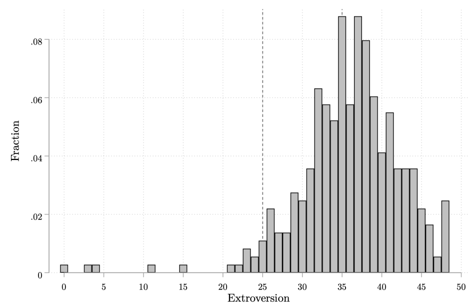
Note: Point estimates from specifications of the dependent variable(s) (selected for the job, fit for the job, and log(salary)) on the dummy denoting Venezuelan status by trial number. We combine trials in pairs to increase power. The regressions control for candidate characteristics, high-skilled position dummy, HRR fixed effects, and trial number fixed effects. Robust standard errors are clustered at the HRR level.

Figure A5: Distribution of cognitive and non-cognitive test results

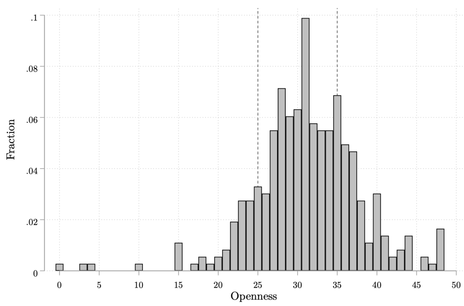
(a) Neuroticism



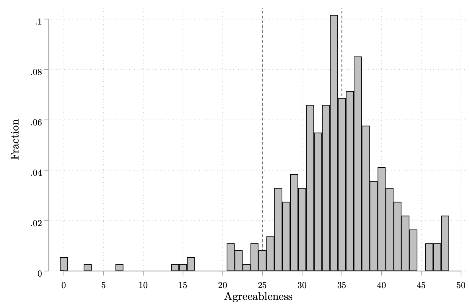
(b) Extroversion



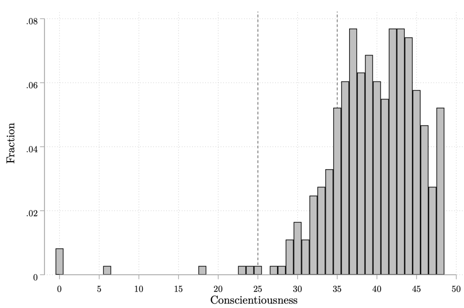
(c) Openness



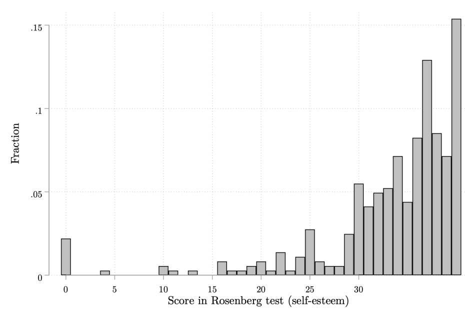
(d) Agreeableness



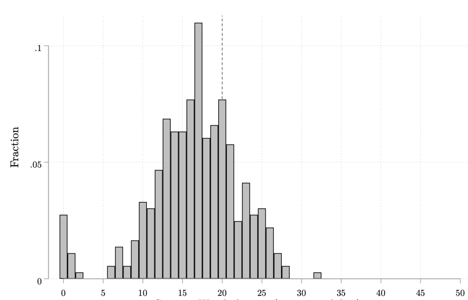
(e) Conscientiousness



(f) Rosenberg (self-esteem)



(g) Wonderlic (cognitive scores)



Note: The subfigures show the distribution of the HRR scores for the OCEAN variables, and the Rosenberg test, and the Wonderlic test. The space between the dotted vertical lines denotes the range of 'moderate' scores for the OCEAN variables. For the Rosenberg and Wonderlic scores, it denotes what is considered an average score.

Table A1: OLS and Oaxaca-Blinder decomposition estimates

Dependent var: Log(wage)	Salaried (1)	Formal Sector (2)
2) Oaxaca: Differential	0.224***	0.156***
	(0.011)	(0.013)
3) Oaxaca: Endowments	0.024	0.053
	(0.024)	(0.038)
4) Oaxaca: Coefficients	0.245***	0.144***
	(0.011)	(0.013)
5) Oaxaca: Interaction	-0.045*	-0.041

Note: Data are from the ENEMDU (2022). The table shows mean outcomes for adults aged 18–65 residing in Ecuador. Column (1) restricts to those working for a salary (including government workers, employees and laborers, and excludes those self-employed, employers, house workers on non-paid employees). Column (2) further restrict the sample to those working for a formal establishment, defined as establishments with a tax ID number or RUC. Row (1) presents coefficients of simple regression of log(wages) on a dummy variable denoting Venezuelan origin. Columns (2)-(5) show estimates from a Oaxaca- Blinder decomposition. All estimations use sample weights and control for the following socio-demographic characteristics: age and age squared, years of experience on the current occupation, as well as dummy variables for gender, years of education, province of residence, and race/ethnicity. *Log(wage)* was constructed taking the logarithm of the *Monthly Income* variable divided by the number of hours the respondent worked during the previous week multiplied by four (which might not correspond to the number of hours worked in that specific month) and adding one to deal with zeros. Stars indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: HRR characteristics: Demographics, Experience, and Test Results Results

Variable	All (1)	LinkedIn (2)	RDS (3)
Panel A. Demographics and experience			
Age	31.42	32.62	30.70
	(7.43)	(7.18)	(7.50)
Female	0.70	0.69	0.71
	(0.46)	(0.46)	(0.45)
Ecuadorian	0.98	0.95	0.99
	(0.15)	(0.21)	(0.09)
Employment Experience (years)	6.82	7.86	6.18
	(5.96)	(5.52)	(6.14)
Employed	0.60	0.54	0.63
	(0.49)	(0.50)	(0.48)
Bachelors degree?	0.92	0.99	0.88
	(0.27)	(0.12)	(0.33)
Human Resources Major	0.74	0.76	0.74
	(0.44)	(0.43)	(0.44)
Knowledge of Quito's Labor Market (share)	0.94	0.96	0.93
	(0.14)	(0.11)	(0.15)
Panel B. Results from cognitive and non-cognitive tests			
Neuroticism	10.32	8.79	11.26
	(6.51)	(5.78)	(6.76)
Extroversion	33.49	33.61	33.41
	(11.07)	(11.97)	(10.52)
Openness	29.10	28.78	29.30
	(10.20)	(10.49)	(10.04)
Agreeableness	31.94	32.07	31.86
	(10.84)	(11.42)	(10.50)
Conscientiousness	36.61	36.52	36.67
	(11.77)	(12.58)	(11.27)
Score in Rosenberg test (self-esteem)	31.05	30.30	31.51
	(11.29)	(12.20)	(10.70)
Score in Wonderlic test (cognitive ability)	15.45	15.07	15.69
	(6.72)	(6.88)	(6.63)
Observations	391	148	243

Note: The table shows summary statistics for HRRs. Column (1) includes all HRRs who participated in the migrant experiment. Column (2) and (3) restrict the sample to HRRs recruited by LinkedIn and by RDS, respectively. *Ecuadorian* is a dummy variable that takes value 1 if the HRR is from Ecuador. *Employed* takes the value one if the HRR reports having another job. *Human Resource Major* takes the value one if the HRR has a professional degree in Human Resources. *Knowledge of Quito's Labor Market* refers to the share of correct answers.

Table A3: Balance in Job Candidate Characteristics by Nationality

Variable	Native (1)	Venezuelan (2)	Difference (3)
Age	29.88	29.74	-0.14
	(3.74)	(3.64)	(0.16)
Female	0.67	0.67	0.00
	(0.47)	(0.47)	(0.02)
Number of Previous Jobs	2.96	2.96	0.00
	(0.76)	(0.76)	(0.03)
Employment Experience (years)	4.63	4.70	0.06
	(1.33)	(1.44)	(0.06)
Professional	0.61	0.61	0.00
	(0.49)	(0.49)	(0.02)
Education: Secondary	0.11	0.11	0.00
	(0.31)	(0.31)	(0.01)
Education: Technical	0.28	0.28	0.00
	(0.45)	(0.45)	(0.02)
Education: Professional	0.61	0.61	0.00
	(0.49)	(0.49)	(0.02)

Note: The table shows the mean characteristics of native and Venezuelan job candidate profiles and their difference. Stars indicate the statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A4: HRRs' Time Use on the Platform

Variable	All (1)	LinkedIn (2)	RDS (3)
Panel A. Opened tabs			
Opened Personal Information tab	0.78	0.86	0.73
	(0.30)	(0.24)	(0.33)
Opened Work Experience tab	0.95	0.98	0.93
	(0.16)	(0.07)	(0.19)
Opened Schooling/Training tab	0.89	0.93	0.87
	(0.22)	(0.16)	(0.25)
Opened Additional Information tab	0.73	0.79	0.70
	(0.32)	(0.27)	(0.34)
Panel B. Time reviewing applications (minutes)			
Total time (min)	6.65	7.90	5.88
	(4.94)	(5.58)	(4.33)
Time on Personal Information tab (min)	0.70	0.80	0.64
	(0.65)	(0.62)	(0.67)
Time on Work Experience tab (min)	3.94	4.73	3.46
	(3.81)	(4.29)	(3.40)
Time on Schooling/Training tab (min)	1.49	1.65	1.40
	(1.57)	(1.79)	(1.42)
Time on Additional Information tab (min)	0.81	1.00	0.70
	(0.91)	(0.99)	(0.84)

Note: In Panel A, the rows present the proportion of times the HRR opened the Personal Information, Work Experience, Schooling/Training, and Additional Information tabs across all candidates. Panel B reports the meantime (in minutes) that HRR spent performing evaluations of job candidates, conditional on the HRR's opening the corresponding tab on the platform. Column (1) shows results for the entire sample of HRRs (N=391), column (2) for those recruited through LinkedIn (N=148), and column (3) for those recruited through RDS (N=243).

Table A5: HRRs: Time Use on the Platform by Type of Candidate

Variable	Native (1)	Venezuelan (2)	Difference (3)
Opened tabs:			
Opened Personal Information tab	0.78	0.78	0.01
	(0.42)	(0.41)	(0.02)
Opened Work Experience tab	0.95	0.95	0.00
	(0.22)	(0.22)	(0.01)
Opened Schooling/Training tab	0.89	0.90	0.01
	(0.31)	(0.30)	(0.01)
Opened Additional Information tab	0.73	0.73	-0.00
	(0.44)	(0.44)	(0.02)
Time reviewing applications:			
Total time (min)	1.25	1.26	0.00
	(1.48)	(1.41)	(0.06)
Time on Personal Information tab (min)	0.16	0.17	0.01
	(0.23)	(0.24)	(0.01)
Time on Work Experience tab (min)	0.75	0.74	-0.00
	(1.24)	(1.21)	(0.05)
Time on Schooling/Training tab (min)	0.29	0.30	0.01
	(0.52)	(0.50)	(0.02)
Time on Additional Information tab (min)	0.21	0.19	-0.01
	(0.37)	(0.36)	(0.02)

Note: In Panel A, the rows present the proportion of times the HRR opened the Personal Information, Work Experience, Schooling/Training, and Additional Information tabs across all candidates. Panel B reports the meantime (in minutes) that HRR spent performing evaluations of job candidates, conditional on the HRR's opening the corresponding tab on the platform. Column (1) shows results for profiles of native candidates, column (2) for profiles of Venezuelan candidates, and column (3) shows the difference between (1) and (2). Stars indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A6: Correlates of Salary Offers

Table A7: Correlates of Salary Offers

	(1)	(2)
High-skilled position	0.61^{***}	
	(0.02)	
Education level		0.33^{***}
		(0.02)
Employment Experience (years)		0.08^{***}
		(0.01)
Male		0.00
		(0.02)

Note: The table shows simple regressions of the natural logarithm of proposed salaries on a dummy variable denoting whether the position was high-skilled (column 1) and the observable characteristics of job candidate profiles (column 2). Robust standard errors are clustered at the HRR level. Stars indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A8: Placebo

	(1)	(2)	(3)	(4)
Panel A. Selected for the job:				
Candidate A	0.02	0.02	0.02	0.02
	(0.05)	(0.05)	(0.07)	(0.05)
Mean Candidate B	0.49	0.49	0.49	0.49
Observations	738	738	738	738
Panel B. Log of salary:				
Candidate A	0.01	0.00	0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Mean Candidate B	6.69	6.69	6.69	6.69
Observations	738	738	738	738
Panel C. Fit for the job:				
Candidate A	0.02	0.02	0.02	0.02
	(0.06)	(0.06)	(0.08)	(0.06)
Mean Candidate B	-0.02	-0.02	-0.02	-0.02
Observations	738	738	738	738
Candidates' characteristics	NO	YES	YES	NO
Recruitment method dummy	NO	YES	NO	NO
Position skill level dummy	NO	YES	YES	NO
HRRs' FE	NO	NO	YES	NO
Trial Number FE	NO	NO	YES	NO
Trial-HRR FE	NO	NO	NO	YES

Note: The table shows coefficients that identify the mean difference in the outcomes associated with randomly assigned candidate A vs. candidate B (a placebo test). In Panel A, the dependent variable is a dummy variable indicating whether the candidate was selected ('Selected for the job') for the position. In Panel B, the dependent variable is the natural logarithm of the salary proposed for the candidates by HRRs. In Panel C, using a standardized scale, the dependent variable represents the candidate's fit for the job. Robust standard errors are clustered at the HRR level and are reported in parentheses. Stars indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A9: Heterogeneity by HRR Demographics

	(1) Selected	(2) Fit for job	(3) Log(salary)
Recruiter: Female			
Venezuelan	-0.18***	-0.23***	-0.02*
	(0.06)	(0.08)	(0.01)
Venezuelan × Female HRR	-0.01	0.01	-0.00
	(0.07)	(0.09)	(0.02)
Recruiter: Years of experience			
Venezuelan	-0.18***	-0.18***	-0.02**
	(0.05)	(0.05)	(0.01)
Venezuelan × HRR Experience (years)	0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.00)
Recruiter: HR major			
Venezuelan	-0.27***	-0.35***	-0.04**
	(0.06)	(0.07)	(0.02)
Venezuelan × HR Major	0.11	0.16**	0.02
	(0.07)	(0.08)	(0.02)

Note: The dependent variables are dummy variables indicating whether the candidate was selected for the position ('selected for job'), a standardized measure of the perception of whether the candidate is fit for the job, and the natural logarithm of the proposed salary. The regressions show a heterogeneity analysis by whether the HRR is female, the HRR's number of years of experience in a related occupation, and whether they have a professional degree in human resources.Regressions control for recruitment method fixed effects and trial number fixed effects. Standard errors clustered at the recruiter level and robust are reported in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

B HRR tests

Wonderlic Intelligence Quotient. This assessment is used to gauge potential employees' cognitive ability and problem-solving aptitude across various occupations. The test consists of 50 multiple-choice questions measuring mathematical, verbal, logical, and analogical reasoning skills to be completed within a 12-minute window. The scaled score ranges from 0 to 50. A score of 20 is the standard benchmark taken as an average score for this assessment.

Rosenberg self-esteem test. This assessment is designed to measure self-esteem. Respondents indicate on a scale of 0 to 3 whether they strongly agree or disagree with statements such as 'I feel I do not have much to be proud of' or 'I feel that I am a person of worth, at least on an equal plane with others'. It is scored in a scale of 0 to 30, and a score less than 15 is considered to be indicative of low self-esteem.

OCEAN-based personality test. The OCEAN personality test empirically assesses five personality traits: openness, conscientiousness, extroversion, agreeableness, and neuroticism. These together form a widely accepted taxonomy of personality traits. Openness is a trait denoting receptivity to new ideas and new experiences. Conscientiousness is the propensity for self-discipline, meeting duties, and pursuing goals. Extroversion is characterized by outgoingness and high energy. Agreeableness reflects a tendency to have and maintain prosocial relationships. Neuroticism is a tendency towards negative feelings such as anxiety, depression and self-doubt.